Improvement of Multi-AUV Cooperation through Teammate Verification

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Abstract

Current methods for Multi-AUV cooperation suffer in low communication environments. State of the art methods employ auctioneering or planning to determine a single AUV's task. These systems require communication for efficient task selection. Most strategies assume a teammate is inoperable if a communication timeout is reached which reduces overall team efficiency. Including teammate prediction has been shown to mitigate efficiency degeneration due to low communication. This position paper posits that multi-AUV cooperation efficiency will improve with the combination of robust teammate prediction along with verification using behavior recognition.

Introduction

Multi-robot systems are capable of addressing many needs because they are robust to failure, cost-effective, and can be more efficient than single robot solutions. In particular, the autonomous underwater vehicle (AUV) community has addressed environmental scientific investigation (Manley 2004) and military scenarios (Castelin and Bernstein 2004) using multi-AUV solutions. Multi-AUV systems not only need to cooperate efficiently but do so in an environment which makes communication difficult.

State-of-the-art methods in multi-AUV systems use auctioneering or planning methods for cooperation. Rajala et al. employs cooperation through the use of time division multiple access (TDMA) for AUV formation control during missions (Rajala, O'Rourke, and Edwards 2006). If an agent does not communicate during their specified time slot then they are assumed to be inoperable and another AUV takes its role in the formation. Examples include the loss of communication from the leader. In such a scenario, another AUV will assume the leader role in the formation. Sariel et al. uses an auctioneering based method for cooperation of a heterogeneous AUV team in the mine counter measure mission (Sariel, Balch, and Erdogan 2008). Teammates with a lower task cost that do not respond to an auction are simply not considered for a task though it would be more efficient. Sotzing and Lane utilize a hybrid architecture in which a deliberative system plans the next task based on a hierarchical planner (Sotzing and Lane 2009). The latter two cooperation schemes use a model of both the tasks and their teammates. Continual broadcast of global task completion and current progress updates these models. This also ensures that information propagates through the network. Based on the models, the agents auction for or plan a task, accordingly.

A limitation with these cooperation systems is their assumption that an agent is inoperable if it does not communicate within a certain threshold of time. Such an assumption is not always the case and introduces inefficiency such as in the form of repeated tasks. This occurs especially in littoral environments, as there are many communication barriers for acoustic communication. Sotzing and Lane improve upon the assumption of a lost teammate model by utilizing location and task prediction based on the Recursive Modeling Method (Durfee 1995) , (Sotzing and Lane 2009). The basic premise is that they predict a teammate's position based on the last communicated state. If the predicted location indicates a completion of the last communicated task then a prediction of the teammate's next task is performed. Thus, an AUV will determine its own next task based on the continued communication or prediction of its teammates. The authors validated their improvement in overall system performance.

Current systems do not employ any verification techniques of their predicted assumptions. An AUV could employ behavior recognition as the tool for verification as it can physically proceed to a predicted location and verify a teammate's current task or true failure. Given current research in behavior recognition, a merger with teammate prediction is a natural progression.

Improved Cooperation

An improved teammate model will allow for incorporation of received communication, prediction, and verification of behavior through behavior recognition. Such a model will be robust to dynamic environmental influences which a prediction alone model may not be robust enough to handle.

Behavior Recognition

Current systems are able to recognize agent behavior using graphical models. Original work was presented by Han and Veloso in which a soccer playing robot's behavior was recognized using an Hidden Markov Model (HMM) through the use of an overhead vision system (Han and Veloso 2000). Feldman and Balch use HMMs to recognize honey bee behaviors after manually labeling actions (Feldman and Balch 2004). Vail et al. use Conditional Random Fields (CRF) as an improved model to determine the behavior recognition of tag playing robots (Vail, Veloso, and Lafferty 2007). In more related work Baxter et al. use real AUV data to train a flat HMM for behavior recognition during post mission analysis (Baxter, Lane, and Petillot 2009). Weaknesses of these systems are that they require continual observation of an agent either through overhead sensory input or post mission continual tracks. However, none of these systems address an agent observing another in situ.

Verification

A great improvement in multi-AUV cooperation could be made if agents verified their teammate's predicted behavior through the use of behavior recognition. This occurs in daily human interaction when a required voice communication does not get a response. The natural course of action is to get closer or attempt another communication medium with the individual. As an AUV agent finishes a task and another must be chosen, it must choose based on task and teammate models which are updated through communication and prediction. If an agent does not have enough confidence in its prediction of a teammate then verification through investigation is in order. During the process of traveling to a teammate's predicted location, a communication may occur as they may have been out of range or occluded. If the sought-after agent is encountered without communication during investigation then behavior recognition can be performed. This author is currently investigating the use of a forward-looking sonar to detect teammates in situ. Based on the teammate's trajectory, it is believed that a trained HMM can determine if a specific behavior is being performed. Given an updated model of its teammate, the agent can now determine the next appropriate task.

Difficulties

There will be difficulties in using behavior recognition for verification, the first of which is sensing. In an AUV environment, such as in a littoral area, a sonar will need to discriminate a teammate from false positives and minimize false negatives. Both agents will also be moving in the environment while one is trying to recognize the other's behavior, making sensing ever more difficult. As a remedy, upon proper identification of a teammate it's motion must be transformed into a proper reference frame. Baxter et al. attempt to make behavior recognition agnostic to the environment by labeling actions and behaviors with respect to the cardinal directions of the environment (Baxter, Lane, and Petillot 2009). Yet it still requires global understanding of proper cardinal directions of a reference map. Finding methods that are agnostic to any global reference will aid in behavior recognition as it could account for both the agents moving in the environment concurrently. Another difficulty that has yet to be explored is at what point is verification required. There must be a balance between the confidence of a prediction and the cost of verification versus the cost of repeating a task.

Conclusion

Cooperation among a multi-AUV team requires improvements in low communication scenarios. Current cooperation schemes are just starting to leverage teammate prediction. Behavior recognition systems allow for an agent to verify teammate tasks. Accurate and robust teammate prediction along with verification through either communication or behavior recognition will greatly increase the efficiency of multi-AUV teams in low communication environments.

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