Communication Protocols for Man-Machine Networks

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Abstract

One of the most challenging coordination problems in artificial intelligence is to achieve successful collaboration across large-scale heterogeneous systems that include **R**obots, **A**gents, and **P**eople (RAP). In the best case, these RAP systems are potentially capable of leveraging the strengths of the individual entities to achieve complex distributed tasks. However, without intelligent communication protocols, man-machine partnerships are likely to fail as the humans become overloaded with irrelevant information. This paper introduces a communication protocol for man-machine systems and demonstrates that its message routing performance approaches the central optimized solution in a simulated smart environment scenario.

1 Introduction

The potential of man-machine teams has tantalized researchers for over a decade. Scerri et al. wrote a seminal paper introducing the acronym, **RAP**, to describe systems consisting of **R**obots **A**gents and **P**eople [Scerri *et al.*, 2003]. RAP systems leverage the strengths of the heterogeneous components, drawing from the common sense knowledge of the human, the robots' ability to perform repetitive physical tasks, and the ability of software agents to solve specialized artificial intelligence problems. They augment large-scale participatory sensor networks composed of humans carrying mobile devices with additional autonomous robot and software agents. Scerri et al. envisioned an architecture in which software agent proxies running on mobile devices could be used to coordinate the man-machine teams. RAP systems are valuable for a variety of problems, including command and control, sensor networks, urban rescue, and personal assistance.

In the future, RAP systems are likely to become an integral part of smart cities, serving the function of proactively helping humans in urban areas. There have been limited demonstrations of HRI (human-robot interaction systems) as museum tour guides [Thrun *et al.*, 1999] and as building receptionists [Sabanovic *et al.*, 2006]. To extend these systems to include multiple robots and humans requires solving coordinated task allocation and scheduling which are NP-hard problems [Koes *et al.*, 2005].

Glas et al. [Glas *et al.*, 2012] introduced a general framework for networked robots that supports different social robot services including the observation of human behavior using environmental sensor networks, structured knowledge sharing, centralized resource and service allocation, global path planning for coordination between robots, and support for selected recognition and decision tasks by a human operator. In this paper, we propose new communication protocols to support this type of man-machine system that includes networked robots cooperating with humans. We demonstrate that our new communication protocols are valuable for reducing communication costs in a simulated NetLogo scenario inspired by the Glas et al. shopping assistance system.

2 Methodology

Our proposed protocol (Financial Incentive History) leverages the history of incentive acceptance to determine the best message routing. We compare our protocol against a centralized optimization algorithm to calculate the best possible agent allocation.

Centralized optimization algorithms are undesirable for RAP systems since they rely on centralized information as well as a single computational node. These characteristics reduce their ability to deal with large scale problems and datasets, due to the high computational complexity. Moreover, it is inefficient to collect and store data in a centralized manner especially when the communication is multicast. In such scenarios, collecting all the necessary information through a central node is both time-consuming and incurs a high communication cost due to the large amount of packet exchange. Having a single point of failure also jeopardizes the inherently resilient nature of RAP systems.

As an alternative to the centralized optimization algorithm, we implemented two heuristics: The first is a simple flooding algorithm and the second is our proposed history-based algorithm that tracks successful assistants.

- Flooding protocol
  The customer broadcasts a request to all agents, using the same protocol commonly used in wireless networks. Agents who occupy the area covered by the customer's sensor are obligated to respond to the request if available and willing to assist, or re-broadcast it to the other agents.

- History-based protocol (FIH)
  In our proposed protocol, the history of previously successful assists is recorded. Customers can make requests to the

set of agents who are stored in his history. We believe that this protocol can reduce communication cost in many applications, especially when customers make repeated requests for similar types of assistance.

We have implemented these two algorithms along with the incentive strategy used for motivating human agents.

3 Results

The results for the centralized optimization model were obtained by solving the ILP model using AIMMS run on a Windows-based 64-bit core-i7 computer with 24GB of RAM. In all the scenarios we considered, LP model executions were fast, never lasting more than few seconds. We implemented the heuristics in a home-grown software framework written in NetLogo. Their executions were similar, lasting only a few minutes according to the number of agents in the simulated environment. After initializing the map, we determine the number of agents (including the number of human agents, robot agents and customers) as well as our budget and the maximum number of human and robot agents that a customer can request as inputs. Our simulation then randomly places humans, robots, and customers on the map of a building, assuming constant sensor radio coverage. For each scenario created in the NetLogo simulation, we run the two communication protocols (flooding and history-based). The map and model info were loaded directly into our AIMMS program in order to execute the optimization procedure. In this way we are able to calculate the results of all three models on the same scenario.

Initialization parameters (including number of agents) were varied; for each set of parameters, 20 different scenarios were generated. The average cost of all 20 different scenarios is used as the communication cost. Figure 1 shows the results; as expected the Financial Incentive History-based algorithm (marked as FIH) had a better performance, closely matching the optimum selection of agents. This occurs due to several facts. First agents who previously participated on a team are likely to be around, having recently finished their previous task. The flooding protocol does not perform well in comparison to the history-based algorithm as it constantly broadcasts to the surrounding agents. Obstacles such as walls do not block signal reception of agents but do block movement. Therefore, an agent may receive a request quickly while needing take a long path in order to reach the customer, due to the existence of solid obstacles.

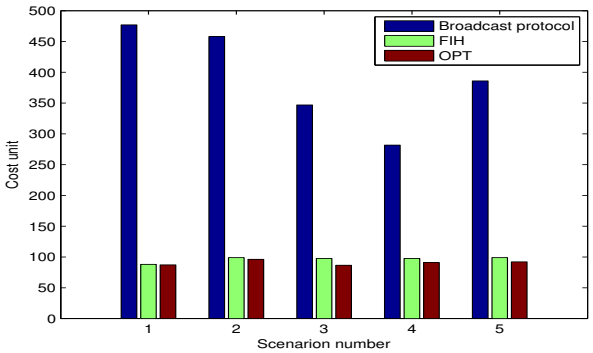

Figure 1: Communication cost for each routing protocol

A matched paired t-test on the mean values of the same scenarios under different algorithms yields no significant difference between our proposed FIH protocol and the optimal ILP solution. Comparing flooding algorithm communication cost protocol with FIH communication cost yielded t equal to -7.937337, indicating that the result is significant at $p \leq 0.01$.

4 Conclusion

This paper introduces a history-based communication algorithm for man-machine systems. NetLogo was used to simulate a shopping assistance scenario in which a smart store environment summons help for the shopper in the form of robots and other humans to help locate items. Although non-human agents have no reason not to respond if available, humans are likely to be performing other shopping tasks and need to be incentivized to render assistance. In our simulation, they are modeled as having time availability preferences and as being less willing to respond to lower incentives outside their peak availability period. We demonstrate that the agent allocation solution reached our proposed algorithm results in an insignificant cost increase over a centralized solution calculated with an ILP solver. Lower communication costs are particularly important in man-machine systems to avoid bombarding the human with unwanted messages. In future work, we plan to implement our communication protocol in ROS (the Robot Operating System) for use in coordinating quadcopters with humans for autonomous photography tasks.

References

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