Simulation of Three-person Cooperation – Effect of Mutual Beliefs on Team Performance

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ABSTRACT

Many human factor studies have explored the cognitive and behavioral factors that affect team performance via verbal protocol and behavioral analyses. As the measurements used in these studies only focused on observable data, there is a fundamental limitation to understanding cognitive mechanisms. Computer simulation is an alternative method for exploring the cognitive aspects of human factors in team cooperation. In this study, we employed an extended mutual belief model to develop an agent-based simulation for a three-person team cooperation. This model describes the cognitive processes in a team of three or more. The results indicate that communication that is generated by mutual beliefs worked effectively and enhanced

team performance. Our simulation method can potentially address the limitations of conventional human factor methods by exploring the cognitive aspects of team cooperation.

Keywords: Team Cognition · Situation Awareness · Agent-based simulation · Team communication

INTRODUCTION

Many human factors researchers have investigated the cognitive and behavioral factors that affect team performance. Protocol analysis and behavior analysis are the major methods used in these studies as measurements of cooperative behavior in team processes (Cooke, Salas, Cannon-Bowers, & Stout, 2000) . For example, Prenston et al.developed several automatic methods for analyzing communication data for measuring team cognition.(Cooke&Gorman, 2009). However, these measurements are only focused on observable data, making it difficult to efficiently and precisely extract the underlying cognitive mechanisms. An alternative approach for exploring different cognitive aspects in team cooperation exercises is through the use of computer simulations that can test various hypotheses regarding team cognition. However, the computational approach for team cognitive studies is still in its infancy. For example, Grand et al. proposed a theory based on knowledge emergence in teams, translated this theory into a computational model, and performed an agent-based simulation(Grand, Braun, Kuljanin, Kozlowski, & Chao, 2016). In this simulation, when an agent communicates with the others, the partner is determined using a static probability, and the content is randomly assigned. However, the model did not consider the mechanisms' underlying communication, such as utterance intentions. In a previous study, Yojima et al. developed an agent-based simulation for cooperative behavior analysis based on a team cognition model proposed by Kanno et al, by employing the concept of mutual beliefs that explains the cognitive mechanisms behind dyadic team cooperation. (Kanno et al. 2013, Yojima et al. 2018) It was concluded that mutual belief played an important role in improving team performance, regardless of the domain knowledge structure. While the previous study modeled and focused only on a two-person team, an actual team in the real world often consists of three or more people, where more complicated cognitive processes are required than those in two-person cooperation (Bosse, Majdanik, Boersma, & Ingibergs, 2013). In this study, to investigate the effect of team cognition on the team performance in a three-person team, we developed an agent-based simulation for three-person team cooperation by employing an extended team cognition model that considers mutual beliefs and mental subgrouping. This extended model describes the cognitive processes in a team of three or more members, using three different layers. We applied this model and simulation to the cooperative diagnosis problem of car failures. We then observed how a team collaboratively collected information on car parts, shared information with other members and identified broken car parts.

THEORETICAL AND SIMULATION MODELS

Extended Mutual Belief Model

Dipta et al. proposed a team cognition model called the extended mutual belief model (EMBM)(Mahardhika, Kanno, & Furuta, 2016). This model consists of the following three layers: a self-cognition layer, a direct belief layer, and a projected belief layer. The EMBM of a three-person team is shown in Figure 1. The self-cognition layer contains any possible cognitive processes or mental statuses. The second layer, or the directed belief layer, contains two cells representing one's belief about each partner's cognition. The third layer, or the projected belief layer, contains four cells and represents one's belief about one's own cognition, and also one's belief in the partner's belief about the other partner's cognition.

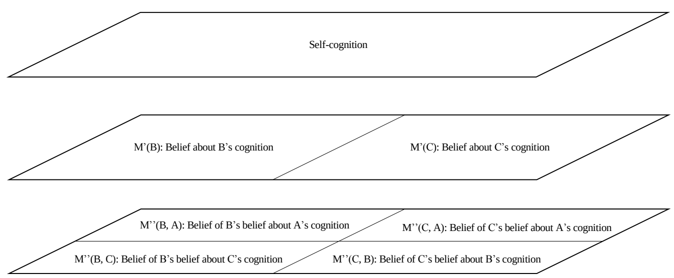

Figure 1. Extended mutual belief model in the case of a team consisting of three members: A, B, and C (in A's mind). The first layer represents the self-cognition of A. The second layer represents M'(B) (A's belief about B's cognition) and M'(C). The third layer represents M''(B, A) (A's belief of B's belief about A's cognition), M''(C, A), M''(B, C) and M''(C, B).Domains of human systems integration. (Adapted from U.S Air Force, 2005)

Simulation Model

The same task used in the car diagnosis was used for the simulation, as was the case in the previous study. The goal of the task is to collaboratively use three agents to diagnose car failures. In this task, each agent can only see a part of the car; thus, the agents need to cooperate with each other to acquire the correct and complete situation awareness (SA). The three agents are used to recognize who can observe which of the nodes are part of their team's knowledge. An agent has an EMBM, wherein each cell is implemented using a single Bayesian belief network (BBN). BBNs represent the agent's domain knowledge structure and cognitive and inference mechanisms. The probabilities of a node in a BBN represent the degree of an agent's belief about a state occurrence. A set of nodes representing the conscious recognition of the state occurrence is defined as as U, and is formulated using Equation (1), where P_i is the probability of state i and T is the threshold for "state occurrence." When new information is entered into a specific node, the probability of the other nodes is updated. BBN can represent a building SA in a situation where information is uncertain and limited.

$$U = \sum_{node} \{ i \,|P_i \geq T\} \,. \tag{1}$$

In the simulation model, agents perform the following four types of actions: observation (Look at) and three types of communication (Query/Inform/Make Clear). Look at is an action to obtain the state of a component by perceiving the environment. In contrast, communications are actions by which an agent resolves the contradictions between self-cognition and mutual beliefs. Query is a communicative action that notifies the partner "Unknown" and requests the partner's SA. Inform is an action that reveals the agent's own SA to the partner and ensure the partner's SA matches the agent's own SA; while Make Clear is an action that reveals the agent's own SA to the partner to remove misunderstandings on the agent's own SA. The processes of updating one's own cognition and inferences about others' cognition or mutual beliefs are interdependent. We assume that these processes are bridged by metacognitive operations and are modeled as interlayer interactions in the simulation model. When an action is taken, several cells in the EMBM are updated using interlayer interaction. All communication takes place between two agents, but information on the agents participating, the type of action, and the contents of the communication are open. Therefore, an agent that is not participating can also obtain information about the communication and update the mutual beliefs based on the information. The action rules of the agents are listed in Table 1. We evaluated the team performance using Team Accuracy that was formulated using Equation (2), in which U_0 represents a set of states for all nodes in the BBN of the car model, and U_{A1} represents a set of states for all nodes in the BBN of agent A's first layer.

$$Team\ Accuracy\ = \left(\frac{|U_0 \cap U_{A1}|}{|U_0|} + \frac{|U_0 \cap U_{B1}|}{|U_0|} + \frac{|U_0 \cap U_{C1}|}{|U_0|} \right) \times \frac{1}{3} \,. \tag{2}$$

Table 1. Action Rules
Table 1 summarizes the action rules for agent A. The other two agents followed the same action rules. C (A) represents A's self-cognition and "Inform B" implies that agent A performs an Inform for agent B. In the case of the first row, when an agent recognizes the contradiction of C(A)≠M'(B), agent A first performs Look at if the node is observable for agent A, and then, if self-cognition changes, agent A performs an Inform for agent B. If the node is not observable, then agent A performs Query on B. In this table, the cases of contradiction between C(A) and M'(C), M' (C, A), and M'' (C, B) are not listed.

Contradiction	**Action**

C(A) ≠ M'(B)	if observable: Look at if cognition changes: Inform B else: Query B
C(A) ≠ M'(B) and M'(B) = Unknown	Inform B
C(A) ≠ M'(B) and C(A) = Unknown	if observable: Look at else: Query B
C(A) ≠ M'' (B, A) and C(A) = Unknown	if observable: Look at else: Query B
C(A) ≠ M''(B, A) and C(A) ≠ Unknown	Make Clear B
C(A) ≠ M'' (B, C) and C(A) = Unknown	if observable: Look at else: Query C
C(A) ≠ M''(B, C) and M''(B, C) = Unknown	Inform C and Make Clear B
C(A) ≠ M''(B, C) and M''(B, C) ≠ Unknown	if observable: Look at if cognition changes: Inform C and Make Clear B else: Query C

An important component of the human systems integration plan should be a verification and validation process that provides a clear way to evaluate the success of human systems integration. The human systems integration team should develop a test plan that can easily be incorporated into the systems engineering test plan. The effectiveness and performance of the human in the system needs to be validated as part of the overall system. It may seem more attractive to have stand-alone testing for human systems integration to show how the user interacts with controls or displays, how the user performs on a specific task. This methodology can address the performance of the human operator or maintainer with respect to the overall system. The most important thing is to develop a close relationship between human systems integration and systems engineering.

SIMULATION

A flowchart for the simulation is presented in Figure 3. First, the model parameters shown in Table 2 were set. Next, the agent that takes the action is randomly determined. Then, the target node is selected from among the nodes where the agent is unsure of its state or where there is a contradiction in the cells. If more than one node is selected, nodes are chosen in order of their impact on the other nodes. After selecting the target node, the action was determined according to the action rules. When an agent performs the action, each cell of the EMBM is updated. Subsequently, it was confirmed whether the termination condition formulated by Equation (3) was satisfied. In Equation (3), $U_{All-Conflicts}$ refers to the set of nodes in which at least one agent has a contradiction and $U_{All-Unknown}$ refers to the set of nodes, in a state of which at least one agent is uncertain. If this is true, then the simulation ends. The simulation was conducted 100 times under the same parameter settings.

$$\begin{cases} \left|U_{All-Conflicts}\right| = \left|U_{All-Unknown}\right| = 0 \\ or \\ The\ total\ number\ of\ action\ \geq 100 \end{cases}. \quad (3)$$

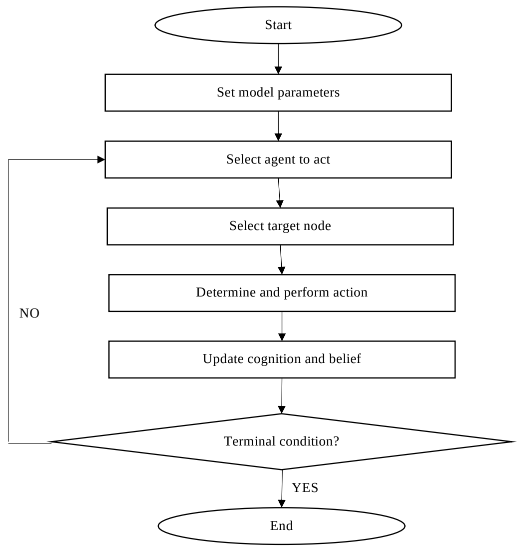

Figure 3. Simulation model flowchart.

Table 2. Parameter setting of Simulation
When the referenced layer is L1, the agent refers to only the 1st layer, and when it is L12, the agent refers to the 1st and 2nd layers when determining an action. When the reference layer is L12, agents can only recognize the conflict between 1st and 2nd layer.

Parameter	Definition	Value
Threshold	Threshold of “state occurance”of an evet	0.75
Case	The set of part states of a car that the agents diagnose	1/2/3/4/5
Human Error	With or without the agents having the wrong SA at the start of the simulation	With
Referenced Layer	The layers an agent refers to when determining an action	L1/L12/L13/L123

RESULT AND DISCUSSION

The results of the simulation with human errors are shown in Figure 4. We repeated the simulation 100 times under the same conditions, sorted the obtained Team

Accuracy in descending order, and constructed a scatter plot of the Team Accuracy with the same rank as those obtained when the referenced layer was L1. A plot that is above the dotted blue line in Figure 4 indicates that the team performance is improved by mutual beliefs and interlayer interactions triggered by meta-cognition. In the graphs, all the plots are above the dotted line, and it was observed that communication generated under the condition of the referenced layers L12, L13, and L123 improved Team Accuracy. This suggests that mutual belief is one of the major factors and driving forces for better team cooperation. This finding, which was also pointed out in the previous study, was confirmed in three-person cooperation. Table 3 summarizes the number of total actions and the average percentage of each action with respect to all actions in one simulation. Under the conditions of L1, communication does not occur, and under the conditions of L12, Make Clear does not occur. This is caused by the following action rules. From Table 3, it can be concluded that the action distributions of L13 and L123 have similar tendencies in that communication is mainly through Inform and Make Clear, and Query rarely occurs.

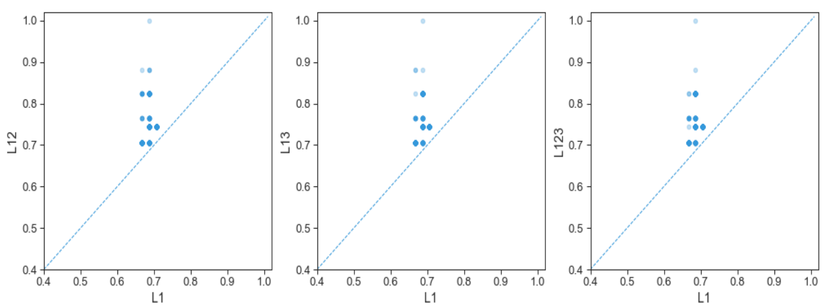

Figure. 4. A Comparative analysis of the result with Human Error. The horizontal axis represents the Team Accuracy when referring only to the first layer, and the vertical axis represents the Team Accuracy obtained when referring to the first and second layers (L12), the first and third (L13), and all three layers (L123), respectively.

Table 3. Parameter setting for the simulation

Referenced Layer	Total Action	Look at	Inform	Query	Make Clear
L1	2.000	1.000	0.000	0.000	0.000
L12	14.284	0.314	0.501	0.185	0.000
L13	22.524	0.215	0.237	0.090	0.458
L123	22.644	0.225	0.312	0.099	0.364

CONCLUSION

To investigate the effect of the cooperative behavior generated by mutual beliefs on the team performance, we developed an agent-based simulation for three-person team cooperation by employing the extended mutual belief model. This model contains three layers and captures the human ability to infer the psychological states of others. We applied this model and simulation to the cooperative diagnosis problem of car failures and observed how a team collaboratively collects information on car parts, shares the information with other members, and identifies broken car parts. From the simulation results, we found that mutual beliefs played an important role in improving team performance, and the communication generated by mutual beliefs worked effectively and enhanced team performance. These findings, which were also reported in the previous study, were confirmed in three-person cooperation. The communication in this simulation model is reduced to updating the cognition and mutual beliefs of each agent, and does not include the exchange of information between the agents. One direction for future research is the development of a communication model that includes the exchange of information. Although further improvements are necessary, we believe that our simulation is a promising method for compensating for the limitations of conventional human factor methods by exploring the cognitive aspects of team cooperation.

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