REPORT DOCUMENTATION PAGE

Form Approved OMB No. 0704-0188

1. REPORT DATE ***(DD-MM-YYYY)***	**2. REPORT TYPE**	**3. DATES COVERED** *(From – To)*
26-08-2009	Final Report	22 August 2008 - 18-Aug-09

4. TITLE AND SUBTITLE

The Timing of Social Comparison in Crowds

5a. CONTRACT NUMBER
FA8655-08-1-3065

5b. GRANT NUMBER

5c. PROGRAM ELEMENT NUMBER

6. AUTHOR(S)

Professor Gal Kaminka

5d. PROJECT NUMBER

5d. TASK NUMBER

5e. WORK UNIT NUMBER

7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES)
Bar Ilan University
Computer Science Dept.
Ramat Gan 52900
Israel

8. PERFORMING ORGANIZATION REPORT NUMBER

N/A

9. SPONSORING/MONITORING AGENCY NAME(S) AND ADDRESS(ES)

EOARD
Unit 4515 BOX 14
APO AE 09421

10. SPONSOR/MONITOR'S ACRONYM(S)

11. SPONSOR/MONITOR'S REPORT NUMBER(S)
Grant 08-3065

12. DISTRIBUTION/AVAILABILITY STATEMENT

Approved for public release; distribution is unlimited.

13. SUPPLEMENTARY NOTES

14. ABSTRACT

Models of crowd behavior facilitate analysis and prediction of the behavior of large groups of people, who are affected by each other's presence and actions. For instance, in defense and security applications, generative models of crowd behaviors are used for decision-support, simulation, and training. Most existing approaches for modeling crowd behavior have focused on algorithmic and mathematical approaches, which generate simulations which are qualitatively or visually appealing, but have not been tied to social psychology, nor to cognitive architectures. In previous work, we proposed a novel model of crowd behavior, based on Social Comparison Theory SCT, a popular social psychology theory. The SCT model relies on simulated entities (agents) to compare themselves to others, but the timing of these comparisons is not well understood: People clearly do not imitate others all the time, yet there is evidence that shows that people (and therefore, the agents), do some comparison at all times (but do not at on these comparisons). While some progress has been made to address this question, it remains open. In this report, we present an extension of the SCT model to address this open question. We argue that comparisons take place all the time (i.e., differences are perceived and processed), but the cognitive architecture limits actions taken to minimize differences to cases where the comparisons yield significant differences. We use both toy domain experiments as well as movies of human pedestrians to argue for our position. Two corollaries of our work are (i) implications for the role of agent modeling and plan recognition in cognitive architectural mechanisms, and (ii) initial steps in accounting for group size in social comparison.

15. SUBJECT TERMS
EOARD, Behavior Based Prediction, Behavioral Science

16. SECURITY CLASSIFICATION OF:			**17. LIMITATION OF ABSTRACT**	**18, NUMBER OF PAGES**	**19a. NAME OF RESPONSIBLE PERSON**
a. REPORT	**b. ABSTRACT**	**c. THIS PAGE**			TAMMY SAVOIE, Lt Col, USAF
UNCLAS	UNCLAS	UNCLAS	UL	29	**19b. TELEPHONE NUMBER** *(Include area code)* +44 (0)1895 616459

The Timing of Social Comparison: Year 1 Final Report

EOARD Contract Number #083065

Natalie Fridman and Gal A. Kaminka
The MAVERICK Group
Computer Science Department
Bar Ilan University, Israel
{fridman, galk}@cs.biu.ac.il

Aug 18, 2009

Contents

List of Tables

List of Figures

List of Algorithms

Abstract

Models of crowd behavior facilitate analysis and prediction of the behavior of large groups of people, who are affected by each other's presence and actions. For instance, in defense and security applications, generative models of crowd behaviors are used for decision-support, simulation, and training. Most existing approaches for modeling crowd behavior have focused on algorithmic and mathematical approaches, which generate simulations which are qualitatively or visually appealing, but have not been tied to social psychology, nor to cognitive architectures.

In previous work, we proposed a novel model of crowd behavior, based on Social Comparison Theory (SCT), a popular social psychology theory. The SCT model relies on simulated entities (agents) to compare themselves to others, but the timing of these comparisons is not well understood: People clearly do not imitate others all the time, yet there is evidence that shows that people (and therefore, the agents), do some comparison at all times (but do not at on these comparisons). While some progress has been made to address this question, it remains open.

In this report, we present an extension of the SCT model to address this open question. We argue that comparisons take place all the time (i.e., differences are perceived and processed), but the cognitive architecture limits actions taken to minimize differences to cases where the comparisons yield significant differences. We use both toy domain experiments as well as movies of human pedestrians to argue for our position. Two corollaries of our work are (i) implications for the role of agent modeling and plan recognition in cognitive architectural mechanisms, and (ii) initial steps in accounting for group size in social comparison.

1 Introduction

Modeling crowd behavior is an important challenge for cognitive science and psychology (Le Bon, 1968; Allport, 1924). Accurate models of crowd behavior are sought in training simulations, safety decision-support systems, traffic management, and organizational science. Indeed, a variety of computational models have been proposed that exhibit crowd-like behavior in different tasks. For instance, cellular automata models are used to model pedestrian movements (Blue & Adler, 2000; Helbing & Molnar, 1997) or people evacuating an area in emergency (Helbing, Molnar, Farkas, & Bolay, 2001; Kretz, 2007).

Unfortunately, only a handful of existing models of crowd behavior have been evaluated against real-world human crowd data. Moreover, essentially no computational cognitive models have been proposed which are tied to cognitive science theory. Instead, existing models are often inspired by particle physics (modeling individuals as particles), or by cellular automata. Thus fitting in the models with a deeper cognitive model of humans, or the mechanisms of a cognitive architecture, is difficult.

In previous work, we presented a novel cognitive model of crowd behavior (Fridman & Kaminka, 2007), which has two key novelties (compared to previous models): First, there is a single computational mechanism (algorithm) used to generate different crowd phenomena (Fridman & Kaminka, 2009; Fridman, Kaminka, & Traub, 2009); and second, it is inspired by social psychology theory. In particular, the model is based on Social Comparison Theory (*SCT*) (Festinger, 1954), a popular social psychology theory that has been continuously evolving since the 1950s. The key idea in SCT is that humans, lacking objective means to evaluate their state, compare themselves to others that are similar.

We believe that social comparison is a general cognitive process underlying social behavior of each individual in crowd. Unlike previous crowd models that concentrate on specific behavior, the SCT model can account for different crowd behaviors, depending on the perceptions and actions available to each individual (Fridman & Kaminka, 2007). However, while the SCT model proved superior to other computational models in behaviors-specific measures (e.g., the formation of lanes in bidirectional movement) (Fridman & Kaminka, 2007), and in validation against human crowd data (Fridman & Kaminka, 2009; Fridman et al., 2009), it leaves open several challenges.

During the course of the year, we had focused on one particular question left open by the SCT model, namely the question of *when* it is used to guide action-selection in agents. In particular, social psychology theory advocate a model in which social comparison occurs only when the agent lacks objective means to evaluate its own progress (Festinger, 1954). This approach, in which the social comparison process is triggered only when the agent is uncertain as to how to pursue its task goals, works successfully when used to simulate bi-directional pedestrian movement. However, it fails when modeling uni-directional movement; here, an approach in which agents compare themselves to others—and act on differences found—at all times is preferable. This on-going comparison approach is also supported by some evidence from social psychology and economics. Earlier successful demonstrations of the fidelity of the SCT model thus switched between different triggering mechanisms ad-hoc; in Section 2 we present the results of experiments which demonstrate that the two triggering mecha-

nisms are mutually-exclusive. This interferes with a clear understanding of how social comparison processes are used within a cognitive architecture; clearly, social comparison at the architecture level cannot change based on the domain.

As part of the research, we hypothesized that social comparison processes are indeed on-going, and that humans are aware of—and compare themselves to—others at all times. Our hypothesis is that action selection mechanisms in the cognitive architecture are responsible for sometimes selecting actions which minimize social differences (i.e., act on the social comparison results), and at other times, selecting actions that serve other goals. We experimented with two alternative mechanisms, and were able to rule one of them out. This result puts constraints on the cognitive architecture mechanisms that are used in social comparison.

Additionally, we examined alternative SCT algorithms, extending and refining the SCT algorithm published earlier, in (Fridman & Kaminka, 2007). An important motivation for this was the fact that the previously published algorithm ignored the group size in comparison, while evidence from social psychology shows that in fact group size is an important factor in the social action-selection of the individual. The refined algorithms are presented and examined experimentally.

The report is organized as follows. Section 2 presents a short literature overview and necessary background, and presents the results of the experiments motivating this research into the triggering of social comparison processes. Section 3 then presents two alternative architectural action-selection mechanisms, and related experiments. Section 4 presents several SCT algorithms that expand and refine the original model, and experiments that provide evidence for their efficacy. Section 5 concludes, lists publications resulting from this research, and discusses directions for continuing it.

2 Background and Motivation

We discuss background literature in Section 2.1. We then discuss our own previous work in Section 2.2. There, we also present results which motivate this research.

2.1 Related Work

Social psychology literature provides several views on the emergence of crowds and the mechanisms underlying its behaviors. These views can inspire computational models, but are unfortunately too abstract to be used algorithmically. In contrast, computational crowd models tend to be simplistic and focus on specific crowd behaviors (e.g, flocking). A common theme in all of them is the generation of behavior from the aggregation of many local rules of interaction, e.g., (Rymill & Dodgson, 2005; Reynolds, 1987, 1999; Kretz, 2007). However, these models have rarely, been validated against human (or animal) data. Indeed, there is generally limited quantitative data on the behavior of human crowds at a resolution which permits accurate modeling. The exception is the formation of lanes (in opposing directions) in human pedestrian movements and evacuation behavior (Daamen & Hoogendoorn, 2003; Kretz, 2007), which have been extensively investigated and for which specific performance measures are well defined

(reduced lane changes, flow, time between alarm and last person that leave the building etc.). We discuss many of these psychology and computational research works below.

A phenomenon observed with crowds, and discovered early in crowd behavior research is that people in crowds act similar to one another, often acting in a coordinated fashion, which is achieved with little or no verbal communication. Moreover, the crowd may cause its members to behave differently than they would have individually. There are several different theories that explain this crowd characteristics, focusing on the cognitive process underlying each individual within the crowd.

Contagion Theory (Le Bon, 1968) emphasized a view of crowd behaviors as controlled by a "Collective Mind", and observed that an individual who becomes a part of the crowd is strongly affected by it, to the extent that she is transformed into becoming identical to the others in the crowd. Le Bon explains the homogeneous behavior of a crowd by two processes: (i) *Imitation*, where people in crowds imitate each other; and (ii) *Contagion*, where people in a crowd behave very differently from the way they usually do, individually.

On the other hand, Convergence Theory (Allport, 1924) states that crowd behavior is a product of the behavior of like-minded individuals. According to Allport's theory, individuals become a part of the crowd behavior when they have a "common stimulus" with people inside the crowd; for example, a common cause (Allport, 1924). Allport agrees with Le Bon (1968) about the homogeneous behavior of the crowd.

Researchers have developed computational models for simulation of collective behavior. However, these models are not often tied to cognitive processes underlying individual behavior in crowd and have rarely been validated against human data.

Reynolds (Reynolds, 1987) simulated bird flocking using simple, individual-local rules, which interacted to create coherent collective movement. There are only three rules: avoid collision with neighbors, match velocity with neighbors and stay close to the center of gravity of all neighbors. Each simulated bird is treated as a particle, attracted and repelled by others. On the one hand there is a desire to stay close to the flock, but on the other hand, there is a desire to avoid collisions. However, this model was limited only to the interaction of the agents, and did not allow for their individual goals (e.g., their own steering behavior).

Tu and Terzopoulos (Tu & Terzopoulos, 1994) simulated motion of artificial fish that addressed individual goals. Like Reynolds' "boids", the artificial fish are autonomous creatures which have simple behaviors and together are able to create a more complex, collective behavior. However, unlike Reynolds' boids, that selected their behavior based on the current state of their neighbors, each fish revealed habits and mental state (for example hunger, fear etc.) that also impact behavior selection. Indeed, Reynolds later expanded his work on collective movement in (Reynolds, 1999) but, this time allowing for a steering behavior for the autonomous agents. In the revised model, each agent has a set of simple steering behaviors such as seek, flee, pursuit, evade, etc. The combination of these simpler behaviors creates a complex steering behavior.

Similar ideas have been applied in swarm robotics. Matarić (Matarić, 1995) sees collective (complex) behaviors as a combination of basic behaviors. Each robot has spatial behaviors (controllers) that are combined to create different kinds of group behavior: for example, flocking consisting of *safe-wandering* (moving around with-

out bumping), *homing*, *dispersion* (moving away from other agents), and *aggregation* (moving towards other agents). The combined outputs of the basic behaviors provide a velocity vector which is used to control the robot.

Yamashita and Umemura (Yamashita & Umemura, 2003) take a different approach in simulating panic behavior. While inspired by Reynolds' boid model, they propose a model where each simulated person moves by three instincts: escape instinct, group instinct and imitational instinct. According to Yamashita and Umemura, when a person is in panic, he or she acts based on their instincts which make their decision making process much simpler.

Henderson compared pedestrian movement to gaskinetic fluids. Based on experiments on real human crowds, he showed in (Henderson, 1971) that crowd distribution is compatible with Maxwell-Boltzmann's distribution. Henderson (Henderson, 1974) developed a pedestrian movement model based on the Maxwell-Boltzmann theory. Since each person has mass and velocity, the crowd may be transformed to liquid gas and under some assumption the Maxwell-Boltzmann theory may be applied. Based on Boltzmann-like equations, Helbing (Helbing, 1993) developed a general behavior model for simulation of crowd dynamics. The proposed model takes into account social forces caused by interaction between the individuals and external or spontaneous forces which are caused by the physical environment.

Helbing et al. (Helbing et al., 2001; Helbing & Molnar, 1997) observed phenomena of self-organization in collective motion which can be caused by interaction among pedestrians. By self-organization, it means that there are some behavioral phenomena which were not planned: for example, creation of lane formation in pedestrian movement. These lanes are created as a result of pedestrians moving against the flow. When a pedestrian moves against the flow, he experiences an interaction which makes him move a little aside, in contrast to a pedestrian who moves with the flow and will not have an interaction. The number of lanes that are created cannot be planned. It depends on the width of the street and on pedestrian density.

Helbing and Vicsek (Helbing & Vicsek, 1999) expanded their physical model by using game theory. The attraction force can be expanded to profitable force which may lead to optimal self-organization in pedestrian movement. Each entity calculates "expected success" per each possible action and the action with maximum success will be chosen. In pedestrian relations, actions are possible directions that an entity can move to and optimal self-organization is minimal interaction between entities.

Adriana Brown et al. (Braun, Musse, Oliveira, & Bodmann, 2003) examined how individual characteristics impact crowd evacuation. They expanded Helbing's physical model by adding to each agent individual parameters, such as dependence level and altruism level. According to the model, there will be a creation of groups which are combined from altruism and dependent agents. By changing these attributes, they examined crowd evacuation by measuring the flow of people passing the door per second and population distribution in the flow.

Blue and Adler (Blue & Adler, 2000) proposed a different approach to module collective dynamics. They used Cellular Automata (CA) in order to simulate collective behaviors, in particular pedestrian movement. The focus is again on local interactions: Each simulated pedestrian is controlled by an automaton, which decides on its next action or behavior, based on its local neighborhoods. These rules are responsible for

making a decision about lane changing and forward movement: If the way forward is free, then it is taken. If not, then the automaton seeks to go left or right. If both lanes are available, one is chosen arbitrarily. Blue and Adler showed that this simple rule results in the formation of lanes in movement, similarly to those formed in human pedestrian movement (Wolff, 1973). Toyama et al. (Toyama, Bazzan, & Silva, 2006) expanded the cellular automata model by adding different pedestrian characteristics, such as speed, gender, repulsion level, etc. The model was examined on bi-directional pedestrian movement behavior and on evacuation behavior. The experiment analysis shows that macroscopic behavior of homogeneous agents is different from heterogeneous agents.

Osaragi (Osaragi, 2004) proposed an agent-based model for simulating pedestrian flow by using the concept of pedestrian mental stress. Pedestrian mental stress increases as a result of other pedestrians (density) and whether the pedestrian is unable to move to her destination using the shortest pass. To decrease her mental stress, the pedestrian may dynamically change her direction or walking velocity. Because of these dynamic changes, the simulated pedestrians are heterogeneous. Unlike in other models, the model parameters were estimated using observed data.

Kretz (Kretz, 2007) proposes the Floor field-and-Agent based Simulation Tool model (F.A.S.T) which is discrete in space and time model for pedestrian motion. The F.A.S.T model can be classified as an extension of probabilistic Cellular Automata (PCA). In this model there are three levels of decision making: 1. The choice of an exit. 2. The choice of a destination cell. and 3. The path between the current and destination cell. The F.A.S.T model has been validated against human data. In particular, the model simulation results of evacuation scenario was compared to results of evacuation exercise at a primary school.

In these previous works above, the behavior of crowds in every domain of study (pedestrian movement, flocking, evacuation, etc.) is computed using a different algorithm, yet the actions and perceptions remain largely invariant (e.g., distances to others, occupied spaces versus empty spaces, goal locations, etc.). Instead, the computation itself changes between modeled behaviors.

For instance, many models for crowd behavior utilize cellular-automata (CA), which differ between domains. One CA model for pedestrian movement (Blue & Adler, 2000) uses a set of 6 IF-THEN rules which work in parallel for all cells, to simulate the movement of pedestrians in cells. The rules utilize knowledge of the occupancy in adjacent (rules 1,3 in (Blue & Adler, 2000)) and farther cells (rule 2), as well as of the distance to oncoming pedestrians in the same lane (rules 4, 6). The rules set the forward velocity and position of the entities, by using a set of non-deterministic choices (sub-rules 5a,5b,5c), biased by distributions which differ depending on the environmental settings (e.g., choose from a uniform 50%/50% split distribution if two nearby cells are occupied, or from a 10%/80%/10% distribution when three cells are available). In contrast, a recent CA model for evacuation (Tissera, Printista, & Errecalde, 2007) uses knowledge of adjacent cells and distances to exits, and sets the position of the entities. Thus the actions and perceptions of each entity are similar to those used in the pedestrian model. But the algorithmic computation of the new position is done in two deterministic rules (Tissera et al., 2007, pp. 17), which involve no arbitrary choices at all.

In contrast to these previous investigations, we seek a single cognitive mechanism

that, when executed by individuals, would give rise to different crowd behaviors, depending on the perceptions and actions available to the agents. In other words, our goal is to unravel a *single computational mechanism*—a single algorithm—which would account for different crowd phenomena, by virtue of the actions and perceptions available to each individual.

2.2 An Existing Model of Social Comparison

Over the last few years, we have been developing a model of social behavior inspired by Festinger's social comparison theory (Festinger, 1954). To the best of our knowledge, social comparison theory has never been applied to modeling crowd behavior. Nevertheless, as we show in the next sections, key elements of the theory are at the very least compatible with those theories discussed above.

According to Festinger's theory, people tend to compare their behavior with others that are most like them and then attempt to correct any differences found. We operationalized these principles in algorithmic form (Fridman & Kaminka, 2007), briefly described below.

An agent that uses social comparison observes agents around it, compares itself to them, and potentially acts on differences found. Each observed agent A is taken to be a tuple of k state features $A \equiv \langle f_1^A, \dots, f_k^A \rangle$. Each feature f_j^i of agent i ($1 \leq j \leq k$) corresponds to a dimension, such that agent i is represented by a point in a k-dimensional space, where the various dimensions correspond to state features (such as location in x,y coordinates, color, heading, etc.

We measure similarity between agents independently along each dimension. The similarities in different dimensions are functions $s_{f_i}(f_i^{A_{me}}, f_i^{A_c}) : f_i \times f_i \mapsto [0,1]$. The function s_{f_i} defines the similarity in feature f_i between the two agents A_{me} and A_c. A value of 0 indicates complete dissimilarity. A value of 1 indicates complete similarity. For instance, one commonly used feature denotes normalized Euclidean distance, inverted: A value of 0 means that the agents are as far apart as possible. A value of 1 means that they are positioned in the same location.

To determine the overall similarity between two agents, we use a weighted sum over the functions s_{f_i}. With each feature f_i, we associate a weight $w_i \geq 0$. The similarity between two agents is then given by Eq. 1 below.

$$Sim(A_{me}, A_i) \equiv \sum_{j=1}^{k} s_{f_j}(f_j^{A_{me}}, f_j^{A_i}) \cdot w_j \tag{1}$$

Each observing agent A_{me} executes the following algorithm (Algorithm 1). For each observed agent $A_o \in O$, we calculate a similarity value $Sim(A_{me}, A_o)$, which measures the similarity between the observed agent and the agent carrying out the comparison process (A_{me}). An agent A_c, with the highest similarity value within the bounds (S_{min}, S_{max}) is selected. We determine the list of features (f_i, w_i) which cause the differences between A_{me} and the selected agent A_c. We order these features in an increasing order of weight w_i, such that the first feature to trigger corrective action is the one with the lowest weight. Then we trigger an action (a) to reduce the discrepancy (a library

of actions is assumed to be available). We use the action a with some scale—which we term gain–given in the calculation of the *Gain* function below (Eq. 2). This gain translates into the amount of effort or power invested in the action. For instance, for movement, the gain function would translate into velocity; the greater the gain, the greater the velocity.

Algorithm 1 Argmax SCT $(O, A_{me}, S_{min}, S_{max})$

$S \leftarrow \emptyset$
for all $A_o \in O$ **do**
  if $S_{min} < Sim(A_{me}, A_o) < S_{max}$ **then**
    $S \rightarrow S \cup A_o$
$A_c \leftarrow \texttt{argmax}_{A_c \in S}(Sim(A_{me}, A_o)$
$D \leftarrow$ differences between me and agent A_c
$a \leftarrow$ SelectAction(D)
Apply action a with its Gain (Eq. 2) to minimize differences in D.

$$Gain(Sim(A_{me}, A_c)) \equiv \frac{S_{max} - S_{min}}{S_{max} - Sim(A_{me}, A_c)} \tag{2}$$

Unfortunately, while early uses of Algorithm 1 were successful in modeling variations on pedestrian traffic (e.g., unidirectional vs. bidirectional, in groups, etc.), it turns out that the procedure triggering the execution of the algorithm had to be changed depending on the crowd modeling task (i.e., the pedestrian simulation variant). Moreover, this result is supported by common-sense observations, as well as expert literature. As the reader knows from her own experience, people do not constantly imitate others. On the other hand, there is evidence that people do compare themselves to others even when they do have objective means of evaluation (Hakmiller, 1966; Singer, 1966) (in contradiction to Festinger's claims in (Festinger, 1954)). The next section will address this question in detail.

3 When are Social Comparison Processes Triggered?

In this section, we address the question of *when* social comparison is triggered. We examine possible answers to it in Section 3.1, and conduct experiments that rule out some candidate solutions and enable others, in Section 3.2.

3.1 Social Comparison at the Cognitive Architecture Level

There are two possible implementations of SCT process in an architectural level. The first, which seems to follow directly from Festinger's Social Comparison theory, treats the SCT process as an uncertainty-resolution method, i.e., as a weak (read: general) problem-solving method, which is *social*. The second, takes a different approach, in which an SCT process is constantly active, in parallel to any problem solving activity which necessitates the agents to be constantly aware of others around them.

According to Festinger, people use social comparison when they have a lack of knowledge to make their decisions. Thus one way of implementing the SCT process in a cognitive architecture is as a response to an uncertainty: When an agent is at an uncertain state, it may call on a comparison process that will be used to assess similarity and propose actions.

We thus may treat the social comparison theory as a new kind of uncertainty-resolution method. Unlike previous uncertainty-resolution (problem-solving) techniques, in which the agent focuses on using its own resources, here the agent uses knowledge of others as a basis for resolving the uncertainty.

Readers familiar with the Soar integrated cognitive architecture will undoubtedly be reminded of the capabilities of Soar to detect *impasses*, situations in which the agent has no direct knowledge of how to proceed in its task, and relies on problem-solving methods to resolve the impasse (Newell, 1990). In this view of SCT as a problem-solving activity, it is modeled in Soar as an impasse-resolution method.

However, elaborations on social comparison theory expanded its view on when comparison takes place. Hakmiller (Hakmiller, 1966) and Singer (Singer, 1966) expanded the theory and demonstrated that people tend to confirm or reassure that their actions or beliefs are the correct ones, by comparing themselves to others. Thus according to this approach people tend to use social comparison in parallel to their decision making process.

We thus offer an account in which a second hypothesis (in which a comparison process is always active) can be made compatible with Festinger's observations (that comparison occurs with uncertainty). Our hypothesis is that social comparison should always be active *alongside* any goal-oriented action-selection processes. When uncertainty is low, this corresponds to the goal-oriented processes being able to produce coherent actions, which are then selected by the agents for execution. But when uncertainty increases (the goal-oriented processes are not suggesting actions for execution), the social comparison processes manages to "push" its own proposed actions for execution.

In other words, an alternative is to view the SCT as an on-going process, taking place (at the architectural level) *in parallel* to any problem-solving activity. Whereas normally, actions are proposed (and selected) by cognitive architecture based on their suitability for a current goal (e.g., through means-end analysis), in a socially-comparing architecture of this type, the agent actions are also proposed based on the results of social comparisons. In other words, the agent would consider actions that advance it towards its goal, *as well as actions that seek to minimize perceived differences to other agents*.

It may appear easy to dismiss the implementation question as insignificant. However, the implementation choice carries significant implication: As SCT processes inherently rely on knowing about the behavior of others, the implementation question raises a more fundamental question about where modeling of others (e.g., using plan recognition) occurs in cognition: Is it a problem-solving activity, or is it carried out all the time, at an architectural level.

3.2 Experiments

We conducted a set of experiments to evaluate which of these two approaches (*Comparison as Problem-Solving* or *Continuous Comparison*) is more applicable in the context of crowd behavior simulations. We recreated the experiment setup and simulation environment used in (Fridman & Kaminka, 2007; Fridman et al., 2009), and rewrote agents to operate in this environment (see Section 3.2.1). We examine the two approaches in the context of pedestrian grouping behavior and bidirectional movement of individual pedestrians, described in Section 3.2.2.

3.2.1 Simulation Environment and Setup

To simulate pedestrian behavior, we used Net-Logo (Wilensky, 1999). We define a sidewalk, 104 units in length, where agents were able to move in a circular fashion from east to west (reappearing in the east side when they go out of bounds in the west) or in opposite direction. Each agent had limited vision distance of 10 patches and cone-shaped-field-of-view of 120 degrees.

Each agent has a set of features and their corresponding weights. For simulating pedestrian movement, we used the following features and weights: *color* (weight 3); *walking direction* east or west (weight 2); and *position* (weight 1), given global coordinates. In grouping pedestrian simulation, to account for the western cultural intuition that friends (and family) walk side-by-side, rather than in columns, we used another feature: The similarity in position along the x-axis - *X-Coordinate* (weight 0.5).

The similarities in different features ($s(f_i)$) are calculated as follows:

- $s(f_{color}) = 1$ if color is the same, 0 otherwise.
- $s(f_{direction}) = 1$ if direction is the same, 0 otherwise.
- $s(f_{distance}) = max(\frac{1}{dist}, 1)$, where *dist* is the Euclidean distance between the positions of the agents.
- $s(f_{x-coordinate}) = 1$ if the x-coordinate is the same, 0 otherwise.

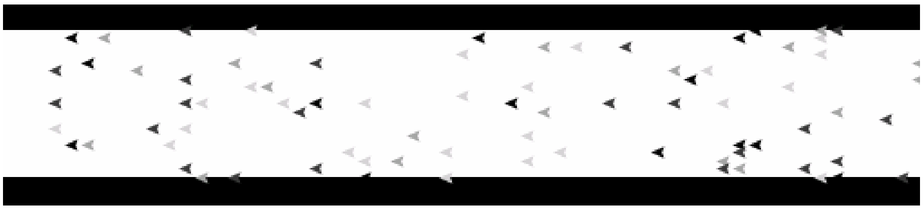
Each agent calculates $S(x)$. If the chosen feature for closing the gap is distance, then the velocity for movement will be multiplied by the calculated gain *Gain*. For other features (which are binary), the gain is ignored (as it has no effect on categorical

The rationale for feature priorities, as represented in their weights, follows from our intuition and common experience as to how pedestrians act. Positional difference (distance, side-by-side) is the easiest difference to correct, and the least indicative of a similarity between pedestrians. Direction is more indicative of a similarity between agents, and color (which we use to denote sub-groups within the crowds) even more so. For instance, if an agent sees two agents, one in the same direction as it (and far away), and the other very close to it (but in the opposite direction), it will calculate greater similarity to the first agent, and try to minimize the distance to it (this may cause a lane change) and only then try to locate itself on the same X-coordinate.

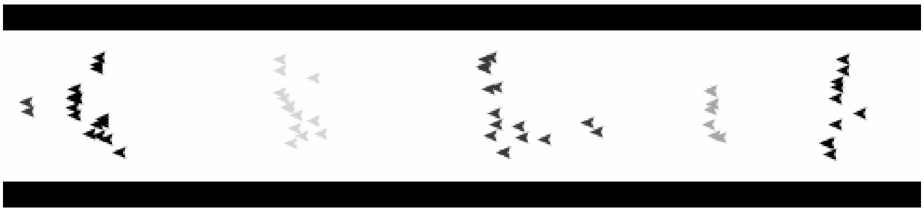
3.2.2 Two Crowd Modeling Tasks

We examine two pedestrian crowd tasks. In the first, the simulated pedestrians are all moving in the same direction (uni-directional traffic), and are divided into five groups, based on their color. Each agent is placed randomly, so that initially the group are dispersed. Successful execution of the task involves moving while creating clusters of groups of the same color. In the second task, the simulated pedestrians are moving in opposing directions (randomly assigned to agents). Each agent is independent of the others—no grouping is expected or desired.

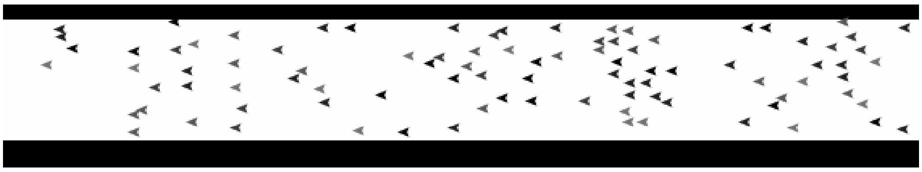
To illustrate, Figure 1 shows screen shots of the simulation running this task. The figures show the initial positions of the agents in one of the trials 1(a), their positions after moving 5000 cycles using the continuous SCT approach 1(b) and their positions after 5000 cycles using the problem-solving approach 1(c). The figures show that the continuous SCT approach accounts for grouping behavior while the problem-solving approach does not.



(a) Initial random positions.



(b) After 5000 cycles of continuous comparison.



(c) After 5000 cycles, social comparison only when stuck.

Figure 1: **Screen shots, Comparison of Implementation approaches in regard to Grouped Pedestrian Movement.**

For each of the two tasks, we compare between the two trigger types: The problem-solving, and the on-going continuous comparison. The only difference in the runs is in *when* the SCT process is activated. In the problem-solving trigger, the social

comparison process is activated only when the agent is stuck and is unable to proceed towards its movement goal. In the continuous mode, the agent constantly compares itself to others and acts on this comparison.

A summary of the results is presented in Table 1. The table examines quantitative task measures for the two different pedestrian crowd tasks. The first column lists the two tasks: Bidirectional traffic is a standard task in which individual agents walk in two opposing directions on a simulated sidewalk. There are no groups; each agent is individual. The second column lists the quantitative measures used to evaluate how well each task was carried out (although the measures are different, they both share the qualitative direction; a lower result is better). These quantitative measures are:

- The accumulated number of lane changes (i.e., how many times did agents need to move left or right). This is a standard measure in such tasks.
- The clustering—measured via hierarchical social entropy (Balch, 1998)—of the agents. A lower number indicated tighter groups (where agents belong to the same group if they are of the same color).

The column titled *Problem Solving* shows the result when the SCT algorithm is triggered only when the agents are otherwise stuck (in pedestrian traffic, this happens when its movement is blocked). The last column, titled *Continuous* shows the results when the SCT is continuously triggered (i.e., it is essentially always in control of the agent's actions). Each entry in the table averages the results of 15 runs; the standard deviation is provided in parentheses.

Pedestrian Task	Measure	Problem-Solving	Continuous
Bi-directional traffic	Accumulating lane changes	**8910.52 (***sd*.2434.7**)**	20942.23 (*sd*.5307.9)
Unidirectional traffic (in groups)	Clustering (Social Entropy)	171.75 (*sd*.11.9)	**102.36 (***sd*.19.15**)**

Table 1: Results for different triggering mechanisms for social comparison, in two different pedestrian traffic tasks. A lower result is better in both tasks. The winning triggering mechanism is different for each task.

The table shows that to get good results in the two tasks, we needed to have changed the triggering mechanism of the SCT algorithm. This result is of course supported by common-sense observations, as well as expert literature. As the reader knows from her own experience, people do not constantly imitate others. On the other hand, there is evidence that people do compare themselves to others even when they do have objective means of evaluation (Hakmiller, 1966; Singer, 1966) (in contradiction to Festinger's claims in (Festinger, 1954)).

4 Continuous Social Comparison with Action Selection

Our goal is to provide a single mechanism that accounts for different crowd behaviors (different tasks). The results above seemingly threaten this goal, as they seem to imply

that the appropriate triggering of social comparison is task-dependent, and therefore, one could argue, comparison does not take place at the level of the cognitive architecture.

In this section, we address this argument in depth. First, we examine it closely and show that in fact it may still be possible to account for the results while allowing social comparison to take place within the architecture (Section 4.1). Then, we examine ways of weighing proposed actions that are motivated by the social comparison process, so as to enable their selection by the architecture in a flexible manner (Section 4.2.

4.1 Social Comparison at the Architecture Level

Let us examine the conclusions of the previous section more closely. Can an architectural triggering mechanism of either type discussed above be made to support this task-dependent behavior? Surely, the problem-solving triggering mechanism cannot emulate continuous comparison. Quite simply, if it is not continuously running, it cannot simulate a process that is continuously running.

However, a continuous comparison mechanism may emulate a sometimes-triggered process, if the action-selection mechanism be made to sometimes ignore the actions chosen by the social comparison process. The change, in other words, would be in the final step of Algorithm 1: Rather than executing the action a, the algorithm should only be recommending it, allowing the action-selection mechanisms of the architecture to decide on its selection for execution. In this section we tackle this modification and its implications.

According to this view, the social comparison process should be implemented as secondary parallel process within the cognitive architecture. Whereas normally, actions are proposed (and selected) by architecture based on their suitability for a current goal (e.g., through means-end analysis), in our agent actions were also proposed based on their suitability for SCT. In other words, at every cycle, an agent would consider actions that advance it towards its goal and, it would also consider social actions that seek to minimize perceived differences to other agents. Thus, the SCT-proposed actions compete with the task-oriented actions for control of the agent.

We consider two potential action-selection mechanisms which allow the competition between goal-oriented actions and socially-oriented actions. For simplicity, we describe these using a hypothetical example in which two actions are proposed: One goal-oriented and one socially-oriented. Let us denote the weight (activation) of the goal-oriented action by α. Let us denote the weight of the social action, stemming from the social comparison process, by β. Then the following two alternative mechanisms are possible for choosing between the actions:

$max(\alpha, \beta)$. In this approach, reminiscent of early work on spreading activation techniques, the action selection mechanism simply selects the action with the greatest weight.

***threshold*β.** In this approach, the social action is selected for execution, but only if β is sufficiently high. That is, only if $\beta > C$ for some given constant C; otherwise, the goal-oriented action is selected.

In both cases, once the action is selected, it is executed. In the next decision-making cycle, new values for α and β are calculated, and again an action is selected, ad infinitum.

We leave the discussion on an agent's α (goal-oriented weight) out of the scope of this report. Work on activation-based action-selection has explored this issue in some detail. For our purposes here, it is suffice to assume that $0 \leq \alpha \leq 1$, where $\alpha = 0$ when the agent has no motivation to carry out the action, and $\alpha = 1$ when the agent is fully motivated to carry out the action.

The experiments which we describe later in this document involved direct comparison between the goal-oriented α and the social-oriented β. It is thus fair to ask how we set values for α, as the values chosen impact the results of the experiments. We selected an experiment design in which agents all have identical goals (movement in their assigned direction), and their α value varies between $\alpha = 1$ when their path is clear, and $\alpha = 0$ when they are blocked. Therefore, when analyzing these behaviors we can disregard the constant α measures and focus only on the changing β measures.

4.2 Calculating β

The bulk of our work during the year has focused on determining appropriate ways to calculate β values which would meet the following requirements:

- Facilitate good simulation of pedestrian traffic *in both tasks* described in Section 3. We saw one such approach in Algorithm 1.
- Work well when the social comparison process is continuously running. This is where Algorithm 1 fails, as it fails in the task of unidirectional traffic in groups.
- Preferably, be justifiable or otherwise compatible with cognitive science and psychology theory.

The β measure is supposed to be a function of the agent's attraction to the observed agents (with whom it compared itself). We distinguish between two approaches. The first approach, which has been taken in our earlier work (Algorithm 1) is based on selecting an individual agent from the group and calculate the attraction to it. In Algorithm 1 the agent chosen was the agent with the highest similarity, that was still less than the maximal similar threshold S_{max}. The second approach, which we have been developing this year, takes an entire group of agents into account when calculating β, without singling out any particular agent.

Algorithm 2 revises the earlier algorithm to allow our revised view of the social comparison process. It differs from the earlier algorithm in several ways. First, rather than selecting an action *a* and executing it, it returns a recommendation for *a*, with a weight β. Formally, it returns a tuple $\langle a, \beta_a \rangle$. Second, it no longer selects a single most-similar agent. Rather, among all observed agents that are not too dissimilar or too similar (i.e, agents in S), a representative agent is selected by GetAgentForComparison(S), which abstracts the selection process. We will discuss several versions of this process. D gets a list of features which corresponds on differences between me and the compared agent A_c. Then, an agent calculates β value, which represents agent's attractiveness to the selected group. The function CalculateBeta(A_c,S, S_{min}, S_{max}) receives

the compared agent (A_c), the selected group (S) and the similarity bounds S_{min}, S_{max}) and returns the β value. In the following section we compared between different methods to calculate the agent's attractiveness to the group (β), which replaces the use of the gain function in the earlier version of the algorithm.

Algorithm 2 *SCT* $(O, A_{me}, S_{min}, S_{max})$

$S \leftarrow \emptyset$
for all $A_o \in O$ **do** {Add only agents not too similar or dissimilar}
  if $S_{min} < Sim(A_{me}, A_o) < S_{max}$ **then**
    $S \rightarrow S \cup A_o$
$A_c \leftarrow$ GetAgentForComparison(A_{me}, S)
$D \leftarrow$ CalculateDifferences(A_c)
$\beta \leftarrow$ CalculateBeta(A_c,S, S_{min}, S_{max})
$a \leftarrow$ SelectAction(D)
return $\langle a, \beta \rangle$.

4.2.1 Individual Argmax Selection: Similarity Range

In our basic SCT model, an agent compares itself to one selected agent. This individual comparison approach is successfully implemented in our previous work, and provided good results in different crowd behaviors (see, for instance, its evaluation with respect to human pedestrian data (Fridman et al., 2009). In this section we present compatibility of the extended model to the basic model and also propose beta calculation to account for the timing extension.

In our basic SCT model (Algorithm 1, between all observed agents $A_o \in O$, the comparing agent selects the most similar agent A_c within the similarity range and compares itself to it. To the correction action *o* that minimized the differences to the selected agent, we attach a *Gain* value which indicates the amount of effort that should be invested in the action. The $Gain(Sim(A_{me}, A_c))$ function represents the normalized distance between my similarity with the selected agent to the two extreme values of similarity (S_{max}, S_{min}). To calculate agent's attractiveness to the selected agent (β), we will use this gain to account for normalized values (between 0 to 1).

There is some evidence for this approach in psychology literature relevant to social comparison theory. In particular, Volkmann (Volkmann, 1951) proposed *range theory of social judgment*, which emphasized the relationship between what is being judged and the two extreme values of the stimulus context. In social comparison, the context is the group, which include other people with whom one's own conditions can be compared with and in our implementation we compare the similarity value.

Thus, in this variant of the extended SCT model, between all observed agents in O, S gets the group of agents with the similarity value within the bounds. A_c gets one agent from $GetAgentForComparison(S)$ method, which selects the most similar one (with highest similarity value within the S). D gets the vector of features with values of 0 or 1 which indicate the feature value differences between me and the selected agent.

To calculate agent's attractiveness to the selected agent (β value), we calculate normalized distance between my similarity with the selected agent to the two extreme

values of similarity (S_{max}, S_{min}). The definition of $CalculateBeta(A_c, S, S_{min}, S_{max})$ in this case is presented in 3.

$$\beta_{argmax} = CalculateBeta(A_c, S, S_{min}, S_{max}) = \frac{(Sim(A_{me}, A_c)) - S_{min}}{S_{max} - S_{min}} \tag{3}$$

4.2.2 Group Comparisons

One area where the individual model fails is in that it ignores the size of the group being compared against. There is much evidence that the size of the group has an effect on the imitational tendencies of the individual. For instance, a well-known experiment in social sciences was performed by Milgram, Bickman, and Berkowitz (Milgram, Bickman, & Berkowitz, 1969). The experiment involves one participant who stood in the middle of a busy street and stared into an empty spot in the sky. The experiments purpose was to examine group pressure. The results showed that when there was only one participant, there were only a few people that passed and briefly glanced up. However, when there were several participants, almost 80 percent of the passers by also stopped and stared into the sky.

We therefore seek to find a model in which the number of similar agents in the group impacts β. We propose two such models, both tied to psychology literature on judgement of stimulus with respect to a context of other stimuli.

Mean Agent. Inspired by Helson's adaptation-level theory ((Helson, 1964)), we propose an alternative approach. Helson proposes that the baseline of judging a stimulus should be the mean of the stimuli that provide the context, such that the rating given to a stimulus is a function of its difference from the mean. Thus, instead of selecting one most similar agent and ignoring all others, we want to take into account the group factor by looking at an abstract mean agent, and determine our similarity to it.

We create the mean agent A_{mean} and calculate the agent's attractiveness to it. The function GetAgentForComparison(S) in this case creates the mean agent A_{mean} from the selected agents in S. Each agent is assumed to be modeled by a set of features, the mean agent is modeled by features with mean values from S[1]. The compared agent A_c is then the mean agent A_{mean}. Note that this agent does not necessarily exist. D gets the vector of features with values 0 to 1 which indicate the feature value differences between A_{me} and the mean agent. The β measure is again according to the range principle which is normalized distance between my similarity with the mean agent to the two extreme values of similarity (S_{max}, S_{min}).

Thus the β measure is calculated as before (Eq. 3), but with a change to the parameters. Rather than A_c being the most similar agent, it is now a hypothetical mean agent calculated as described:

$$\beta_{mean} = CalculateBeta(A_c, S, S_{min}, S_{max}) = \frac{(Sim(A_{me}, A_c)) - S_{min}}{S_{max} - S_{min}} \tag{4}$$

[1] For categorical features, we use mode values.

Range-Frequency Theory. We consider a second model, inspired by Parducci's Range-Frequency theory (Parducci, 1995). According to the theory, overall judgement of a stimulus should not rely only on its range to the mean, but instead should take into account its relative frequency—via its percentile rank—in the group of stimuli. Thus judgement should be modeled as a a weighted sum of its range and percentile rank (frequency).

We thus propose an alternative approach for β calculation (Eq. 7), which takes into consideration in addition to range, also the group distribution (via the percentile rank of the result). The β is then a weighted sum of range to the mean (Eq. 5) and frequency values (Eq. 6), as shown in Eq. 7.

The range calculation 5) is identical to that calculated for the mean agent model; it is the range to the hypothetical mean agent. We also calculate the percentile rank (frequency, in the terms of Parducci's theory). For all agents in the selected group (S), we calculate their similarity value to the mean agent ($Sim(A_k$,A_{mean}), and also calculate compared agent's similarity to the mean agent (Sim(A_{me},A_{mean} my similarity). We calculate the number of agents with same similarity value as similarity value of the compared agent (my similarity) divided by the number of agents $|S|$.

$$Range = \frac{Sim(A_{me}, A_{mean}) - S_{min}}{S_{max} - S_{min}} \tag{5}$$

Let I_{Sim_i} denote the number of agents with similarity value identical to mine. $|S|$ is the total number of agents. Then the frequency value *Frequency* is calculate according to following equation:

$$Frequency = \frac{I_{Sim_i}}{|S|} \tag{6}$$

To compromise between range and frequency, we use the weight p to determine the proportions that the range and frequency components are assigned in the weighted sum. Usually, we will give the equal weight to both the results. The β is weighted sum between the Range and Frequency values and calculated according to following equation:

$$\beta_{RF} = CalculateBeta(A_c, S, S_{min}, S_{max}) = p \cdot Range + (1-p) \cdot Frequency \tag{7}$$

4.3 Experiments

We carried out several experiments to evaluate the hypotheses discussed in this section. The experiment design and setup were already discussed in Section 3.2.1. In Section 4.3.1 we present the results of experiments in applying social comparison continuously, using both the $max(\alpha, \beta)$ and the threshold β action-selection mechanisms. We show that one of these mechanisms works well for the two tasks. Then in Section 4.3.2 we present the results of experiments with the three β models, comparing them (alas, indirectly) to human pedestrian data.

4.3.1 Experimenting with Action-Selection Mechanisms

Our first task is to determine which, if any, of the two hypothetical action-selection mechanisms may be used to allow social-comparison to take place in parallel to any goal-oriented action-selection process. The two proposed mechanisms were $max(\alpha, \beta)$ (in which the highest gain wins) and threshold β (in which the socially-motivated action wins if its threshold is higher than some fixed constant C). We varied the separator C value between 0.2, 0.3 and 0.4 (chosen based on pilot experiments). The weight p in the RF model was set at 0.8.

In these experiments, we used the two mechanisms in variations on the pedestrian tasks described above. These variations included bidirectional individual movement in high-density settings, bidirectional individual movement in low-density settings, and unidirectional movement in groups. As before, in the bidirectional movement tasks, we measure performance by the accumulated number of lane changes (as before); in the unidirectional grouping task, we measure clustering by hierarchical social entropy (Balch, 1998).

In the pedestrian traffic tasks, the goal-oriented α is always set according the following rule: α is 1 if the agent's path is clear, or 0 otherwise. Because of this rule—fixed along all tasks and experiments—we can control the action-selection mechanism and evaluate its performance in the different tasks, with respect only to the socially-motivated actions, proposed with weight β.

Table 1(a) shows the results of the experiments. The left column in each table shows the β variant in use. The next two columns show the results for the bidirectional movement task, in two different densities. The last column shows the results for the unidirectional grouping task.

Several conclusions can be drawn from these results. First, the reader should note that *all* results for the unidirectional grouping task in Table 1(a) (last column) are lower than the respective results in Tables 1(b)–1(d). In the bidirectional movement tasks, the results are inconclusive. Thus we can conclude that the $max(\alpha, \beta)$ mechanism is inferior to the threshold β mechanism.

Second, we can conclude that the RF model is superior to the mean-agent model, when using the threshold β action-selection mechanism. In all cases except for one (when $C = 0.2$), the results for the RF model improve on those of the mean-agent model.

Third, in general, the β_{argmax} model is superior to the others. This came out as a surprise to us, given its failure to account for group size. However, while we are investigating this further, a comparison to human data has shown that in fact this model may be generating movement patterns that are unrealistic. This is discussed in the next section.

4.3.2 Comparison with Human Pedestrian Data

The previous sets of results have all been based on quantitative measures of performance, on an absolute scale where a lower result was better. These are well-recognized measures, but they are artificial; they have not been applied to human data. Thus, we do not know the nominal values for normal human pedestrian traffic. Thus better (lower)

(a) $max(\alpha,\beta)$.

β model	Bidirectional Traffic High Density (Lane changes)	Bidirectional Traffic Low Density (Lane changes)	Unidirectional (Grouping) (Hier. entropy)
β_{argmax}	25531.75	8707.48	168.89
β_{mean}	35110.93	9864.27	170.47
β_{RF}	29199.73	9592.33	172.64

(b) threshold β (threshold$=0.2$).

β model	Bidirectional Traffic High Density (lane changes)	Bidirectional Traffic Low Density (lane changes)	Unidirectional (Grouping) (hier. entropy)
β_{argmax}	26086.47	9607.27	108.41
β_{mean}	37533.33	9279.07	162.44
β_{RF}	64401.2	40128.13	136.79

(c) threshold β (threshold$=0.3$).

β model	Bidirectional Traffic High Density (lane changes)	Bidirectional Traffic Low Density (lane changes)	Unidirectional (Grouping) (hier. entropy)
β_{argmax}	25587.87	9833.53	108.3
β_{mean}	37819.13	10837.4	155.66
β_{RF}	32349.8	7697.13	147.34

(d) threshold β (threshold$=0.4$).

β model	Bidirectional Traffic High Density (lane changes)	Bidirectional Traffic Low Density (lane changes)	Unidirectional (Grouping) (hier. entropy)
β_{argmax}	23414	8638.27	109.19
β_{mean}	39198.8	11033.91	160.58
β_{RF}	36539.53	8769.6	149.6

Table 2: The results of applying two action selection mechanisms in the two tasks, for the β_{argmax}, β_{mean} and β_{RF} variants. Table (a) shows the results in the $max(\alpha,\beta)$ mechanism. Tables (b)–(d) show the results when applying the threshold β mechanism, with a threshold of $C=0.2$, $C=0.3$, $C=0.4$, respectively. All results are averaged over dozens of trials (15–50). Lower results are better.

results on the absolute scale may in fact be unrealistic.

Thus, as a final evaluation, we also conducted experiments which indirectly compare the performance of the various models to human crowd data, which we have published in (Fridman et al., 2009). The experiments were carried out as follows.

First, in (Fridman et al., 2009) we allowed human subjects to qualitatively compare various variants of the β_{argmax} model, based on continuous comparison, with movies of human pedestrians moving bidirectionally, in groups. The models were also compared to the *random selection* process, which is often used in the literature as baseline. While a detailed discussion of the results of the paper are outside the scope of this document, we will mention that one clear winning model—one of the β_{argmax} variants—emerged. We denote this model as SCT_{argmax}. This model relied on using SCT as a problem-solving activity, where the social comparison process is only triggered occasionally. As shown in Section 3, this type of triggering mechanism is problematic.

However, given the success of the SCT_{argmax} compared to other models, we can now use it as a basis for comparison against newer models, such as those investigated in the course of this research. In particular, we contrast the results from using this model, on the same task used in the comparison with human data, with results from applying the various variants described above.

The results of this experiment are shown in Table 3. The table shows both lane-changes and hierarchical social entropy results for the same task (bidirectional movement in small groups). The table compares several models: The original (which was judged by human subjects to be the closest to human movement), shown in the second column; the β_{argmax} model, in the next column; and finally the β_{mean} and β_{RF} model, in the last two columns, respectively.

The table shows that the β_{RF} model, introduced in this paper, seems the closest to the original winning model in terms of the number of lane changes, and is also very close to it in terms of the social entropy measure used to evaluate grouping. It thus shows much promise for future development.

Note also that the other models—in particular the β_{argmax} model—provide smaller numbers, which are considered better on an absolute scale, but are shown here to be too good to be realistic. We hope to carry out a thorough investigation as part of our research in the coming year.

Measure	Baseline	β_{argmax}	β_{mean}	β_{RF}
Lane Changes	5974.5	2880.67	4283.97	5267.73
Social Entropy	22.32	25.99	22.4	21.69

Table 3: A comparison of different crowd models in the task of bidirectional pedestrian traffic in small groups. The first column shows the baseline, which was shown in our earlier work to be closet to human data of previous models.

5 Conclusions and Future Directions

In this report we summarize our work in the past year on a revised and extended social-comparison model of crowd behavior. We have explored—and provided initial answers—two key questions raised by earlier work. Our methodology involved both experiments in synthetic simulations, as well as comparisons of their predictions to human pedestrian data.

First, we have shown that it is possible to have a task-neutral, architecture-level, social comparison process capable of working well across multiple tasks. We have explored alternative action-selection mechanisms that enable continuous comparison (required for such process), and provided evidence that one of these mechanisms, based on threshold-ed selection, was superior.

Second, we have revised the underlying comparison process itself to account for the comparison group size, another key issue ignored by previous work. We have shown that the revised model offer, in some cases, superior performance to that of the previous model. However, the results here are less conclusive than we'd like.

5.1 Future Directions

Indeed, there is many open questions still. First and foremost, while the revised comparison models show much promise, the use of the β_{RF} model has not produced results that are clearly superior to others in all cases. More work is needed in identifying its strengths, possibly in additional crowd modeling tasks.

Other directions are left open as well. Preliminary experiments with human subjects' evaluation of synthetic situations have consistently yielded replies that indicate expectations not only of reduced attraction in some cases, but of actual avoidance. In other words, in some settings, human subjects sometimes expected agents to move away from a group, rather than simply not move towards it. This avoidance is also discussed in more modern elaborations of social comparison theory, but is yet not accounted for in our models.

Another important open issue is that of accounting for culture and embodiment of the simulated agents. It has been shown, for instance, that pedestrians prefer to walk behind *and slightly to the side* of others (Wolff, 1973), likely to decrease occlusion of oncoming obstacles. Such constraints made by the bodies of others are not accounted for. The existing model also do not account for the differences in "personal space" in different cultures.

5.2 Resulting Publications

Publication of (Fridman et al., 2009) was supported in part by this grant. A journal article extending these results is currently in preparation, as is a paper based on the new results in this report.

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