Context-Aware Emotion-Based Model forGroup Decision Making

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Involving groups in important management processes such as decision making has several advantages. By discussing and combining ideas, counter ideas, critical opinions, identified constraints, and alternatives, a group of individuals can test potentially better solutions, sometimes in the form of new products, services, and plans.

In the past few decades, operations research, AI, and computer science have had tremendous success creating software systems that can achieve optimal solutions, even for complex problems. The only drawback is that people don't always agree with these solutions. Sometimes this dissatisfaction is due to an incorrect parameterization of the problem. Nevertheless, the reasons people don't like a solution might not be quantifiable, because those reasons are often based on aspects such as emotion, mood, and personality. At the same time, monolithic individual decision-support systems centered on optimizing solutions are being replaced by collaborative systems and group decision-support systems (GDSSs) that focus more on establishing connections between people in organizations. These systems follow a kind of social paradigm.

Combining both optimization- and social-centered approaches is a topic of current research. However, even if such a hybrid approach can be developed, it will still miss an essential point: the emotional nature of group participants in decision-making tasks.

We've developed a context-aware emotion-based model to design intelligent agents for group decision-making processes. To evaluate this model, we've incorporated it in an agent-based simulator called ABS4GD (Agent-Based Simulation for Group Decision), which we developed. This multiagent simulator considers emotion- and argument-based factors while supporting group decision-making processes. Experiments show that agents endowed with emotional awareness achieve agreements more quickly than those without such awareness. Hence, participant agents that integrate emotional factors in their judgments can be more successful because, in exchanging arguments with other agents, they consider the emotional nature of group decision making.

Underlying Principles

Here, we describe the influence of emotions in decision processes and we detail some aspects of GDSS and context awareness.

Emotion and Decision

A few years ago, experts in the area of decision making began considering emotion as an influential factor in the decision-making process. The seminal work of neuroscientist Antonio Damásio significantly helped increase interest in the relevance of emotions in individual and, consequently, group decision-making processes.[1] Damásio proposed a somatic-marker hypothesis that describes how emotions are biologically indispensable for decisions. This hypothesis claims that deficits in emotional signals lead to deficient judgments in decision making, especially in the personal and social spheres. According to Damásio, experiments with neurological patients affected by brain damage show that the absence of emotion and feelings can break down rationality.

Psychology research includes several examples of how emotions and mood affect the individual decision-making process. For instance, individuals are more predisposed to recall memories that are congruent with their present emotional state. Also, experiments show that emotional state can influence information-seeking strategies and decision procedures. An individual's emotional state can affect that person's behavior and interaction with other group members. Moreover, a person's emotional state varies with time and is influenced by the emotional states of the remaining group members.

The *emotional-contagion process* is the tendency to express and feel emotions that are similar to those of others. This process could be analyzed on the basis of the emotions that a group member is feeling or on the overall mood of the group.

According to Rosalind Picard,[2] one reason to assign emotional characteristics to machines is to help those machines better model human emotions, because an individual's emotional state affects his or her performance and relationships within a group.[2]

Because of these factors, interest in developing architectures for emotional agents has recently increased. Some examples of developed architectures are Fatima,[3] Tabasco,[4] Mamid (Methodology for Analysis and Modeling of Individual Differences),[5] and EMA (Emotion and Adaptation).[6]

Group Decision-Support Systems

Nowadays, there is increasing interest in developing GDSSs to formalize and develop group decision-making processes for *any time and any place* rather than merely for *the same time and same place*. This interest emerges with the need to bring together the best possible group of participants. Until a few years ago, the only possible scenario was to wait until all the participants met together. But potential group participants such as experts in specific areas are often located in different parts of the world, so it's usually not practical to assemble them in the same room. Thus, there is growing interest in developing systems to overcome this limitation, leading to an increased focus on ubiquitous GDSSs (UGDSSs).

Group decision making seems prudent in many areas. One of the most cited areas in literature is healthcare, because a patient's treatment often involves several experts, such as physicians, nurses, laboratory assistants, and radiologists. These experts could be distributed in different departments, hospitals, or even countries. Hermes, a Web-based GDSS, was tested using this scenario. Other UGDSSs include GroupSystems and VisionQuest software.

Using these systems, researchers have identified two ways to support decision makers. The first is to support them in a specific decision situation. The second is to provide training facilities so that they can acquire competency and knowledge for an actual group-decision meeting.

context awareness

The concept of context awareness was introduced in 1994 by Bill Schilit, Norman Adams, and Roy Want,[7] who defined it as software that adapts according to the location where it's used, the collection of nearby people and objects, and changes to those objects over time. More recently, Anind Dey defined context-aware systems as those that use context to provide relevant information or services to users (where relevancy depends on the users' tasks).[8]

Context information could be related to the current moment or could be historical—that is, when user, computing, physical, and time contexts are stored within some time span. Historical context information can help establish patterns and predict possible user actions. However, it's important to carefully consider which historical information is worthy of being kept and at what precision level. Storing all context information collected would make the process of evaluating that information too costly.

Participant Agents

Multiagent systems are especially suitable for modeling distributed problems involving many different intelligent agents. These agents can have characteristics such as proactivity, reactivity, socialization, and autonomy, and they can represent different entities and tasks.

In our approach, we use agents to represent meeting participants, a meeting coordinator or facilitator, and important tasks such as voting, to effectively represent the distributed problem of group decision making. Our agents consider emotions from a context-awareness perspective (emotion-based awareness) because emotions play an important role in group decision processes.

In an earlier work,[9] we identified the main agents involved in a simulation of a group decision meeting: the participant agents, the facilitator agent, the register agent, the voting agent, and the information agent. The participant agents play an important role in the group decision process because they simulate human participants at a meeting.

The architecture of the participant agents has three layers: knowledge, reasoning, and interaction (see Figure 1).

In the knowledge layer, the agent has information about its environment, the profiles of the other participants' agents in the simulation group, and its preferences and goals (that is, its profile). The information in the knowledge layer involves a certain level of uncertainty, but accuracy increases over time as the agent interacts with other participants.

The reasoning layer contains three major modules: the argumentative system, the decision-making module, and the emotion system. The argumentative system is responsible for generating both explanatory and persuasive arguments. These arguments are related to the internal agent's emotional state and how it perceives the other agents' profiles (including their emotional states).[9] The decision-making module helps agents choose the preferred alternative and classifies all alternatives into three classes: preferred, indifferent, and inadmissible. The emotion system generates emotions and moods affecting the choice of which arguments to send to other participants, the evaluation of the received arguments, and the final decision.

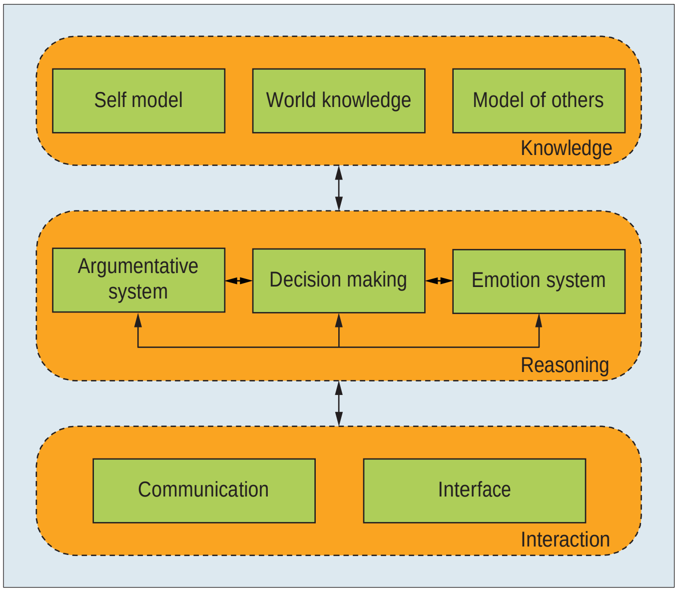

Figure 1. Architecture of the participant agents involved in a simulation of a group decision meeting. The three main layers are knowledge, reasoning, and interaction.

The interaction layer is responsible for communication with other agents and acts as an interface with users of the group decision-making simulator.

Modeling Emotions Using the OCC Model

The OCC (Ortony, Clore, and Collins[10]) model proposes that emotions are the results of three types of subjective appraisals:

- the pleasantness of events with respect to the agent's goals;
- the approval of the agent's actions, or those of another agent, with respect to a set of behavioral standards; and
- the like or dislike of objects with respect to the agent's attitudes.

The OCC model generally treats emotions as valenced reactions to three different types of stimuli: objects, event consequences, and agent actions.[10] These are the three major branches of emotion types. The objects branch includes the emotions of love and hate. The event-consequences branch includes the emotions of being happy for someone or something, gloating, pity, resentment, satisfaction, hope, fear, confirmation of fear, relief, disappointment, joy, and distress. The agent-action branch includes the emotions of pride, shame, admiration, and reproach. The model also considers four compound emotions—gratification, remorse, gratitude, and anger—which are consequences of events and agent actions.

For our purposes, the original OCC model, with its 22 different types of emotions, is probably too fine grained. Andrew Ortony presented a simplified version of this theory in 2003,[11] in which he considered only two different categories of emotional reactions: positive and negative. As in the original model, emotions are the results of goal-, standard-, and taste-based types of subjective appraisals.

Table 1 reviews the 2003 OCC model. However, despite several implementations, the OCC model's most-common shortcomings are that it doesn't retain memory of past emotions (interactions) and it is unable to model an emotion mixture.

logical Formalization of the Occ Model

Before the logical formalization of emotions can be characterized using logic programming, extended by

Table 1. Specializations of generalized good and bad feelings.

Category	Positive reaction	Negative reaction
Undifferenti-ated	Joy (because something good happened)	Distress (because something bad happened)
Goal based	Hope (about the possibility of something good happening)	Fear (about the possibility of something bad happening)
	Relief (because a feared bad thing didn't happen)	Disappointment (because a hoped-for good thing didn't happen)
Standard based	Pride (about a self-initiated praiseworthy act)	Remorse (about a self-initiated blameworthy act)
	Gratitude (about an other-initiated praiseworthy act)	Anger (about an other-initiated blameworthy act)
Taste based	Like (because someone or something seems appealing or attractive)	Dislike (because someone or something seems unappealing or unattractive)

explicit or strong negation, the agent knowledge base must be addressed. We built the KB for our model around a set of logical terms, subject to proof.

Definition 1: Agent KB Representation
The participant agents' KBs consist of logic clauses in the form

$$r_k{:}P_{i+j+1} \leftarrow (P_1 \wedge P_2 \wedge \ldots \wedge P_{i-1}) \text{ not } (P_i \wedge \ldots \wedge P_{i+j})$$

where $(i, j, k) \in N_0$, and $(P_1, \ldots, P_{i+j})$ are literals. (That is, they are formulas of the form p or $\neg p$, where p is an atom and $\neg$ denotes strong negation, indicating what should be interpreted as false.) Also, r_k is the clause's identifier, "not" is the negation-by-failure (proof-fails) operator, P_{i+j+1} is the rule's consequent, and $[(P_1 \wedge P_2 \wedge \ldots \wedge P_{i-1})$ not $(P_i \wedge \ldots \wedge P_{i+j})]$ is the rule's antecedent. If $i = j = 0$, the clause is called a *fact* and is represented as $r_k{:}P_1$.

This work builds on the work of José Neves,[12] who studied the representation of incomplete information and reasoning based on partial assumptions using the representation of null values to characterize abnormal and exceptional situations.

Definition 2: Agent KB
Let $\wedge$ be the community of participant agents. The KB of a participant agent i is

$$KB(i) = \{goals(i), goals(i, j), profile(i), profile(i, j), world(i) \mid i \neq j, (i, j) \in \Omega\}$$

where $goals(i)$ is the set of goals that agent i aims to achieve, $goals(i, j)$ is the set of goals that agent i assumes agent j holds, $profile(i)$ contains the model of the agent i profile, $profile(i, j)$ indicates how i perceives the agent j profile, and $world(i)$ contains the knowledge agent i has about the world.

Definition 3: Agent Profile
Let $\wedge$ be the community of participant agents. The participant agent profile is

$$profile(i) = \{mood(i), benev(i), prefarg(i), gratitude(i, j), enemies(i, j) \mid i \neq j, (i, j) \in \Omega\}$$

where $mood(i)$ characterizes the mood of agent i and can be positive, negative, or neutral; $benev(i)$ indicates whether agent i is benevolent; $prefarg(i)$ denotes that agent i can have a specific preference about the arguments to send; $gratitude(i, j)$ results from previous interactions (simulations) in the community of participant agents between participants i and j; and $enemies(i, j)$ indicates that (for whatever reason) agent i doesn't like to interact with agent j.

The Emotion System

The emotion system includes three main components: appraisal, selection, and decay. In addition, we've incorporated considerations of agent mood to improve the system's accuracy.

appraisal

To better understand the emotion-triggering process, consider the following practical example in which a community of four agents want to select a trip destination. This example uses three different types of arguments that we've applied in our argumentation system: appeals (common practices, counterexamples, self-interests, and past rewards), promises, and threats.

Definition 4: Set of Triggered Emotions
If $Em(i)$ is the set of emotions that can be triggered in a specific moment by agent i, then

$$Em(i) = \{joy(i, F(\varphi), int), distress(i, \neg F(\varphi), int), hope(i, P(\varphi), int), fear(I, P(\neg\varphi), int), relief(i, \neg F(\neg\varphi), int), disappointment(i, P(\varphi), \neg\varphi, int), pride(i, \alpha, int), remorse(i, \alpha, int), gratitude(i, j, F(\varphi), int), anger(i, j, F(\neg\varphi), int), like(i, j, int), dislike(i, j, int) \mid i \neq j, (i, j) \in \Omega, F(\varphi) \in KB(i), P(\varphi) \in KB(i), int > 0\}$$

In this definition, $joy(i, F(\varphi), int)$ means agent i feels joy because it has accomplished goal $F(\varphi)$ (notice that φ can consist of a set of subgoals). For instance, agent i feels joy because the group chose Paris as its preferred destination. On the other hand, $distress(i, \neg F(\varphi), int)$ means agent i wasn't able to achieve φ. For instance, its preferred destination was Paris, and it performed actions to achieve that goal, but the group chose London instead.

The term $hope(i, P(\varphi), int)$ means agent i has begun a plan to achieve φ. For instance, agent i asked other agents in the group to choose Paris as the preferred destination, and is hopeful that this request will be accepted. On the other hand, *fear*(I, $P(\neg\varphi)$, *int*) means agent i is afraid that $\neg\varphi$ might happen. For instance, if agent j sends a threat to agent i, saying that if it does not accept London as the preferred destination, no one can go on the trip, agent i will experience fear.

The term *relief*(i, $\neg F(\neg\varphi)$, *int*) means agent i feels relief because the possibility of $\neg\varphi$ occurring did not come to fruition. In the example given for the emotion fear, if agent j (the opponent of agent i in this case) doesn't complete its threat, agent i will experience relief. On the other hand, *disappointment*(i, $P(\varphi)$, $\neg\varphi$, *int*) means agent i was engaged in a plan to achieve φ, but φ was not accomplished. For instance, suppose agent i sends a request to agent j to choose Paris, and agent j answers that it will not attend to the request.

The term *pride*(i, α, *int*) means agent i feels pride for accomplishing action α. For instance, suppose agent i sends a request to agent j, supported by an appeal to a self-interest argument in which it justifies why it will be positive for agent j to perform a specific action. So, agent i feels pride for sending that argument. On the other hand, *remorse*(i, α, *int*) means agent i feels remorse for accomplishing action α. For instance, suppose agent i has sent a threat to agent j and now feels remorse for sending that threat.

The term *gratitude*(i, j, $F(\varphi)$, *int*) means agent i is grateful to agent j for having achieved goal φ. For instance, if agent i sends a request, supported by a promise, to agent j to choose Paris as the destination, and agent j agrees to meet this request, agent i will be grateful to agent j. On the other hand, *anger*(i, j, $F(\neg\varphi)$, *int*) means agent i is angry with agent j for contributing to the failure of goal φ. For instance, if agent i sends a request to agent j, supported by an appeal to a past-reward argument, and agent j refutes the existence of that past reward and denies the request, then agent i will feel angry.

The term *like*(i, j, *int*) means agent i likes agent j, whereas *dislike*(i, j, *int*) means agent i doesn't like agent j.

Finally, every emotion has an associated intensity attribute, *int*, which is assigned different values, depending on the situation that generated the particular emotion. Also, the emotions felt by the agent influences its KB—namely, its own profile (for example, the emotion gratitude is strictly related to the gratitude characteristic that exists in the agent profile).

The OCC model establishes the intensity of each emotion in terms of potential and threshold. Therefore, we define a new set of trigger emotions incorporating the concept of threshold:

$$Q(Em) = \{(emotion, \delta) \mid emotion \in Em, \; 0 < \delta < 1\}$$

Whether the agent expresses a particular emotion depends on the intensity of that agent's other emotions.

Selection

This component selects the dominant emotion. Let

$$emotion(t, i) = \{\max[int(Em(i, t))] \mid Em(i) \in Q(Em), i \in \Omega\}$$

The selected emotion for agent i in instant t is the one with a higher difference between the intensity and the activation threshold.

Decay

Emotions have a short duration, but they don't go away instantaneously, so they have a period of decay. As Picard suggests,[6] we represent decay via an inverse exponential function. Given initial intensity q_i, the time t_0 when the emotion was triggered, the current time t, and a constant b that defines how quickly the emotion decreases, our decay function is given by

$$int(q, t, b) = \frac{q_i}{e^{-bt}}$$

Since constant b influences the decay function, it can be used to model different behaviors for each emotion. Therefore,

$$decay(Em) = \{[Em(i, b)] \mid Em(i) \in Em, \; b \in [0, 1]\}$$

Mood

Our model calculates an agent's mood on the basis of the emotions that agents have felt in the past and on how agents perceive the mood of the remaining participants. In our emotions-contagion process, we consider only three stages for mood: positive, negative, and neutral. A specific participant's mood is determined according the following:

$$K^+ = \sum_{i=t-n}^{t-1} I_i^+, \; K^- = \sum_{i=t-n}^{t-1} I_i^-$$

where K^+ and K^- are the sum of the positive and negative emotions, respectively, felt in the past n periods, and n can be parameterized by the simulator user.

We only considered emotions that are above the activation threshold:

$$mood(i, K^+, K^-, l) = \begin{cases} \text{positive} \mid K^+ \geq K^- + l, \; i \in \Omega \\ \text{negative} \mid K^- \geq K^+ + l, \; i \in \Omega \\ \text{neutral} \mid |K^- - K^+| < l, \; i \in \Omega \end{cases}$$

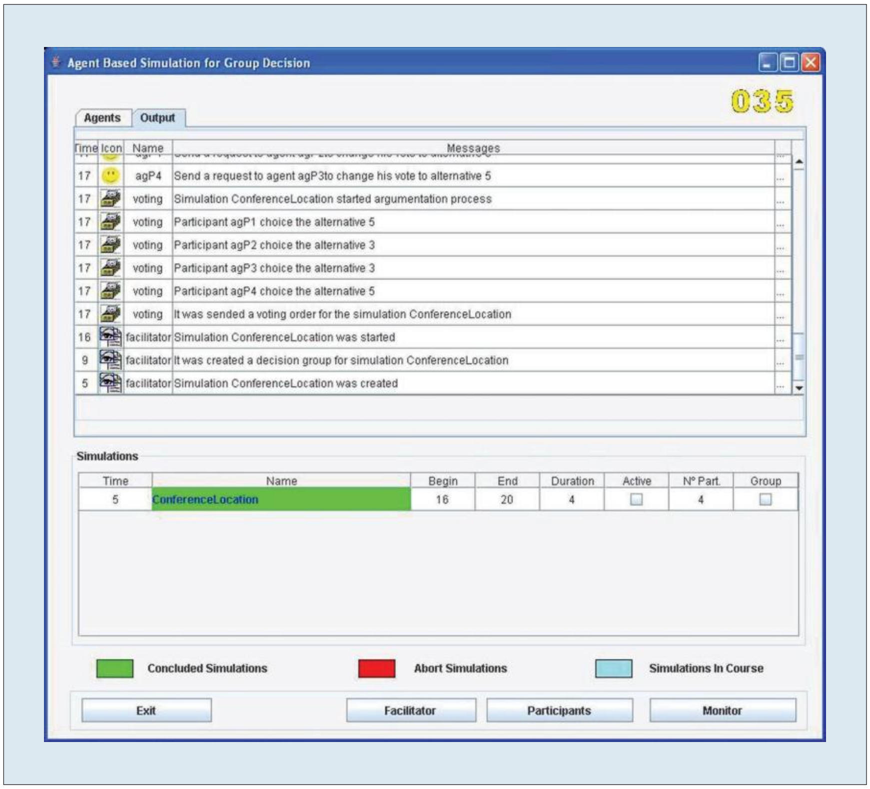

Figure 2. Screenshot of the ABS4GD (Agent Based Simulation for Group Decision) system showing simulation results.

where the value of l varies according to how a specific participant perceives the group's overall current and potential mood, as follows:

$$l = \begin{cases} 0.10, \text{ if group mood is positive and } K^- \geq K^+ \\ 0.10, \text{ if group mood is negative and } K^+ \geq K^- \\ 0.05, \text{ if group mood is neutral} \\ 0.01, \text{ if group mood is positive and } K^+ \geq K^- \\ 0.01, \text{ if group mood is negative and } K^- \geq K^+ \end{cases}$$

Moreover, each participant agent has a model that includes information about the other agent's mood.

The emotion system in our model is based on the OCC model. However, one of the major criticisms that this model has received is that it doesn't handle the treatment of past interactions and past emotions. The inclusion of mood in our model addresses this problem.

The ABS4GD Simulation System

To evaluate our proposed model, we developed the ABS4GD system. This multiagent simulator system consists of several agents, but the most relevant ones are the participant agents, since they simulate human participants at a decision meeting. We developed the ABS4GD system in the Open Agent Architecture (OAA), Java, and Prolog.

OAA has the following benefits:

- It is structured to minimize the effort involved in creating new agents.
- It can be written in different languages and operate on diverse platforms.
- It encourages the reuse of existing agents.
- It facilitates dynamism and flexibility in the creation of agent communities.

(More information about OAA is available at www.ai.sri.com/oaa.)

Figures 2 and 3 show screenshots from the ABS4GD prototype. Figure 2 shows an extract of the arguments exchanged between the participant agents. Once a simulation is accomplished, each agent updates its knowledge about the other agents' profiles (for example, agent credibility). Figure 3 shows the collection of agents that work at a particular moment in the simulator. These include

- 10 participant agents;
- the facilitator agent, which is responsible for the organization of the meeting simulation;
- the voting agent;
- the clock agent (OAA is not specially designed for simulation, so we needed to introduce a clock agent to control the simulation);
- the OAA monitor, an agent belonging to the OAA platform that traces, debugs, and profiles communication events for an OAA agent community; and
- the application agent, which supports communication between the community of agents and the simulator interface.

Case Study

We conducted a simple case study to evaluate our model. Our system deals with multicriteria problems, which can vary in complexity and importance. Hence, this case study involved a group of four people evaluating four candidates for a university position on the basis of five criteria: teaching ability, academic degrees, scientific research activity, management ability, and professional experience. Table 2 shows the results of our evaluation.

On the basis of this problem, we established several scenarios to discover whether emotion-based agents have more success in simulations than non-emotion-based agents. Table 3 shows the initial preferences of the agents of the four people conducting the evaluation.

On the basis of Tables 2 and 3, we created five variations of each preference, resulting in 25 test scenarios. Then, on the basis of these 25 scenarios, we conducted experiments using the simulator, and Table 4 lists the results.

On the basis of these experimental results, we conclude that clusters of agents bearing emotion-based features tend to achieve agreements more quickly than those without such features (see Figure 4). This also indicates that meeting participants who take into account emotion-based factors (their own as well as those of other participants) tend to have achieve better results.

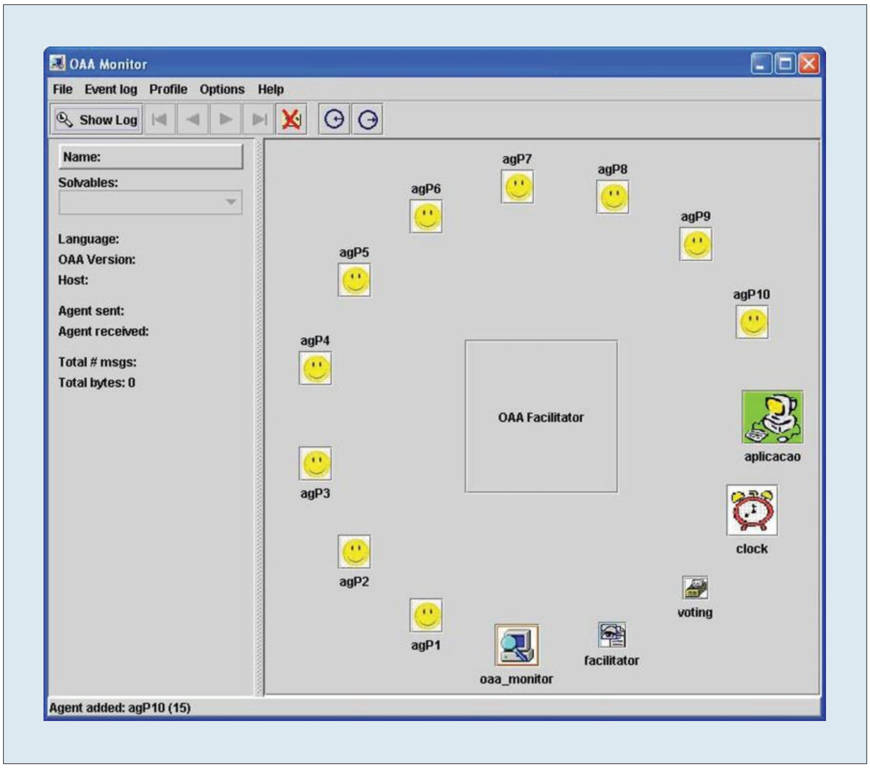

Figure 3. Screenshot of the ABS4GD system showing a community of participant agents. This community includes 10 participant agents, the facilitator agent, the voting agent, the clock agent, the Open Agent Architecture (OAA) monitor, and the application agent.

Table 2. Evaluation of four candidates for a university position.

Criteria	Candidate n_1 (%)	Candidate n_2 (%)	Candidate n_3 (%)	Candidate n_4 (%)
Teaching ability	70	60	30	50
Scientific research	20	30	80	70
Academic degrees	80	40	80	60
Management ability	30	60	10	30
Professional experience	20	30	10	30

Table 3. Initial weighted preferences of the four evaluators' agents regarding the five criteria.

Evaluator agent	Teaching ability	Scientific research	Academic degrees	Management ability	Professional experience
Agent 1	0.10	0.40	0.40	0.05	0.05
Agent 2	0.15	0.40	0.15	0.15	0.15
Agent 3	0.40	0.10	0.10	0.30	0.10
Agent 4	0.40	0.10	0.30	0.10	0.10

Our simulator uses intelligent agents to represent participants in a meeting. However, this agent-based simulator is not intended as a substitute for an actual meeting or even some meeting participants, especially in an activity as complex as decision making. Rather, it is a decision-support tool for meeting participants. Our experiments show that agents endowed with emotion-based awareness can achieve agreements more rapidly.

An effective GDSS should embody an understanding of the various mechanisms underlying human personality, emotions, and intentions—features that play a crucial role in the choices people make. Thus, in the future, we plan to incorporate a computational model of personality in a GDSS. By combining agent technology with computational models of personality and emotion in such a system, we expect to predict user intentions and thus facilitate the negotiation process among a group of decision-makers.

Table 4. Simulation results from our experiments on 25 test scenarios.

Parameter	Quantity
No. of simulations	25
No. of simulations in which more exchanged arguments used emotion-based agents than non-emotion-based agents	2
No. of simulations in which more exchanged arguments used non-emotion-based agents than emotion-based agents	23
Max no. of exchanged arguments for emotion-based agents	9
Min no. of exchanged arguments for emotion-based agents	2
Max no. of exchanged arguments for non-emotion-based agents	13
Min no. of exchanged arguments for non-emotion-based agents	5
Average no. of exchanged arguments for emotion-based agents	5.4
Average no. of exchanged arguments for non-emotion-based agents	7.1

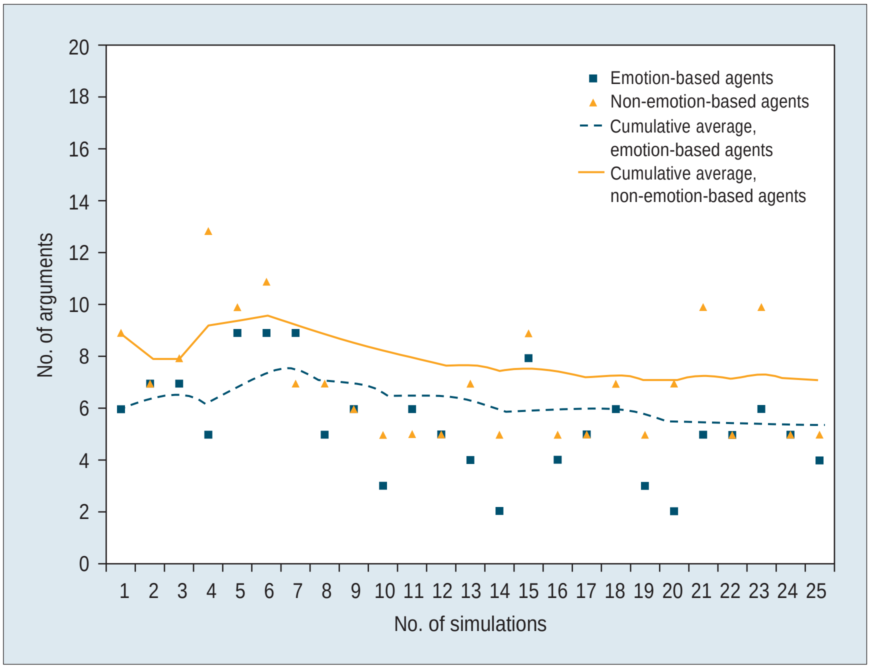

Figure 4. The average number of arguments by agent type (emotion- versus non-emotion-based). Clusters of agents with emotion-based features achieve agreements more quickly than those without such features.

Acknowledgments

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