The AAAI 2017 Spring Symposium on
Computational Context: Why It's Important, What It Means, and Can It Be Computed?
Technical Report SS-17-03

Challenges with Incorporating Context into Human-Robot Teaming

**Kristin E. Schaefer,[1] Jessie Y. C. Chen,[1]
Julia Wright,[1] Derya Aksaray,[2] Nicholas Roy[2]**
[1]US Army Research Laboratory, [2]MIT

Abstract

Incorporating contextual cues and contextual understanding into the development of an autonomous robot can advance the robot's decision-making capabilities, but may also help improve the human's understanding of those decisions to improve team effectiveness. While a number of these benefits are discussed below, there are just as many, if not more, challenges associated with developing context-driven autonomy. These benefits and challenges are discussed below to support ongoing and future human-robot teaming efforts.

Overview: Human-Robot Teams

As the future of human-robot interaction moves towards interdependent teaming initiatives, the integration of the appropriate decision-making processes is an essential part of the design and development of an autonomous robot. The complexity of these decisions has moved beyond that of the simple decision trees of preprogrammed systems to inference and planning algorithms using models acquired from real-world data. But it is not enough to only focus on the development of a world model or the underlying algorithms to allow the robot to make highly-complex decisions using these models. Within the structure of interdependent teams, it is important to recognize there is a human team member that interprets the actions and behaviors of the robot. The human situation awareness, separate from the actual system design capabilities, is often what drives expectations for the interaction. If the expectations do not match the robot's actions, there can be a degradation of trust that can directly impact the effectiveness of the team (Schaefer et al., in press). Therefore, the problem in developing the next generation of human-robot teams is two-fold: 1) advancement of basic inference and planning algorithms require the capability to support complex decision processes within a human-robot team, and 2) advancement of algorithms for shared situation awareness may need to incorporate agent-based transparency to engender trust in the team.

It is reasonable to assume that for the near-future, humans and robots faced with the same circumstances will not make the same decisions, even under the same set of apparent constraints, nor will they necessarily even have the same consequences resulting from those decisions. Therefore, it is imperative to develop the underlying protocols for addressing this divergence. The U.S. Defense Science Board's recent report (2016), *Summer Study on Autonomy*, identified six barriers to human trust in autonomous systems, with 'low observability, predictability, directability, and auditability' as well as 'low mutual understanding of common goals' being among the key issues (p. 15). We propose that integrating aspects of context into inference and planning may help improve not only the underlying decision-making processes, but also assist in communicating intent reasoning so that actions better match human expectations (i.e., increased transparency; Chen et al., in press). Here, we briefly review prior research into the integration of context into robot autonomy in order to identify potential benefits and challenges in developing context-driven robot teaming, and suggest directions for future research based on these observations.

Potential Benefits of Context for Teaming

As with human team members, it is crucial that a robot has the ability to infer, represent, and reason about the world in order to develop shared situation awareness and effectively communicate intent. Even for a single robot carrying out a higher-level task (e.g., moving through an indoor environment), spatial and temporal contextual cues have been identified as significantly improving the performance of many components of a robot system, including perception, inference, and planning. By incorporating these contextual elements, the robot's reasoning process is more easily understood by and communicated to the human team members.

For example, robot perception algorithms can be used to develop a shared, common understanding of the world by processing sensor inputs to form representations of the static and dynamic environment (Mitchell & Bornstein, 2012). Semantic labeling of that environment can provide higher level reasoning allowing the robot more fine-grained classification of the world to improve decision-making. But every environment is unique, and dynamic environments are always changing. Therefore, contextual information, such as the type of room being examined, could be used to aid in the spatial-semantic recognition to predict objects that are likely to be present (Meger et al., 2008). Thus, incorporating context into a semantic mapping and labeling can significantly improve the speed and scale of the task, allowing a robot to label scenes over tens of kilometers in real time (Posner, Cummins, & Newman, 2009).

Similarly, contextual cues in a planning task can help prioritize the search direction and prune parts of the state space. For example, environmental features, such as terrain or weather, can inform path planning and replanning decisions related to potential hazards, levels of risk, and vehicle capabilities (Evers et al., 2014; Lin & Goodrich; 2009). But understanding how the models that support inference and planning should account for these elements is only one part of teaming effort. The robot's spatial reasoning behaviors are an emergent feature of the interaction between the robot and the environment which informs the mental model of the human team member (Rauh et al., 2005). Identification and integration of appropriate contextual cues in the robot's intelligence architecture is important, because any incongruity between the human's mental model of the robot's spatial solution and the actual behavior can impact shared understanding and trust (Perelman, Mueller, & Schaefer, 2017).

As operational needs for human-robot teams increase in complexity, uncertainty, and dynamic mission replanning, appropriate bi-directional communication becomes an essential part of the teaming effort. One area of research is looking at natural language communication, of which temporal context could provide some benefits (Kübler et al., 2010). With the correct temporal-causal context, even a simple action or utterance can communicate intent (Kruijeff & Brenner, 2007). This temporal context ties directly into the task or mission specific goals and the human component of the human-robot team. Considerable effort has been put into inferring and using human activity recognition as contextual cues that a robot can use to help make decisions. For example, the architecture described by Fong et al. (2006) specifically included a context manager to maintain a history of task status and execution, agent activities, agent dialogue, and others that could be summarized and used within a human-robot interaction task.

There are a number of benefits to integrating multiple contextual elements into the models used by an autonomous robot. Some of these include environmental, spatial, and temporal contexts which are influenced by mission-specific tasks and team interaction goals. Overall, the main benefit of integrating contextual elements into autonomy design is the advanced communication of the robot's reasoning process for making a set of decisions.

Challenges with Incorporating Context in Inference and Planning Models

But along with the multiple potential benefits comes a number of challenges with the process of incorporating context into the inferences and planning models. First, it is important to recognize that context is fundamentally an abstraction of physical properties of space, time, the mission, and history of the robot behaviors. As a result, context can have different scale or meaning depending on the activity and mission, and it may also be a result of other abstract notions such as a human teammate's intentional or emotional state (Scheutz et al., 2005). For example, the context of being outdoors may be sufficient for improving the performance of the robot and sharing information with human teammates for some tasks and missions, but other tasks and missions may require finer-grained context than merely being outdoors (e.g., urban outdoors, forested, or a specific location). Therefore, it is not sufficient to infer a single context variable, but a truly robust robot should instead be able to reason across different spatial, temporal and mission scales, and reason about context as a component of a bigger world model.

Most of the existing work in incorporating context into robotic systems has assumed either a fixed or known ontology of semantic context. With a few exceptions, the research has focused on how to incorporate context into the perception, inference, or planning process. But, there does not exist a widely agreed upon representation of what constitutes context. The literature indicates that there is a general sense that context is a state variable that can be used to select relevant parts of the state space, or select relevant perceptual feature functions for object recognition. This implies that context represents a discrete selector variable, possibly with a distribution attached to it. For example, the context of an outdoor environment may lead the robot to reason about a different state space and object classes than the context of an indoor environment. In this sense, the context is an ontological model (Suh et al., 2007). On the other hand, the context may be *a priori* over concepts in the environment, rather than a selector variable; in this sense, context requires a probabilistic model (Zender et al., 2008). Developing the appropriate models is further complicated by determining which contextual elements are important to represent, and which elements have a higher weight in the decision-making process.

Implications for Future Research

The difference in semantics for context has implications for how it is both represented and used by the relevant perception, inference, and planning algorithms. For example, the notion of context in a human-robot dialogue is more about the state of the world and the history, rather than a selection of parts of the model. In this sense, context is not a model, but an instantiation or possibly a history (or summary or statistic) of the world. Reconciling these very different views of context and developing a coherent representation that can be used in different ways is an open research question.

An additional open question is how to infer context from sensor data, and in particular, learn new forms of context over time. Given a finite set of possible contexts (e.g., spatial areas, indoor vs outdoor, etc.), it is possible to learn classification schemes to determine the current context. However, pre-specified context variables are unlikely to be sufficient for long-duration robots operating in populated environments. People naturally grow their sense of context over time, and a robot must be able to do the same. Even for a single spatial context variable that behaves as a selector for state or perception features, new contexts may be encountered and must be added to the representation. As new missions are encountered or as human teammates demonstrate new activities, the representation of context must expand in concert.

Current Research

Three current research efforts address the question of context from both sides of this challenge: developing context-driven decision-making of the robot and the associated human interaction and perception of the resulting decisions. The first is a basic research approach to identify appropriate environmental and team-specific contextual support cues that occur during a joint human-robot team room reorganization task (e.g., moving boxes out of the way for efficient navigation). The results of this research will support techniques for developing the underlying context dependent variables that impact decision-making processes and associated team communication protocols. The second is the Autonomous Squad Member simulation research (Boyce et al., 2015). The current iteration of this project is expected to show how robot errors in identifying context impact human evaluation of the robot. Finally, the Applied Robotics for Installations and Base Operations (ARIBO), Ft Bragg driverless vehicle (Brooks, 2016) will assess the impact of context in a real-world environment. This assessment will be used to inform the design of the decision-making architecture of the vehicle, as well as the user display design. Conclusions from these three projects will be used to support peer-to-peer tactical teaming (i.e., two-way dialogue with explanations) and proactive, fine-grained contextual understanding of the environment and recognition of humans and social cues.

Acknowledgments

Research was sponsored by the Army Research Laboratory and was accomplished in part under Cooperative Agreement Numbers W911NF-16-2-0216 and W911NF-10-2-0016. The views and conclusions contained in this document are those of the authors and should not be interpreted as representing the official policies, either expressed or implied, of the Army Research Laboratory or the U.S. Government. The U.S. Government is authorized to reproduce and distribute reprints for Government purposes notwithstanding any copyright notation herein

References

Boyce, M.W., Chen, J.Y.C., Selkowitz, A.R., & Lakhmani, S.G. 2015. *Agent Transparency for an Autonomous Squad Member* (ARL-TR-7298). Aberdeen Proving Ground, MD: Army Research Laboratory.

Brooks, D. 2016. *Robot Drivers and in Fort Bragg's Future.* FayObserver. Avaliable: http://www.fayobserver.com/military/robot-drivers-are-in-fort-bragg-s-future/article_e4c7a996-f26f-5041-85c8-f6c872a6c2d9.html

Chen, J.Y.C., Lakhmani, S., Stowers, K., Selkowitz, A., Wright, J., and Barnes, M. In Press. Situation awareness-based agent transparency and human-autonomy teaming effectiveness. *Theoretical Issues in Ergonomics Science.*

Defense Science Board. 2016. *Defense Science Board Summer Study on Autonomy*. Washington, D.C.: Under Secretary of Defense.

Evers, L. Dollevoet, T., Barros, A.I., and Monsuur, H. 2014. Robust UAV mission planning. *Annals of Operations Research*, 222(1), 293-315.

Fong, T., Scholtz, J., Shah, J.A., et al. 2006. A Preliminary Study of Peer-to-Peer Human-Robot Interaction. In *IEEE International Conference on System, Man and Cybernetics.*

Kübler, S. Scheutz, M., Baucom, E., and Israel, R. 2010. Adding Context Information to Part Of Speech Tagging for Dialogues. In *The 9th Interanational Workshop on Treebanks and Linguistic Theories*, 115-126.

Kruijff, G.J.M., and Brenner, M.. 2009. Modelling Spatio-Temporal Comprehension in Situated Human-Robot Dialogue as Reasoning about Intentions and Plans. In *AAAI Spring Symposium: Intentions in Intelligent Systems*, 19-25.

Lin, L., and Goodrich, M.A. 2009. UAV Intelligent Path Planning for Wilderness Search and Rescue. In *IEEE/RSJ International Conference on Intelligent Robots and Systems*,709-714.

Meger, D. Forssen, P-E., Lai, K., et al. 2008. Curious George: An Attentive Semantic Robot. *Autonomous Robots*, 56, 503-511.

Mitchell, R., and Bornstein, J. 2012. *Robotics Collaborative Technology Alliance (RCTA): FY 12 Annual Program Plan*. US Army Research Laboratory: Aberdeen Proving Ground, MD.

Perelman, B., Mueller, S., and Schaefer, K.E. 2017. Evaluating Path Planning in Human-Robot Teams: Quantifying Path Agreement and Mental Model Congruency. In *IEEE Conference on Cognitive and Computational Aspects of Situation Management.* Savannah, GA.

Posner, I., Cummings, M., and Newman, P. 2009. A Generative Framework for Fast Urban Labeling using Spatial and Temporal Context. *Autonomous Robots*, 26, 153–170.

Rauh, R., Hagen, C., Knauff, M., et al. 2005. Preferred and Alternative Mental Models in Spatial Reasoning. *Spatial Cognition & Computation,* 5(2-3), 239-269.

Schaefer, K.E., Straub, E.R., Chen, J.Y.C., Putney, J., and Evans III, A.W. In Press. Communicating Intent to Develop Shared Situation Awareness and Engender Trust in Human-Agent Teams. *Cognitive Systems Research.*

Scheutz, M. Schermerhorn, P., Middendorff, C., et al. 2005. Toward Affective Cognitive Robots for Human-Robot Interaction. In *American Association for Artificial Intelligence (AAAI)*, 61-66.

Suh, I.H. Lim, G.H., Hwang, W. Choi, J.H., and Park, Y.T. 2007. Ontology-based Multi-layered Robot Knowledge Framework (OMRKF) for Robot Intelligence. In *IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, 429-436.

Zender, H., Mozos, O.M., Jensfelt, P., Kruijff, G.J.M., and Burgard, W. 2008. Conceptual Spatial Representations for Indoor Mobile Robots. *Autonomous Robots*, 56, 493-502.