Toward an Actualization of Social Intelligence in Human and Robot Collaborative Systems

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Abstract—As robot technology is evolving and creating a social community between humans and robots, it is necessary to research and develop a new type of intelligence, which we refer to as “social intelligence”. Social intelligence enables natural and socially appropriate interactions. Its importance is gaining a growing interest among not just the human-computer interaction researchers but also robot technology researchers and developers. This article discusses the definition, importance, and benefits of social intelligence in human and robot collaborative systems. The virtual social environment is employed to implement an experimental social intelligence system because of its low cost and high flexibility. Software robots (i.e. agents) with the social intelligence model have been implemented by featuring an emotion model and a personality model under the virtual environment. The social intelligence model that handles affective responses is based on the theories of personality, emotion, and human-media interaction such as cognitive appraisal theory and Media Equation. The experiment was conducted with the virtual learning collaborative system to examine the effect of the social intelligence model in the collaborative system. The data showed that the users had more positive impressions about the usefulness and the application and learning experience when the cooperative agent displayed some social responses with personality and emotions. It should be noted here that the cooperative agent did not provide any explicit assistance for the human user such as giving clues and showing answers, and yet the user’s evaluation on the usefulness of the learning system was influenced by the social agent. The data also suggested that the cooperative agent contributed to the effectiveness of the learning system.

Keywords sociality, personality, emotion, mind model, agent, robot, e-learning, human-machine collaboration, social intelligence, social responses to communication technology

I. INTRODUCTION

The growth of the robot technology (RT) today is quite amazing especially in the humanoid technology area. As shown in this growth, the role of robots has been evolving from simple substitution of human physical power to collaboration/companionship with humans. In the near future, human beings and robots may form a much more sophisticatedly collaborative community. In this sense, robots need to have another type of intelligence in addition to ordinary intelligence that has long been studied in the artificial intelligence field. The new type of intelligence may be called “social intelligence”. Katagiri argued for the importance of social intelligence contrasting with “rational intelligence”, which refers to the ordinary problem-solving intelligence [1]. According to [1], rational intelligence is goal-oriented intelligence that enables one to find an
answer to a question, generate a solution to a problem, and so on. In contrast, “social intelligence” is the type of intelligence that enables one to share information and feelings with others, behave in such a way one is accepted as a member of a community, and so on.

To develop social intelligence for a human-robot collaborative system, we have been researching social responses of machines to human. As an experimental system for our study, we developed a virtual social environment as a simulation of real robots and social environment to study social intelligence in the human-robot collaborative system because of its low cost and high flexibility. In the virtual social environment, a software robot with an emotion model and personality design has been developed to be used in experiments on social intelligence. The emotion model and the personality model (i.e. social intelligence model) can be transported in real robots.

There have been several studies on social intelligence in the RT area. Duffy has studied and developed social robots from the point view of anthropomorphism in a robot’s physical design and behavior [2]. Okuno has developed a humanoid employing personality as a means of controlling non-verbal behaviors [3]. Miwa has used a three-dimensional mental space to realize robot personality [4].

In this paper, we present the theory and implementation of the social intelligence model and report the experiment that we conducted by using the virtual social environment. Through the experiment, effectiveness and efficiency of social intelligence in a human and robot collaborative system were investigated. The results support the worth of the studies on social intelligence in the human and robot collaborative system as mentioned before.

II. VIRTUAL SOCIAL ENVIRONMENT

We have developed a virtual social environment. As an application of the environment, we have developed a learning system incorporating social intelligence for human-machine interaction. In addition to the social intelligence model, a notable characteristic of our system is the introduction of a co-learner agent as a social actor in the virtual environment. The reasons why we employed a learning application as the virtual environment are as follows:

1) The application should be a representative one such that it illustrates what roles both the human and robot play to achieve an objective.
2) A moderate complexity of the system and benefits to the society should also be considered in the application selection.
3) It is desirable to choose a domain that can show that human motivation influences the consequence of the task or activity with the application.

In addition to these reasons, from a point view of learning environment, while there have been developed a number of learning systems involving software robots (i.e. agents), the nature of interaction that takes place in many of those systems such as tutoring systems is one-to-one interaction between the teacher agent and the human learner. We argue that the presence of the co-learner agent provides much richer social interactions including imitation [5] and observation [6] than an individualized learning system. As shown in Figure 1, our learning system employs a classroom metaphor. There are three cartoon characters in the classroom: a teacher agent, a student agent, and an avatar for the human learner. Thus, there occur interactions between the teacher and a learner and interactions between the learners. Furthermore, one type of interactions may influence the other type of interactions. For example, when the teacher gives the co-learner feedback to its answer, the human learner could tell what he or she should do or may want to comment on that.

III. SOCIAL INTELLIGENCE MODEL

In this section, we discuss the theory and implementation of our social intelligence model.
A. Theoretical Aspects

There have been many arguments concerning social intelligence in the areas of philosophy, psychology, and artificial intelligence.

1) Mind

Dreyfus pointed out that people interpret the meaning of matters according to their desires and concerns [7]. Dennett claimed that intentional stance is a strategy of interpreting behavior of entities such as human, animal, and artifacts. According to Dennett, the human treats these entities as if they were rationally selecting their action based on the consideration of their belief and desire [8]. Humphrey said that people or higher animals communicate with simulating other’s minds with using their mind [9].

2) Emotion

James emphasized that emotion is a predominant operation mediating both cognition and action [10]. Minsky argued that emotion has influence on goal constructing in problem solving and that artificial intelligence should have the ability of processing emotion [11]. These arguments lead to the concept of cognitive appraisal theory [12]. The theory was proposed by Ortony, Collins, and Clore in 1988[12] and is known as the OCC model. According to the theory, appraisal of humans based on their emotion consists of three main variables—desirability, praiseworthiness, and appealingness.

3) Personality

People recognize and respond to personalities of other individuals that they interact with. Personality is often used to describe and predict an emotional state and behaviors of an individual. It is considered to be a more stable trait of an individual. It is considered to be a more stable trait of a person’s subjective state. In other words, it does not change dramatically in a short period of time depending on the changes in the environment though it may change over time in the long run. In psychology, so called “Big Five” is known to characterize some major attributes of personality [13]. They are openness, conscientiousness, extraversion, agreeableness, and emotional stability.

Reeves and Nass assert that friendliness (friendly vs. unfriendly) and dominance (dominant vs. submissive) are two major attributes of personality, especially that of mediated agents [14].

B. Implementation

We have developed a social intelligence model called the Mind and Consciousness Model (MaC model)[15]. We claim that agents with a mind model will be required to realize smooth communication and comfortable control in the human-machine collaboration system because agents must have the feature of autonomy, flexibility, and social orientation [16]. Figure 3 shows the conceptual architecture of the MaC model. The model is based on the cognitive appraisal theory. We’ve extended the OCC model in two areas to develop the MaC model. The first one is to add an information path from the emotional process to the cognitive process. By this extension, cognitive process will have the capability of highly sophisticated processing mechanism with a high-level problem solution task such as recognition, decision-making, planning, etc. The second is a couple of layered information process loops. The first loop is the reflex, in which the reflex component processes the data from sensors to control the actuators, in the way of a rough but speedy process method. The second is the deliberative loop that is corresponding to a richer information processing based on the cognitive appraisal theory. Deliberative process is accurate but slow. The combination of these loops tends to give agents more flexible and intelligent capabilities.

Emotion plays a dominant part in the MaC model and also strongly related to social behavior. We employed the theory of the Urge system proposed by Toda [17] to implement our emotion engine as the role of Emotional Process of the MaC model in Figure 3. According to the theory, emotion can be logically explained in terms of situation and emotional factors. The emotion engine calculates six basic emotions. We defined explicit components for emotion types proposed by Ekman [18]. Each component of the emotional factors and the basic emotions has the degree of activation level. Fuzzy inference component calculates the degree of the each emotional factor from the situation. Then, each activation value is calculated. Activation level of the basic emotions is used to select a behavior such as facial expression and domain specific action.

The MaC model has several parameters to tune behavior control of agents. Some examples of the parameters are desire level for innate goal, attenuating ratio for persistence, and threshold values for basic emotion and for behavior selection. By these parameter settings, the MaC model can give certain personality of an agent embedding the model in itself. Figure 4 illustrates examples of personality design of agents using the two-dimensional personality map. The dimensions are friendliness and dominance [14].

IV. EXPERIMENT

This section presents the experiment that we conducted to examine the effect of the social intelligence model in the collaborative learning system described above.

A. Method

1) Participant:
A total of seventy-seven (77) undergraduate students at International Christian University (ICU) participated in the experiment. All participants were native speakers of Japanese learning English.

2) Design:
Three versions of the application were prepared for the experiment:

a) No co-learner agent (No Agent Condition)
   On the interface, there were only the teacher agent and the avatar.

b) Co-learner agent without social intelligence model (No Social Intelligence Model Condition)
   On the interface, there were the teacher agent, the co-learner agent, and the avatar. The co-learner agent did not have social intelligence. It did not display any emotional or social responses, having a 'poker face.'

c) Co-learner agent with social intelligence model (Social Intelligence Model Condition)
   On the interface, there were the teacher agent, the co-learner agent, and the avatar. The co-learner agent did not have social intelligence. The co-learner agent was controlled by the social intelligence model. It had friendly and mildly dominant (or, confident) personality, and displayed emotional and social responses depending on the human learner’s performance.

3) Procedure:
   The experiment was conducted in ICU’s language lab, where all the participants participated in the experimental session together. Each of the participants was randomly assigned to one of the conditions. The participants first received the instructions on how to work with the application verbally and in writing. Following the self-enrollment procedure, the participants had the experimental session of learning English idiomatic expression using the application. The format of learning was a sequence of question, response, feedback, and explanation. The session was conducted in the following way. For each problem, the teacher agent presented a question, showing it on the blackboard. Then the human learner made a response, by choosing one of the alternatives. In this case, the response was not disclosed to the teacher or the co-learner. In other words, the learner simply thought of an answer in his or her mind. The teacher either called on the human user (avatar) or the co-learner agent to answer. The teacher agent then gave feedback (correct or incorrect). If the human learner had answered, the co-learner agent made a reaction to the situation. If the co-learner agent had answered, the human learner was given a few possible reactions to choose from. Then, the teacher agent gave a brief explanation about the expression. After the session was over, the participants responded to a questionnaire that was presented on the computer. The questionnaire was created on a web page and displayed on the Internet browser. It included questions concerning impressions on the application, the co-learner agent, and user experiences. A short quiz was followed to measure the participants’ performance. The experiment took approximately an hour.

B. Results and Discussion

1) Quiz Results and Self-assessment of Learning
   The effectiveness of the application was first examined based on the results of the quiz, which are shown by TABLE I. The participants in the two agent conditions (Social Intelligence Model and No Social Intelligence Model) marked higher scores than those in the no-agent condition. These results seem to indicate that the application was more effective for learning when there was a co-learner agent. Furthermore, the no-response rate was much lower with the Social Intelligence Model Condition than with the other conditions. This seems to suggest that the participants felt more reciprocally motivated to answer the questions when they worked with the co-learner agent with social intelligence model.

<table>
<thead>
<tr>
<th>Conditions</th>
<th>Correct</th>
<th>No Answer</th>
</tr>
</thead>
<tbody>
<tr>
<td>No Agent</td>
<td>.51</td>
<td>.27</td>
</tr>
<tr>
<td>Agent (No Social Intelligence Model)</td>
<td>.60</td>
<td>.22</td>
</tr>
<tr>
<td>Agent (Social Intelligence Model)</td>
<td>.69</td>
<td>.07</td>
</tr>
</tbody>
</table>

The questionnaire assessed how much (in a 10-point scale) the participants felt they had learned the materials. TABLE II shows the results. The statistical analysis showed that the participants’ self-assessment of their learning was significantly higher for the co-learner agent conditions (Social Intelligence Model and No Social Intelligence Model) than for the No Agent condition [F(1, 76) = 5.32, p < .05]. This pattern of results indicates that the participants had a more positive impression about their experience and the content of learning when they worked with the co-learner agent than when there was no co-learner agent. Combining the results of the quiz performance, it seems to be legitimate to infer that the data supported the hypothesis that the application is more effective when there is a co-learner agent working with the user than when there was no co-learner agent.
However, the difference between the two co-learner agent conditions (Social Intelligence Model and No Social Intelligence Model) did not turn out to be significant [F(1, 76) = .26, n.s.]. Does this mean that the social intelligence model had no effect on the students’ learning experiences? To examine this question, further analyses were performed on other aspects of the participants’ learning experiences and impressions.

### TABLE II. SELF-ASSESSMENT OF IDIOM LEARNING

<table>
<thead>
<tr>
<th>Condition</th>
<th>Mean</th>
<th>SD</th>
</tr>
</thead>
<tbody>
<tr>
<td>No Agent</td>
<td>3.86</td>
<td>2.08</td>
</tr>
<tr>
<td>Agent (No Social Intelligence Model)</td>
<td>4.96</td>
<td>2.34</td>
</tr>
<tr>
<td>Agent (Social Intelligence Model)</td>
<td>5.28</td>
<td>2.31</td>
</tr>
</tbody>
</table>

#### 2) Evaluation of Co-learner Agent

We first tested whether the participants’ impression (evaluation in a 10-points scale) varied depending on the presence or absence of social responses. The analysis showed that the Social Intelligence Model condition marked significantly higher scores than the No Social Intelligence Model condition in the following evaluation items:

- **a)** Cooperativeness [F(1, 51) = 13.82, p < .01]
- **b)** Trustworthiness [F(1, 51) = 8.56, p < .01]
- **c)** Feels warm [F(1, 51) = 6.65, p < .02]

These results showed that the social intelligence model and behaviors generated by it had more positive influence on the impressions of the co-learner agent.

#### 3) Evaluation of Learning System

As stated above, the purpose of this study was to investigate the effect that the affective aspects of social intelligence may have on the usefulness and impression of the learning system. The question we should ask is how those impressions and evaluations that the participants had about the agents influenced the evaluation of the application as a whole. In other words, how could the social intelligence model affect the evaluations of the agents, and in turn have an effect on the evaluation of the learning system itself?

Before broaching into this question, there is one factor that we should take into consideration. The analysis indicated that under both of the Social Intelligence Model condition and the No Social Intelligence Model condition, the impressions on the application was dependent on how the participant was attracted by the agent [F(1, 76) = 12.16, p < .01]. This means that regardless of the presence of social intelligence, liking varied from person to person. In other words, some individuals liked the agent without social responses more than others and some liked the agent with social responses less than others, depending on their personal preferences. Thus, it is necessary to control for this personal preference effect in analyzing the effect of the social intelligence model.

The analysis of covariance was performed with the personal preference on the agent as a covariate. The result revealed that the main effect of the social intelligence model on the evaluation of the application was found in the following items:

- **a)** Ease of use [F(1, 51) = 6.11, p < .02]
- **b)** Satisfaction (Would recommend it to others) [F(1, 51) = 4.82, p < .04]
- **c)** Pleasantness in learning (Not frustrated) [F(1, 51) = 6.62, p < .02]
- **d)** Supportiveness [F(1, 51) = 3.28, .05 < p < .08]

For these evaluation items, the Social Intelligence Model Condition marked higher scores than the No Social Intelligence Model Condition. These results seem to suggest that the social intelligence model and the social responses (i.e., friendly and confident) that are generated by the model had positive impact on the impressions on the learning system as a whole.

Finally, some may argue that it was not the model-based affective responses that impacted on the participants. In other words, as long as they are friendly, random and superficial responses could do as well as the model-controlled social responses. To this question, the present experiment does not offer a definitive answer since the study compared the agent with the social intelligence model and the one without. However, a closer analysis on the No Social Intelligence Model condition revealed some insight at least indirectly. Since the co-learner agent without social intelligence had a animated appearance that suggested some anthropomorphism and yet did not make socially appropriate responses, that could violate the participants’ expectations and lead to negative impressions. The analysis of covariance with the system impression as a covariate showed that the participants felt significantly less fun to work with the system in the No Social Intelligence Model condition not only than the Social Intelligence Model condition but also than the No Agent condition [F(1, 76) = 5.25, p < .03]. This result seems to indicate that the lack of appropriate affective responses of an embodied agent is worse than the absence of an agent. In light of this finding, we would argue that one would not respond to the superficial level of affective responses of an agent (i.e., randomly generated affective response) be sensitive to the naturalness of such response patterns. In that regard, the social intelligence model plays an important role in the interaction.

In summary, the results of the experiment provided support for the following assertions:

- **a)** The co-learner agent contributed to the effectiveness of the learning system.
- **b)** The users had more positive impressions about the usefulness and the application and learning experience when the co-learner agent displayed some social responses with personality and emotions.
It should be noted here that the co-learner agent in the experiment system did not provide any explicit assistance for the learner such as giving clues and showing answers. It only made some limited social responses such as praising, encouragement, and comforting. Yet, the participant’s evaluation on the usefulness of the learning system was influenced by such an agent. These results are consistent with the claim that Media Equation theoretical framework [14] makes. That is, even if the co-learner is an artificial entity like a virtual agent with simple animation or a real robot, a social relationship can be formed and that social-psychological behaviors of the user can be influenced according to the nature of interactions that takes place on that relationship.

V. CONCLUSION

In this article, we discussed the social intelligence that renders social behaviors of software robots (i.e. agents) as substitutes for real robots and its application to a collaborative learning environment. We argued that socially appropriate affective behaviors would provide a new dimension for collaborative systems. We presented the experiment that tested our hypothesis using our implementation of the collaborative system. As noted above, our study is on the initial stage and the social intelligence model is still rather simple and limited. It is encouraging that even such a simple model could generate significant effects on certain aspects of the user experience and achievement of the goal. Even if the co-learner agent lacks any intelligence to support the human learner in a direct manner such as giving hints, providing explanations, and guiding him/her through a problem, the learner left supported and displayed more active involvement in the learning. Thus, the experimental data seem to agree that the social and affective intelligence model has a potential to enhance human-robot collaboration, especially when the goals of the system are shared by humans and robots. One implication that this study may make is that one way to build robots that act supportively is to implement the ability to make social responses appropriate to the situation and to the human user’s internal state, as is partially done by our social intelligence model. This, of course, presumes the presence of such intelligence that enables understanding of the human’s goals and other internal states.

Needless to say, there are more challenges and issues with the development of and research on social intelligence. Obviously, the social intelligence model should be further enhanced. In order for that, a better understanding of social intelligence, especially in terms of modeling, must be gained. Second, we should investigate more into the social and affective aspects of collaboration between human and robots under social environments. There are probably some universal characteristics about the nature of interactions and collaborations across different domains, but there must also be differences depending on the learning domain and also on the learning goals. The better we understand the dynamics of social interactions, the better the social intelligence model can be. In that regard, collaborations among researchers in the related fields such as human-computer interaction, artificial intelligence, psychology, and robot engineering should be sought out. Our team is certainly growing in that direction, and we expect to make more progress in the near future.

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