Expectedness in Human-Robot Collaboration (Extended Abstract)

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ABSTRACT

We have investigated the mutual influences of affective and collaborative processes in a cognitive theory to support interaction between humans and robots or virtual agents. We build primarily on the *cognitive appraisal* theory of emotions and the *SharedPlans* theory of collaboration to investigate the structure, fundamental processes and functions of emotions in a collaboration. We have developed new algorithms for appraisal processes as part of a new overall computational model. In this paper, we provide the *expectedness* appraisal algorithm for collaboration context. We have evaluated our implemented algorithm by conducting an online user study.

Keywords

Algorithms; Appraisal; Human-Robot Collaboration

1. INTRODUCTION

Collaborative robots are expected to become an integral part of humans' environment to accomplish their industrial and household tasks. In these environments, humans will be involved in robots' operations and decision-making processes. The involvement of humans requires the robots to evaluate the collaborative environments and maintain the collaboration respectively.

This work is implemented as part of a larger effort to build robots capable of generating and recognizing emotions in order to be better collaborators. In this paper, we report on the specific problem of appraising the expectedness of events within a collaborative interaction. Our contribution is to ground general appraisal concepts in the specific context and structure of collaboration. This work is part of the development of *Affective Motivational Collaboration Theory* [6] which is built on the foundations of the *SharedPlans* theory of collaboration [3] and the *cognitive appraisal* theory of emotions [2].

There are several appraisal models (e.g., EMA [5]) contributing in different applications such as social sciences, virtual agents, and robotics. However, none of these models have focused on the appraisal processes during collaboration. We believe appraisal plays a key role in collaboration due to its regulatory and evaluative nature. Also, collaboration induces some changes to underlying appraisal processes due to its unique nature.

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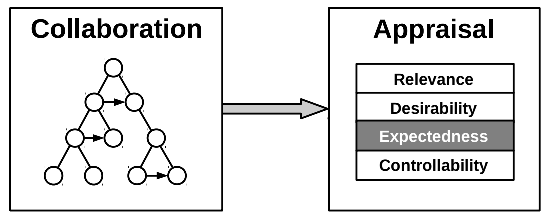

Figure 1: Influence of Collaboration on Appraisal (mechanisms in our framework).

The computational collaboration model in our work is strongly influenced by the SharedPlans theory [3]. However, our algorithms are also compatible with other collaboration theories, e.g., Joint Intentions theory [1]. These theories have been extensively used to examine and describe teamwork and collaboration. Yet, collaboration and emotion theories have never been combined, as they are in our work. We believe a systematic integration of collaboration theories and appraisal theory can help explain the underlying processes of collaboration structure.

2. COLLABORAITON

The Collaboration mechanism constructs a hierarchy of goals associated with tasks in a hierarchical task network (see Figure 2), and also maintains the constraints and other required details of the collaboration including the inputs and outputs of individual tasks, the preconditions (specifying whether it is appropriate to perform a task), and the postconditions (specifying whether a just-completed task was successful). Collaboration also monitors the focus of attention, which determines the salient objects, properties and relations at each point, and shifts the focus of attention during the interaction.

- *recognizeGoal*(ε_t) returns the unique goal to which the given event (action, utterance, or emotional expression) directly contributes; it is only one goal since the robot can only do one primitive action at a time in our collaboration model, i.e, in the goal tree, a given primitive action can only directly contribute to one parent goal. The method returns *ambiguous* if it does not recognize a goal in the plan[1].
- *getTopLevelGoal*(g_t) returns g_t's top level goal.

[1]Ambiguity introduces some extra complexities which are beyond scope of this paper.

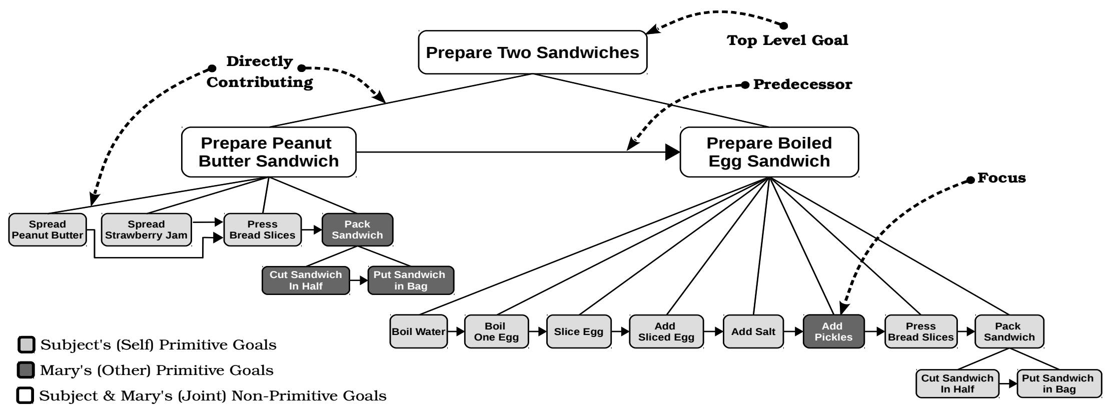

Figure 2: Example of collaboration structure (also used as task model for the evaluation).

- *isLive*(g_t) returns *true* if all the predecessors of g_t are ACHIEVED and all the preconditions are SATISFIED, i.e., PENDING or IN PROGRESS goals; otherwise returns *false*.
- *isFocusShift*(g_t) returns *true* if the given goal is not the previous focus (top of the stack); otherwise returns *false*.
- *isNecessaryFocusShift*(g_t) returns *true* if the status of the previous focus was ACHIEVED; otherwise returns *false* [4].
- *isPath*(g_1, g_2) returns *true* if there is a path between g_1 and g_2 in a plan tree structure; otherwise returns *false*.

3. EXPECTEDNESS IN COLLABORAITON

Expectedness is the extent to which the truth value of a state could have been predicted from causal interpretation of an event [5]. In the collaboration context the expectedness of an event evaluates the congruency of the event with respect to the existing knowledge about the shared goal. Thus, expectedness underlies a collaborative robot's attention. Congruent beliefs in a robot's mental state will lead to more consistent and effective outcomes of the processes in the overall architecture. The collaboration mechanism uses expectedness to maintain the robot's attention and subsequently its mental state with respect to the shared goal. Reciprocally, the appraisal mechanism uses the underlying information of the collaboration structure to evaluate the expectedness of an event. Therefore, a collaborative robot uses expectedness to maintain its own mental state towards the shared goal. The robot will also be able to respond to unexpected but relevant events.

Algorithm 1 (Expectedness)

function ISEVENTEXPECTED(Event ε_t)

$g_t \leftarrow recognizeGoal(\varepsilon_t)$
$g_{top} \leftarrow getTopLevelGoal(g_t)$

if ($isLive(g_t)$) **then**
  if ($\neg isFocusShift(g_t)$
    $isNeccessaryFocusShift(g_t)$) **then**
     return MOST-EXPECTED
  else
     return EXPECTED
else
  if ($isPath(g_t, g_{top})$) **then**
     return UNEXPECTED
  else
     return MOST-UNEXPECTED

In Algorithm 1 we provide the process of computing the expectedness based on the shared plan and status of the shared goal. The key point in this algorithm is the status of the current shared goal (g_t) that is associated with the event ε_t and its relationship with the top level goal (g_{top}).

The intuition captured here is that one expects the current goal to be finished before undertaking another activity, but the goals that are the next focus of attention are also to be expected [4]. Therefore, if the goal is live, the algorithm checks whether the goal has not changed, or the interpretation of the last event results in a necessary focus shift. Shifting the focus to a new goal is necessary when the former goal is achieved and a new goal is required. Consequently the new event is the MOST-EXPECTED one. However, even if the focus shift is not necessary, the new event can be considered as EXPECTED, since the corresponding goal is already live. For goals that have not yet been started (that is, are not live), the algorithm must determine how unexpected it would be to pursue one now; if the goal is at least in the plan, i.e., on the path to the top level goal, it is just UNEXPECTED while any others are MOST-UNEXPECTED.

4. EVALUATION

We conducted a user study to test our hypothesis that humans and our expectedness algorithm will provide similar answers to questions related to different factors used to compute expectedness. We conducted a between-subject user study using an online crowdsourcing website – CrowdFlower[2]. We had a questionnaire with 12 questions (including 2 test questions). There were originally 40 subjects. We limited the subject pool to those with the highest confidence level on the crowdsourcing website in the United States, Britain, and Australia. Test questions were included to check the sanity of the answers. We eliminated subjects providing wrong answers to our sanity questions, and subjects with answering times less than 2 minutes.

To minimize the background knowledge necessary for our test subjects, we used a simple example of preparing a peanut butter and jelly sandwich, and a hard boiled egg sandwich. We provided textual and graphical instructions for the questionnaire; Figure 2 shows the corresponding task model. The instructions presented a sequence of hypothetical collaborative tasks to be carried out by the test subject and an imaginary friend, Mary. We also provided a simple definition for expectedness appraisal variable. The questions introduced specific situations related to the shared plan, which included

[2]http://www.crowdflower.com

blocked tasks and failure or achievement of a shared goal. Each question provided three answers which were counterbalanced in the questionnaire. We provided an option like C in all questions, because we did not want to force subjects to choose between two options when they did not have a good reason. There were two questions designed based on each factor that we use in our algorithm. The questions were randomly placed in the questionnaire. Figure 3 shows an example question from the questionnaire. The input for our algorithms was the task model depicted in Figure 2.

Imagine you have pressed the two slices of bread (one covered with strawberry jam and one covered with peanut butter) together and passed it to Mary. Which of the following two actions is **more expected**?

A. Mary puts the given sandwich into a zip lock bag after cutting it in half.

B. Mary puts some pickles on another slice of bread.

C. Equally expected.

Figure 3: Example Expectedness Question.

Average results and standard deviation of the fractions of subjects' answers agreeing with our algorithm output was 0.785 and 0.120 respectively. Each question had 3 answers. Therefore, a random distribution would result in 33% agreement with our algorithm's output. However, the average agreement between our algorithm and the human subjects was 78.5%. Our results indicate that people largely performed as our hypothesis predicted. The p-value obtained based on a one-tailed z-test shows the probability of human subjects' answers being generated from a random set. The very small p-value (<0.001) indicates that the data set is not random; in fact, the high percentage of similarity confirms our hypothesis and shows that the algorithm can help us to model expectedness as an appraisal in collaboration.

5. CONCLUSION

The SharedPlans theory and other computational collaboration theories (e.g., Joint Intentions) emphasize the importance of commitment in collaboration. According to these theories collaborators are required to commit to their shared plan or intentions to successfully collaborate and achieve a shared goal. This commitment requires them to appraise their environment based on the shared plan structure. In our next step, we want to test our appraisal algorithms and their influence on action selection during collaboration. This study will be conducted between a KUKA youbot and human subjects on a different task model.

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REFERENCES

[1] P. Cohen and H. J. Levesque. *Teamwork*. SRI International, 1991.

[2] J. Gratch and S. C. Marsella. A domain-independent framework for modeling emotion. *Cognitive Systems Research*, 5(4):269–306, 2004.

[3] B. J. Grosz and C. L. Sidner. Plans for discourse. In P. R. Cohen, J. Morgan, and M. E. Pollack, editors, *Intentions in Communication*, pages 417–444. MIT Press, Cambridge, MA, 1990.

[4] N. Lesh, C. Rich, and C. L. Sidner. Collaborating with focused and unfocused users under imperfect communication. In M. Bauer, P. J. Gmytrasiewicz, and J. Vassileva, editors, *User Modeling 2001*, volume 2109, pages 64–73. Springer Berlin Heidelberg, 2001.

[5] S. C. Marsella and J. Gratch. EMA: A process model of appraisal dynamics. *Cognitive Systems Research*, 10(1):70–90, March 2009.

[6] M. Shayganfar, C. Rich, and C. L. Sidner. An overview of affective motivational collaboration theory. In *Proceedings of AAAI Workshop on Symbiotic Cognitive Systems, Phoenix, Arizona*, 2016.