On Shared Situation Awareness for Supporting Human Decision-Making Teams*

Xiaocong Fan and **Shuang Sun** and **John Yen**
School of Information Sciences and Technology
The Pennsylvania State University
University Park, PA 16802
{zfan,ssun,jyen}@ist.psu.edu

Abstract

One of the challenging issues in homeland security area is the early detection and successful processing of potential terrorist threats, which demands effective team collaboration. In this paper we investigate how team-based agent approach can be applied in helping human decision-making teams make better decisions. By extending Kleins Recognition-Primed Decision model, we propose a Collaborative RPD model (C^2RPD) which allows us to investigate both agent-agent collaborations and agent-human collaborations during the decision-making process. This model encourages proactive information seeking, linking and sharing in distributed teamwork settings, thus can be incorporated into cognitive agent architectures to support distributed team cognition and decision making.

Motivation

There are many challenging issues that demand team collaboration in various sectors of homeland security (HS). For instance, to enable early detection and successful processing of potential terrorist threats, team members must effectively work together to quickly gather and make sense of information from multiple sources. However, teamwork in this area is often threatened by the fact that team members need to process voluminous amount of dynamically changing information under time pressure. Moreover, the information and knowledge resident within the broad scope of homeland security situations are typically distributed across people, objects, tools, and environments due to security concerns often associated with their roles and responsibilities. These unique and complex challenges can significantly hamper the quality and the timeliness of decision making in homeland security areas, which can have extraordinary and possibly catastrophic consequences.

The objective of this research is to investigate cognitive agent architectures that can support human decision-making teams in (a) achieving shared situation awareness, (b) accumulating and learning from experiences, (c) building stories out of incomplete situations, (d) proposing potential decisions, and (e) monitoring the status of expectancy with respect to a potential decision. This objective significantly affects the choosing of decision-making models to be built in the agent architecture.

There has been a long history of arguing on whether satisficing or optimizing should be the core of practical decision making (e.g., (Simon 1955)). More recently, there has been significant interest in applying decision-theoretic principles to build intelligent systems. For instance, work on Markov Decision Process (e.g., DEC-MDP, POMDP) has gained increasing attention in recent AI conferences (Shen, Lesser, & Carver 2003; Nair *et al.* 2004). There is no doubt that agents with sufficient computational resources can use the MDP approaches to help people make decisions on well-defined problems. On the other hand, researchers in the camp of naturalistic decision making take the opinion that when making decisions, people usually do not know the probabilities of all the choices; they even do not know all the possible options. They argue that communities dealing with time stress tasks often demand simulation systems with realistic (human-like) decision representation (Sokolowski 2002).

Rather than trying in vain to have another critique review of these two approaches, in our study we choose a specific naturalistic decision-making model—the Recognition-primed decision model (RPD)(Klein 1989; 1997)—for two major reasons. First, RPD offers a well-structured process for better solving ill-structured problems where there is no time for extensive reasoning. Team wide collaboration opportunities can be naturally embedded into the RPD process; this enables us to further investigate dynamic information sharing problems and distributed team cognition problems. Second, RPD focuses on recognizing the similarity between the current decision situation and previous decision experiences, which is claimed as what experts usually do when making decisions in dynamic environment. Implementing agents with a computational RPD can encourage close *agent-human collaboration* in the decision-making process (adjustable autonomy); this advocates the view of human-centered teamwork (Sierhuis *et al.* 2003), where from humans perspective, agents are not just black-boxes providing decision making supports, but rather active peers that humans can directly interact with. In summary, RPD model is a natural choice because it allows us to investigate

*This research has been supported by AFOSR MURI grant No. F49620-00-1-0326.

both agent-agent collaborations and agent-human collaborations during the process.

The remainder of this paper is organized as follows. In Section 2 we briefly review the RPD model and explore the potential opportunities in the decision-making process where team collaboration may play a better role than single agent. A collaborative RPD model (C^2RPD) is given in Section 3, describing how distributed agents can work together to create shared situation awareness, to learn from experiences, to build stories out of incomplete situations, and to monitor the status of expectancies. Section 4 focuses on how a human user may interact with his/her assistant agent in the RPD process. A fictitious example is given in Section 5 to illustrate the use of C^2RPD in the homeland security domain, and Section 6 summarizes the paper.

Collaboration opportunities in the RPD model

We first briefly review the RPD model. Then we justify why team-based RPD works better in dynamic, distributed situations, and examine the potential opportunities in the RPD process where a team of agents can collaborate based on their shared understanding of the decision problems and overlapping situation awareness.

The RPD Model

The RPD model (Klein 1989) captures how domain experts make decisions based on the recognition of past experience similar to the current situation. RPD has two phases: recognition and evaluation. In recognition phase, an agent needs to develop situation awareness and recognize which course of actions makes sense. In evaluation phase, an agent needs to carry out singular evaluation by imaging how a course of actions will evolve. In case that a course of actions does not work for the current situation, the agent can either adjust the action course, or reject it and examine another option until a workable solution is obtained.

In this paper, we focus on the recognition phase. Feature-matching and story-building are two diagnostic strategies employed by decision makers to develop situation awareness. Feature-matching is tried first, by which a decision maker tries to match the set of observed cues or pattern of cues with domain features pertinent to the decision request. In case that feature-matching cannot provide an adequate picture due to lack of information or experience, story-building will be used to construct a story (i.e., a causal sequence of events), linking the pieces of observed and available information into a coherent form. To better explain the observed events, story-building also allows a decision maker to explore several potential hypotheses and evaluate how well each of them fits the observations. The story provides an explanation of how the current situation might have been emerging.

Due to the dynamic and uncertain nature of the environment, a decision maker may have misinterpreted the current situation but he/she cannot recognize it until the situation further evolves to certain point. Thus, a recognition result is normally associated with expectancies to be monitored and assumptions to be confirmed. More specifically,

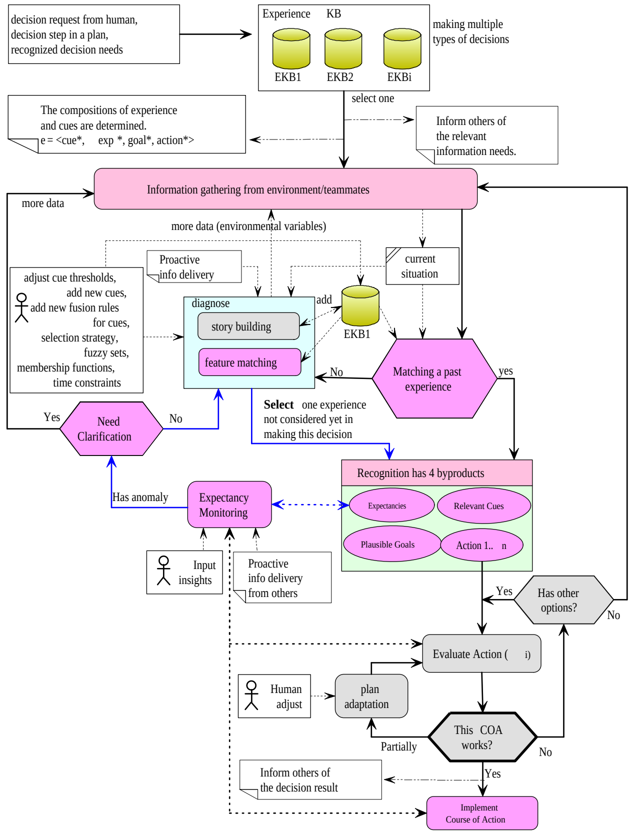

Figure 1: The C^2RPD Model illustration: agent-agent collaboration, and agent-human collaboration

an expectancy states what will happen, serving as a gate-condition for continuing working on the current recognition; the decision maker may need to further diagnose the current situation (e.g., to gather more information) in case that the expectancy conflicts with new observed facts. An assumption states what much be, serving as a point for gaining confidence; the recognition is more justified as the assumption is confirmed by new acquired information. In addition to expectancies (assumptions), a recognition result also includes relevant cues (what to pay attention to), plausible goals (which goals make sense), and course of actions (what actions worked in this type of situation).

Collaboration Opportunities

The RPD model captures the cognitive activity undergoing in the mind of a decision maker when he/she faces a decision task. In essence, RPD is an individual process because it is within the decision maker's mental model. However, this does not mean the other team members knowing RPD cannot establish a shared mental model about the dynamic RPD process that is pursuing by the decision maker, and take appropriate opportunities to contribute to the decision task. Emphasizing the individual nature of the RPD process leaves open the roles others may play in the process, expecially from the information seeking and sharing perspective.

On the other hand, as domain complexity increases, decision making often involves various kinds of expertise and experiences, which are typically distributed among a group of decision makers (Hollenbeck *et al.* 1997). In such cases, it is crucial to do what is needed to get the most out of the information available to the team. Information needs anticipation and proactive information sharing are certainly key factors to enhancing decision making under time pressure.

Thus, in the following framework, we consider the situations where a group of people who are experts in different areas, each assisted by one RPD-agent (i.e., agent capable of making decisions using RPD model), face the pressure to make better and faster decisions in an environment characterized by a high domain complexity. In such a setting, collaboration may exhibit among RPD-agents, between a RPD-agent and its human user, and among the human experts. We focus our investigation on the former two kinds of collaboration.

A careful scrutiny of the RPD model under teamwork settings reveals that potential agent-agent collaboration opportunities include:

- Situation Awareness: each agent may be only sensitive to certain kinds of information and thus have partial view of the global state. They need to effectively share their information to achieve situation awareness;
- Feature Matching: In feature matching, an agent can proactively request new information from other teammates;
- Story Building: The agents can collaboratively build a story, progressively anticipate other teammates' information needs in exploring a potential hypothesis.
- Expectancy Monitoring: All the agents keep an eye on the expectancies resulted from the recognition and report changes to others when applicable.

Potential agent-human collaboration opportunities include:

- Situation Awareness: People can add new cues for the assistant agent to consider; the agent can show its human user the cue patterns being considered;
- Feature Matching: People can adjust the matching strategy to be used, suggest assumptions to the value of some missing information, suggest expectancies to be considered, adjust the presureness (the deadline to have a decision made, etc. The agent can show its human user the matching result, the degree of similarity between each of the matched experience and the current situation;
- Story Building: People can suggest hypotheses to explore, additional cues to consider, etc. The agent can show its human user the causal links among the available information, what's missing in creating a consistent story;
- Expectancy Monitoring: People can input insights on how to handle the violated expectancies. The agent shows its human user how significant the recognition will be affected by the violation.

Figure 1 shows when these two different kinds of collaborations happen in the RPD process.

Then, The main body of this paper will focus on a computational collaborative RPD model, which captures both agent-agent collaborations and agent-human collaborations. We investigate in detain how agents take the aforementioned opportunities to help make better decisions.

References

Hollenbeck, J. R.; Major, D. A.; Sego, D. J.; Hedlund, J.; Ilgen, D. R.; and Phillips, J. 1997. Team decision-making accuracy under difficult conditions: construct validation of potential manipulations using the TIDE^2 simulation. In Brannick, M. T.; Salas, E.; and Prince, C., eds., *Team performancs assessment and measurement*. 111–136.

Klein, G. A. 1989. Recognition-primed decisions. *Advances in man-machine systems research (Ed: W. B. Rouse)* 5:47–92.

Klein, G. A. 1997. The recognition-primed decision (rpd) model: Looking back, looking forward. *Naturalistic decision making (Eds: C. E. Zsambok and G. Klein)* 285–292.

Nair, R.; Roth, M.; Yokoo, M.; and Tambe, M. 2004. Communication for Improving Policy Computation in Distributed POMDPs. In *Proceedings of The Third International Joint Conference on Autonomous Agents and Multi-agent Systems*, volume AAMAS04. ACM Press.

Shen, J.; Lesser, V.; and Carver, N. 2003. Minimizing Communication Cost in a Distributed Bayesian Network using a Decentralized MDP. In *Proceedings of Second International Joint Conference on Autonomous Agents and MultiAgent Systems (AAMAS 2003)*, volume AAMAS03, 678–685. Melbourne, AUS: ACM Press.

Sierhuis, M.; Bradshaw, J. M.; Acquisti, A.; van Hoof, R.; Jeffers, R.; and Uszok, A. 2003. Human-agent teamwork and adjustable autonomy in practice. In *7th International Symposium on Artificial Intelligence (I-SAIRAS)*.

Simon, H. 1955. A behavioral model of rational choice. *Quarterly Journal of Economics* 69:99–118.

Sokolowski, J. 2002. Can a composite agent be used to implement a recognition-primed decision model. In *Proceedings of the Eleventh Conference on Computer Generated Forces and Beharioral Representation*, 431–436.