A Method in Social Reasoning Mechanism for Intelligent Agents Using Fuzzy Inference

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Abstract- *Artificial agents should be socially intelligent in order to integrate with human society. Socially intelligent agents should be capable of reasoning about dependence relation, and we reconsider past research of dependence reasoning mechanism and integrate fuzzy inference with it to improve agents' reasoning ability. The simulation system consisting of agents within the social system is developed by incorporating the concept of trust and character of agents. These agents form a multiagent system made of three agents organized hierarchically. Fuzzy rules were implemented in our simulation system, and different experiments were performed.*

Keywords: intelligent agents, social reasoning, multiagent systems, fuzzy inference.

1. Introduction

The study of artificial intelligence on social interaction is divided into two different approaches [1]: the distributed intelligence approach and the social simulation approach.

The social simulation approach is about "simulating society", and one of the main characteristics of society is that it has no aim, or no overall goal, to achieve. The social simulation approach is about understanding social interaction itself, how social laws and social mechanisms shape agents' minds and actions and the way they act toward others. Moreover, it is to understand the emergent structural phenomenon of agents' social interaction. [2]

Although the social simulation approach to multiagent system has nothing to do with overall system goal achievement, agents built within this approach are not merely rational, functional, but relational [3]. These agents which endowed with social intelligence have the ability to recognize each other, to engage in social interactions, to possess histories and to communicate with and learn from each other [4].

Such an agent is not only an entity that is able to interact with the environment, nor is it an entity that is *goal-oriented*, capable of receiving and exploiting relevant information from and about the world, but also an entity that is *goal-directed*, having internal goal representation, which selects and controls actions, and evaluates actions as success or failure. For a socially intelligent agent, the "mind reading" ability is also needed in order to help, to cooperate, and to collaborate [5]. It sees others in the intentional stance and also has concept about beliefs and desires [6].

The focus of this paper is to improve agent's sociability. First, we develop a reasoning mechanism for socially intelligent agents based on Castelfranchi and Sichman's works of social dependence reasoning. Second, we build a simulation environment to give agents their "situatedness" to overcome the defect of past social reasoning research of dis-embedding agents from their environment. Finally, we modify the reasoning mechanism by employing fuzzy reasoning while adopting the concept of trust allowing agents to help others.

This paper is organized as follows. Section 2 gives a review of past researches. In Section 3, we propose our reasoning mechanism, and we explain our implementation in Section 4. A conclusion is given in Section 5.

2. Background and Related Work

Our social reasoning mechanism is based on previous work of the social dependence reasoning [1]. Social reasoning mechanism is based on the concept of social dependence. True autonomous agents enter social interactions because they need to, and prefer to do so. They are dependent on others; therefore, they enter social interaction.

The concept is that agents who lack depend on others who provide, and agents that are able to provide have power over the ones who lack. Whenever agents are dependent on each other, it might involve power or benevolence or following certain social norm [7]. Dependence has its influence and forms the foundation of the social reasoning mechanism [8].

Next, the concept "trust" is also an important social phenomenon. It can be decomposed in to the belief that others have the payback opportunity, the payback ability, the payback willingness, and the stable remembrance that it is to payback after helping them [9].

Finally, Using Sichman's social reasoning mechanism for our further discussion [10] [11]. The mechanism works through four stages:

a) Dependence reasoning: an agent reasons about its dependence situation regarding every other agent
b) Goal selection: the agent chooses a goal it wants to achieve according to its preferences (criteria)
c) Plan selection: it chooses a plan that accomplishes this chosen goal
d) Partner selection: If the agent does not have every action and resource needed, it continues the reasoning process, chooses a partner who is able to provide the action or resource needed, asks whether it is willing to cooperate, and waits for its reply

Unfortunately, there are five major theoretical drawbacks from the mechanism:

a) Sichman's goal-plan selection simply blocked out all unachievable goals and that's unreasonable to human social action.
b) Sichman's agent will reject the proposal if their dependent relationship is either mutual dependence or reciprocal dependence without considering future probable profit.
c) The principle of non-benevolent – agents helping others without receiving payback – is violated within the mechanism [9].
d) Making a contradictory between benevolence and autonomous in its principle of non-benevolence.
e) Dependence is defined as qualitative rather than quantitative.

We address these drawbacks by reconstructing the social reasoning mechanism. First, we use fuzzy reasoning to make a better balance between achievability and the importance and urgency of goal. Second, we introduce variables to let agents memorize their reaction with others. Third, there will be a spectrum of agents' character from benevolent to selfish. Forth, dependence will be quantitative, mixture of different types of dependent relations. Finally, we let agents have multiple amounts of identical resources, multiple plans for identical goal, and multiple partners for coalition.

3. Integrating Fuzzy Inference into A Social Reasoning Mechanism

3.1 Reasoning functions

3.1.1 Evaluation of dependence. Given a goal-plan pair, an agent can estimate its dependent relationship toward others. If an agent is s-autonomous (having all actions and resources needed) regarding the given goal-plan pair, then its dependency toward others is zero. If there is an action/resource missing, possessed by some other agent, for example Agent Y, then agent's dependency toward Agent Y regarding the missing action/resource is calculated by using the formula below:

This formula has three variables, importance, urgency and accessibility (according to its kind of

$$\left(\frac{\text{importance}}{3}\right)\times\frac{1}{3}+\left(\frac{\text{urgency}}{3}\right)\times\frac{1}{3}+\left(\frac{3-\text{accessibility}}{6}\times 100\right)\times\frac{1}{3}$$

dependence). Missing an action/resource (denoting an action or resource that an agent needs) would cause a plan to be unfeasible and may cause the associated goal to be unachievable. This happens if the unfeasible plan is the only plan agent knows in order to achieve goal. Therefore, an agent may need such action/resource badly, especially when the associated goal is urgent and/or important, making the agent strongly-dependent on any agent who possesses such action/resource. Accessibility is also an important factor contributing to dependency. If the action/resource needed is rare, it would increase the agent's dependency degree toward agents who possesses such action/resource. On the contrary, if the action/resource abounds, it would decrease the agent's dependency degree toward agents who possess such action/resource.

Given a goal and a plan, an agent can calculate the "plan-level dependent value" regarding a specific agent. The plan-level dependent value is the summation of all dependent values of missing actions/resources within the given plan. Given a goal and a set of plans an agent can calculate the "goal-level dependent value" regarding a specific agent. The goal-level dependent value is the minimum of all related plan-level dependent value. Given a goal-plan set (a set of goals and plans) an agent can calculate the "agent-level dependent value" regarding a specific agent. The agent-level dependent value is the summation of all goal-level dependent value.

3.2.2 Selection of goal-plan. The goal selection process and the plan selection process are united into one process, and the aim is to select a goal-plan pair for execution. Four variables are considered: importance, urgency, feasibility and cost.

A goal-plan pair is more likely to be selected if the goal is important and urgent, and the plan is feasible and costless. A plan's feasibility is calculated by averaging the accessibility of each action/resource needed for the plan. An action/resource's accessibility is 3 if agent possesses it, -3 if no agent possesses it, else it would be the z score of its amount (the z score is limited from -3 to 3). A plan's cost is calculated by summing up all costs of the needed action/resource, and then compared with all other plans' cost, resulting in a z score ranging from negative infinity to positive infinity.

These four values are then put into the fuzzy inference system, with a priority value returned. All goal-plan pairs are to be evaluated this way, each pair given a priority value, and the one with the highest priority is found by using sequential search, chosen to be executed.

3.2.3 Selection of partner. After an agent has chosen a goal-plan pair, it will check and see if there is any item missing. If so, check if there is any agent that possesses such item, enter the partner selection process, choose a partner among all possible agents (ones that possess the missing item), propose to him, and see if it is willing to lend. This partner selection process is similar to the goal-plan selection process, and the aim is to choose the best partner to propose to. Five variables are considered: cost of the item proposed, relationship between one another, dependence between one another, whether the item is going to be used by the agent being proposed, and the willingness of the agent being proposed.

If the item's *cost* is high, the possibility for others to lend this item will be low. *Relationship* variable increases if one has had accepted other's proposals; decreases if one has had rejected other's proposals. Low relationship value toward others means others are more likely to reject one's proposal, but likely to accept one's proposal, if relationship value is high. *Dependence*, the agent-level dependent value that others have toward one, will also affect the possibility of being accepted or rejected. If the dependence value is high, others will be more likely to accept, wishing that someday theirs might be accepted. If the item being asked for is going to be *used* by the agent being proposed, or if the item is described in one of its plans, the possibility of lending will be low.

We introduce a variable *willingness* in order to model an agent's character, selfish or benevolent. An agent with a high willingness will tend to lend their possession no matter what the cost, relation, dependence values are. Willingness is recognized by learning process during the interaction between one another. Willingness increases whenever an agent thinks that its proposal is to be rejected, but unexpectedly being accepted; decreases whenever an agent thinks that its proposal is to be accepted, but unexpectedly being rejected [13].

These five values are then put into the fuzzy inference system, with a possibility value returned. All possible partners are to be evaluated this way. Each possible partner given a possibility value, the one with the highest possibility is found by using sequential search, chosen to be proposed to.

3.2.4 Responding to others' proposal. Agents may be proposed by others for some action/resource, but it is for them to decide whether to accept or reject the proposal. An agent will reject the proposal if it no longer possesses the requested item, that the requested item is used for the current executing plan, or that it has no information about the proposing agent. It will consider four variables: cost of the item, relationship between one another, dependence between one another, and whether the item is to be used in its plans. These four values are then put into the fuzzy inference system, with a value returned. If the returned value is greater than the given threshold, the agent will accept the proposal, and lend the item; it will reject the proposal, if the returned value is lower than the given threshold. The agent then updates its relationship toward others; raising the value if it accepts, lowering the value if it rejects.

3.3 Fuzzy inference and reasoning process

We need to define the input and output variables, membership functions, fuzzy rules, inference mechanisms and the defuzzifying method. The definitions that we made are shown in the Table 1. All three of them use minimum as the T-norm, and the center of gravity as the defuzzifying method.

Table 1. Definition of fuzzy variables, rules and methods

	Input Variable (Number of MF)	Output Variable (Number of MF)	Number of If-Then Rule	T-Norm	Defuzzifying Method
Goal-plan	importance(5) urgency(5) feasibility(4) cost(5)	Priority(5)	125	Minimum	Center of gravity
Partner	cost(5) relationship(3) dependence(5) use(2) willingness(3)	Possibility (5)	450		
Reply	cost(5) relationship(3) dependence(5) use(2)	r_possibility(5)	150		

Figure 1 is a conceptualized structural view of the functional modules and their relationships. Four functions together form a functional module, the social reasoning module, which realizes the reasoning concepts discussed above. The fuzzy inference module contains the fuzzy rules according to different agents involved in a society. Facts are divided into two groups, long-term facts (data such as external description, goal, and plan) and short-term facts (facts that are generated during the reasoning process). The goal-plan selection function, partner selection function, and reply function uses the fuzzy inference module, but only one set of data is allowed to enter the fuzzy inference module at any given time.

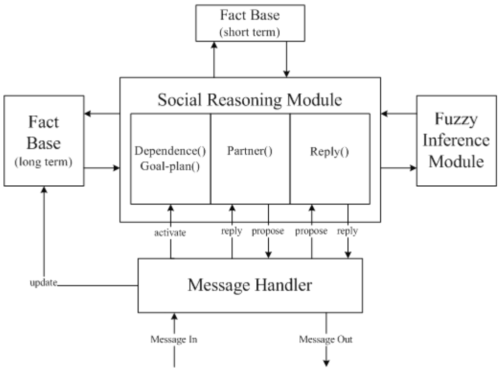

Figure 1. Reasoning mechanism

Starting with dependence evaluation and goal-plan selection, an agent reasons about its dependence relation toward others, and then reevaluates all goal-plan. If there is a goal-plan pair with a priority value greater than the current executing goal-plan, then the agent will replace the latter with the former.

The agent then checks on the selected goal-plan, sees if there is any item missing. If there is no item missing, the agent will start executing the goal-plan. If there is an item missing, partner selection function will help find out all possible partners. If there is no possible partner, the agent will start out wandering, look for agents who possess the item it needs. If there exist more than one possible partners, the partner selection function will then pick out the one with the highest possibility and propose to him.

As response, others may reject or accept the agent's proposal. If the proposal is rejected, the agent will check if there is any more possible partner, propose again if there is, and go wander if there is not. If the proposal is accepted, the agent will check if there is any other item needed. If there still are items missing, the interaction process is repeated. If all items are collected, the agent will then start executing the current goal-plan. During this reasoning process, dependence reasoning function and goal-plan selection function may reactivate, resulting in a goal-plan switch and the whole process will be restarted.

4. Building A Social Reasoning System

4.1. Agent architecture

In our simulation system, we use our social reasoning system to control robots through socially intelligent agents. Socially intelligent agents are built using a three-layered hybrid architecture (VOMAS) [14]. Our socially intelligent agent is therefore itself a multiagent system, made up of three agents: SRAgent, virtual operator, and robot agent (Figure 2). The *SRAgent* is a rule-based deliberative subsystem and reasons according to the social reasoning mechanism stated in Section 3. The *virtual operator* is responsible for executing missions coming from above (SRAgent) such as wandering. As the same time, it monitors information coming from below (Robot Agent), filters the information, and passes relevant information up to SRAgent. The *robot agent* is a behavior-based reactive subsystem, responsible for low-level control (obstacle avoiding & goal seeking).

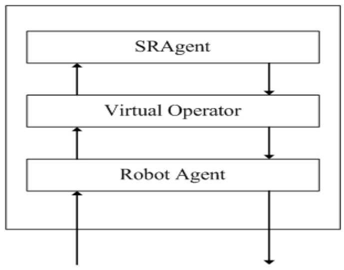

Figure 2. Our agent architecture

The advantage of using such three-layered hybrid architecture is that we can make SRAgent completely context free. This also allows us to make the robot agent completely context dependent, focusing itself on detailed low-level control, keeping its task simple and pure. The virtual operator functions as an interface between the two.

We implemented our agents by using JADE (Java Agent DEvelopment Framework) [15]. The social reasoning mechanism is implemented by Jess (Java Expert System Shell) [16]. SRAgent is the one that does the reasoning, so we embed Jess engine inside SRAgent. Messages sent to SRAgent will be translated into Jess facts and inserted into the Jess engine. The interface is written in C++.

4.2. Social reasoning system

4.2.1. Initialization of Agent. We built a function to produce goals, plans and external descriptions randomly. Three parameters are put into the function: number of agents, number of goals, and number of item types. The number of goals being created is assigned by the parameter "number of goals" and all goals are given different names. A goal's urgency and importance are given randomly. Goals are equally distributed to agents. Each goal has two plans. Each plan is designed as requiring three resources and three actions. Plans are randomly distributed to agents. Half of the action/resources will be distributed to the agents.

4.2.2. Representation of Robot and Goal. Within the simulator, robots are represented as black dots and goals are represented as red dots (Figure 3). An agent (controlling a robot) will decide which goal it is to purse, and if it has all the resources and actions needed, it will go near the goal and delete the red dot. A goal's urgency is updated regularly after a certain interval of time. If a goal's urgency exceeds 300, it will be expired and automatically deleted.

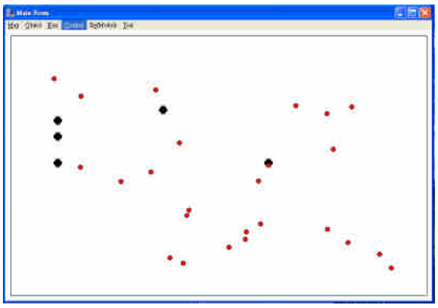

Figure 3. Representation of robots and goals

4.2.3. Revealing to Others – Simulating Accurate-Observance. An agent's view sight is limited, and can only perceive agents who are within a certain distance. We let agents reveal their own external description, goal, and plan to others, to mimic the phenomena of accurate-observance. During each clock cycle, an agent will randomly choose which information it will reveal to others: thirty percent chance it will reveal to others about its external description, thirty percent chance it will reveal its goals (one at a time), forty percent chance it will reveal its plan (two at a time, one is randomly picked, the other is the current executing plan). The information to be revealed will be sent to all agents whom are in the agent's view sight.

Agents who receive information messages will update their belief (long-term memory). If an agent receives other's *external description*, it will first recalculate the amount of action/resources. Then, it will check and see if it has got a goal description which is not in the external description. If so, it means that others have already accomplish the goal or that the goal has already been expired, and so the goal description is to be deleted. On the other hand, it will check to see if there is a goal described in external description but has no corresponding goal description. If so, the agent will create a goal description for such goal (set both urgency and importance to 150). Information consistency is therefore kept between external description on the one hand, and goal description and action/resource description on the other hand. If an agent receives a *goal description*, it will check and see if there is a corresponding external description; otherwise, it will create one. If an agent receives a *plan description*, it will check and see if it himself has this plan description; otherwise, it will adopt this plan.

Agents who are in wanders will randomly choose a target (this is handled by virtual operator) and move toward it. After it reaches the target, it will re-choose a target, and move toward it. This process ends when wandering is put to stop by SRAgent.

4.4 Experiments

Three experiments were performed by using our social reasoning system.

4.4.1. Experiment 1. Ten sets of data are generated by the function we mentioned in Section 4.3. Each set of data has eight goals for each agent. Each set of data is applied to three different kinds of society: the society made of benevolent agents, the society made of normal agents, and the society made of selfish agents. Five agents are within each society. The performance is measured by summing up the total "importance" and "urgency" of the accomplished goals [17]. And the results show that a society made of benevolent agents will together achieve the highest total performance. A society made of normal agents will perform better than the society made of selfish agents.

4.4.2. Experiment 2. The above experiments are done by setting relation's default value as 50. If we raise the default value to 90, which indicates that agents have high trust between one another, the total performance of a society will increase. Experiments are done by applying the same sets of data to a society made of normal agents. The results show that a society made of agents with high trust toward others will increase the total performance.

4.4.3. Experiment 3. Applying the same sets of data to a society made of one benevolent agent and four normal agents, has the result shown below (compared with a society made of normal agents). The benevolent agent's performance dropped about 8 percent, while others experienced a slight increase of 0.4 percent on their performance. This experiment shows that when an agent is benevolent while others are all normal, its performance will degrade and others' will remain constant. If the benevolent agent evaluates its performance according to the amount of goals it accomplishes, this will then explain why society members tend to be selfish. All would perform better if all were to be benevolent, but what actually happens is that all tend to be selfish, because being benevolent is risky. It is risky because if others are to remain normal, one who is benevolent will have its performance lowered.

5. Conclusion

Agents should be socially intelligent in order to be integrated within human society. While dependence is the core of sociality, socially intelligent agents must be able to reason about the dependence between each other. Researchers, such as Castelfranchi and Sichman, have promoted this idea within multiagent research, but limited in their reasoning methodology and the number of variables being considered, leading agents to perform actions that are quite unsocial. Adding variables such as trust and character will help improve agent's sociability. Integrating fuzzy inference will help improve the reasoning mechanism, such that agents can make a better balance between different variables.

For such reasons, we have described four reasoning functions. The dependence evaluation function reasons about the dependency between one another. The goal-plan selection function uses fuzzy inference to decide which goal-plan pair an agent is to pursue. The partner selection function uses fuzzy inference to decide which partner an agent is to propose to. The reply function uses fuzzy inference to decide whether an agent is to accept or reject a proposal. These different functions are modularized so that they can work concurrently.

Our socially intelligent agent is implemented as a multiagent system composed of three agents, layered hierarchically. Agents communicate with each other using ACLMessage. Fuzzy rules are implemented in such agents. Experiments show that a society made of benevolent and trustful agents achieves the highest total performance.

6. Ackknowledgment

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Reference

[1] C. Castelfranchi. "Social Power: A missing point in MultiAgent, DAI and HCI". In Y. Demazeau and J. P. Muller (eds.) *Decentralized A.I.*, Elsevier Science Publishers B. V., 1990, pp. 49-62.

[2] C. Goldspink. "Methodological Implications of Complex Systems Approaches to Sociality: Simulation as a foundation for knowledge," *Journal of Artificial Societies and Social Simulation*, Vol. 5, no. 1, 2002, pp.1-19.

[3] N. Herzfeld. "Creating in our own image: Artificial intelligence and the image of God," *Zygon*, Vol.37, no.2, 2002, pp.303-316.

[4] T. Fong, I. Nourbakhsh and K. Dautenhahn. "A survey of socially interactive robots," *Robotics and Autonomous Systems*, 42, 2003, 143–166.

[5] C. Castelfranchi. "Modeling Social Action for AI Agents," *Artificial Intelligence*, 103, 1998, 157-182.

[6] M. Wooldridge. *An Introduction to Multiagent Systems*. John Wiley & Sons Ltd, 2002.

[7] C. Castelfranchi, M. Miceli, and A. Cesta. *Dependence relations among autonomous agents*. In E. Werner and Y. Demazeau, editors, Decentralized A.I. 3, Elsevier Science, 1992, pp. 215-231

[8] S. Brainov and T. Sandholm. "Power, Dependence and Stability in Multiagent Plans," *Proc. of the 16th National Conference on Artificial Intelligence and Eleventh Conference on Innovative Applications of Artificial Intelligence*,1999, , pp.11-16.

[9] C. Castelfranchi and R. Falcone. "Principles of trust for MAS: Cognitive anatomy, social importance, and quantification," In Y. Demazeau (ed.), *Proc. of the 3rd International Conference on Multi-Agent Systems*, 1998, pp. 72-79.

[10] J. S. Sichman, R. Conte, Y. Demazeau, C. Castelfranchi, "A social reasoning mechanism based on dependence networks," In Tony Cohn, editor, *Proceedings of the 11th ECAI,* Amsterdam, Netherlands, 1994, pp. 188-192.

[11] J. S. Sichman. *DEPINT:* "Dependence-Based Coalition Formation in an Open Multi-Agent Scenario," *Journal of Artificial Societies and Social Simulation*, vol. 1, no.2.

[12] N. R. Jennings. "Coordination Techniques for Distributed Artificial Intelligence," In G. M. P. O'Hare and N. R. Jennings eds. *Foundations of Distributed Artificial Intelligence*, John Wiley & Sons, pp. 187-210, 1996.

[13] T. Malsch and G. Weiß. "Conflicts in Social Theory and Multiagent Systems: On Importing Sociological Insights into Distributed AI," In C. Tessier, L. Chaudron & H.-J. Müller (Eds.), *Conflicting agents. Conflict management in multi-agent systems.* Kluwer Academic Publishers. Chapter 4, pp. 111-149, 2000.

[14] H.C.H. Hsu and A. Liu. "Multi-Agent Based Formation Control Using a Simple Representation," *Proc. of the IEEE International Conference on Networking, Sensing and Control*, 2004, pp.276-281.

[15] JADE, *JADE programmer's guide*, 2003, http://jade.tilab.com/.

[16] Jess, http://herzberg.ca.sandia.gov/jess/.

[17] N. David, J. S. Sichman, H. Coelho. "On being responsible: how to be individualistic and smile benevolence to the others," *Proceedings of the 3rd European Conference on Cognitive Science, ECCS99*, Sienna, Italy, 1999, pages 57-62.