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 in 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 influences the efficiency of robots' interaction and performance, and makes the robots sensitive to humans' cognitive abilities and behaviors.

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 relevance and controllability 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* which is built on the foundations of the *SharedPlans* theory of collaboration [5] and the *cognitive appraisal* theory of emotions [4].

There are several appraisal models (e.g., EMA [10]) 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. For instance, although the appraisal models mostly use utility to compute the relevance of an event, we have found new cognitive components involved in determining utility because of the influence of the collaboration. These components, such as the recurrence of a belief by the human collaborator or the influence of the human collaborator's perceived emotion on the robot's decisions emphasize the fact that collaboration requires different procedures in appraisal processes. In this paper, we provide the relevance and controllability appraisals of an event in the collaboration context.

Our work builds on the general notions of appraisal theory [4, 11, 16, 17], but is focused on its application in human-robot collaboration. Computational appraisal models have been applied to a variety of uses in psychology, robotics, AI, and cognitive science. For instance, in [10] EMA is used to generate specific predictions about how human subjects will appraise and cope with emotional situations. Furthermore, appraisal theory has been used in robots' decision making [3], or in their cognitive systems [6, 9]. In the virtual agents community, empathy and affective decision-making is a research topic that has received much attention in the last two decades [12, 13, 14, 19]. However, EMA and other work in artificial intelligence and robotics which apply appraisal theory do not focus on the dynamics of collaborative contexts [1, 7, 10, 15].

The computational collaboration model in our work is strongly influenced by the SharedPlans theory [5]. However, our algorithms are also compatible with other collaboration theories, e.g., Joint Intentions theory [2], or STEAM [18]. 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. 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 [10]. 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

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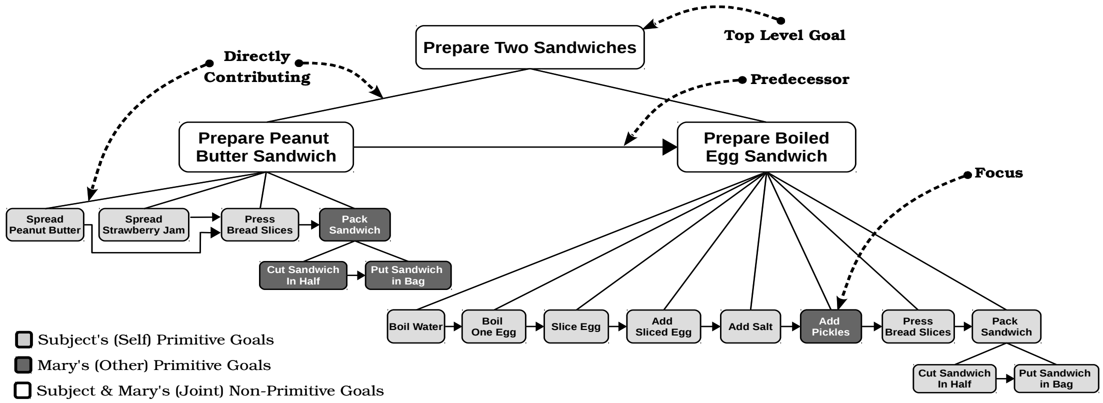

Figure 1: Example of collaboration structure (also used as task model for the evaluation).

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 [8]. 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.

3. EVALUATION

4. CONCLUSION

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