Research Summary and Plans

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My primary research interests include machine learning, knowledge representation and reasoning, computer vision, and cognitive science, as applied to autonomous mobile robots and adaptive agents. Sophisticated algorithms have been developed for robots to learn from sensor inputs, and from extensive human training and supervision. However, real-world application domains characterized by partial observability, non-determinism, and unforeseen changes, frequently make it difficult for robots to process all sensor inputs, obtain labeled training samples of relevant domain objects and events, or operate without human feedback. At the same time, human participants typically do not have the time and expertise to interpret raw sensor inputs, or to provide elaborate and accurate feedback in complex domains. My research seeks to jointly address these knowledge representation, reasoning and learning challenges in human-robot collaboration, enabling robots to acquire and use sensor inputs and human feedback based on need and availability. Specifically, I develop algorithms that enable robots to autonomously and incrementally learn models of relevant domain objects based on different sensor inputs, using the learned models to detect and adapt to unforeseen changes. Robots also represent and reason with incomplete domain knowledge, adapting learning, sensor input processing and acting to tasks at hand. Furthermore, robots learn from the information shared by teammates and limited high-level feedback acquired from non-expert human participants when such feedback is necessary and available.

Mobile robots equipped with multiple sensors and algorithms cannot always be equipped with accurate domain knowledge, and receive far more raw data than can be processed in real-time. My current research develops a novel knowledge representation and reasoning architecture that integrates declarative programming with probabilistic graphical models to address the fundamental challenge of representing and reasoning with incomplete domain knowledge consisting of qualitative and quantitative descriptions of uncertainty. My postdoctoral research laid the foundation for this architecture by developing a novel hierarchy of partially observable Markov decision processes (POMDPs) that enabled a robot and a human to jointly manipulate and converse about tabletop objects, considering the reliability and complexity of available information processing algorithms to automatically determine the sequence of algorithms appropriate for any given task—this research won a Distinguished Paper Award at the International Conference on Automated Planning and Scheduling. Current research uses Answer Set Programming, a declarative programming paradigm, to represent and reason with incomplete domain knowledge extracted from sensor inputs and human feedback, merging the beliefs extracted from this domain knowledge with probabilistic beliefs encoded by hierarchical POMDPs to plan learning, sensing and acting on robots collaborating with humans in real-world domains. This research recently won a Paper of Excellence Award at the International Conference on Development and Learning.

While reasoning with domain knowledge helps constrain learning to objects and events relevant to tasks at hand, the challenges in learning from sensor inputs are further offset by the observation that many objects have distinctive characteristics and motion patterns, although these characteristics and patterns may not be known in advance and may change over time. In addition, only a
subset of domain objects and events are relevant to any given task. My current research develops *stochastic bootstrap learning* algorithms that enable robots to exploit the complementary strengths of appearance-based and contextual visual cues to automatically and efficiently learn representative models of relevant domain objects from a small number of images. These learned models are revised incrementally, and used in information fusion and energy minimization algorithms to support reliable and efficient object recognition in novel indoor and outdoor scenes. One underlying motivation for this research is to fully exploit the information encoded in visual inputs from monocular, stereo, and RGB-D cameras. I also use these algorithms to support research in multirobot collaboration in the competitive domain of robot soccer.

Robots equipped with the knowledge representation architecture and learning algorithms are likely to need human feedback to respond to unforeseen situations. Although human input can provide rich information about the task and domain, humans are unlikely to have the time and expertise to interpret raw sensor inputs, or to provide elaborate and accurate feedback. My research enables robots to learn associations between multimodal cues, building rich object representations by associating vision-based learned object models with high-level verbal descriptions of object properties. These associations enable robots to map observed object features to words, resolving ambiguities by posing high-level verbal queries for human feedback. Furthermore, I develop online *augmented online reinforcement learning* algorithms that enable robots to automatically identify the need for human feedback, merging limited feedback from non-expert human participants with the information extracted from sensor inputs.

My algorithms have enabled the deployment of mobile robots in many real-world application domains. I helped design visual homing and navigation algorithms for an autonomous underwater vehicle, which was used to measure the chemical properties of the water body and to create a high-resolution bathymetric map of the glacier face and lake bottom under the ice-shelf of West Lake Bonney in Taylor Valley, Antarctica (2008-2010). Application areas for my current research efforts include tasks such as surveillance, and the use of robots as assistants in indoor domains such as offices, homes and assisted living centers. For instance, robots deployed in offices and homes guide humans to specific locations, localize and fetch desired target objects, and draw the attention of humans to anomalies and ambiguities. I am also exploring the use of autonomous robots in assistive roles in agricultural applications.

In parallel to my research on autonomous robots, I design learning and inference algorithms to address challenges in application domains such as agricultural irrigation management, event stream processing, and climate science. For instance, in collaboration with researchers at Texas A&M AgriLife Research and the U.S. Department of Agriculture’s Agricultural Research Service, I adapt non-parametric Bayesian learning algorithms to predict crop (reference) evapotranspiration values from imprecise measurements of weather parameters, and to estimate crop yield from satellite images, thus minimizing water wastage and maximizing yield. Other collaborative research projects focus on learning and extracting patterns of events from complex event streams, and on downscaling global climate models for regional climate predictions.

To summarize, my research addresses key challenges in learning, knowledge representation and reasoning, as applied to human-robot collaboration and other real-world domains. These research thrusts are inspired by the goal of enabling widespread deployment of autonomous mobile robots and adaptive agents that assist and collaborate with humans. I aim to pursue my research objectives in a vibrant inter-disciplinary atmosphere in collaboration with colleagues and students. All associated publications can be downloaded online: [http://www.cs.ttu.edu/~smohan/Publications.html](http://www.cs.ttu.edu/~smohan/Publications.html)