Efficiency as a Motivation to Team*

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Abstract

We explore bases for deciding to team among agents and present an algorithm that bases that decision on performance. We illustrate the algorithm in a task shared among satellites.

1. Introduction

There are many conditions that motivate team formation. One reason for team formation is *lack of ability.* When the agent is not capable of accomplishing a task alone it will seek others for help. For example, an object might be too heavy for one robot to push and two are needed. As another example, one robot might be able to physically capable of rescuing victims of an accident but the time urgency often makes a coordinated effort among a number of robots necessary. Another reason for team formation is *efficiency*. For instance, a team of agents might finish a job in a shorter amount of time, with lower overall effort, etc. A rescue robot that is fast at running but slow at climbing can benefit from teaming with another robot that has a complimentary ability of being fast at climbing if the robots carry out the mission so that the robots perform tasks in which they specialize. *Redundancy and fault-tolerance* is another motivation for teaming. If resources are volatile and subject to unpredictable failure, redundant members can be used to safeguard against such failures. Beyond the selfish reasons for teaming, an agent might want to be in a team for benefit of other agents. Let's call this the *Good Samaritan* motivation. An agent might stop to help a motorist to change a flat tire and they may form a team to proceed with the task. Let's call these team motivators.

There is much discussion and theorizing about agent teams (Cohen, et al 1997; Jennings and Watts, 1998; Wooldridge 2000). However, there does not exist any automated decision-making about teaming. (Dignum, et al, 2000) offer general formalisms for agents to engage in a dialogue for teaming. Agents who have entered a dialogue are convinced have already made a decision to team. Furthermore, there are many situations where dialogue is not needed and teaming takes place nonverbally, (Tuomela, 2000). We are interested in how agents become inclined to team and are suggesting that efficiency is one such motivation. In this paper we will present an algorithm for quantifying efficiency and using it in a decision for team formation. Our approach will be empirical and will limit itself to direct experiences of the agent.

In the rest of this paper we first describe an algorithm for teaming based on efficiency, then we will describe a satellite simulator and experiments with teaming based on this algorithm.

2. A Teaming Algorithm

Let's consider a finite number of agents who without knowing other agents abilities, will prefer to team and not be autonomous. This will lead to zealous teaming. Let's formalize this a bit. Consider TeamInclined(a, t, m, c) to be a function that takes an agent a, a task t, and team mates m, a condition c that constrains team seeking, and returns a binary value of [0 or 1] for an agent a of whether to seek a team. An example of condition c is cardinality of m, e.g., a team should be no larger than 3 members. For the agent recruiting for the first time, m will be empty and the function will return 1. Let's assume agents who are asked to be teammates, without any experience will accept. 'm' is nonempty for the agent being recruited in TeamInclined(a, t, m, c) and contains the recruiter agent and the function still returns 1. In fact when the recruiter recruits a second agent to be in a team or one of the subsequent teammates recruits additional members, without prior experience, as long as c is not violated, TeamInclined will return 1. Of course, status of condition c must be shared among the agents at all times.

After completion of the task, each team member records the performance of the team on the task. Formally, let Effect(a, t, m, c) return a rational value between [0.0-1.0] for agent a. This number is the

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performance of the agent while in a team with other agents in m, for task t, and under condition c. Agents keep an average of prior episodes in Effect as their accumulate experiences. Note that unless the impact of each agent on task t can be discerned, Effect is not personalized so agents will not reason about selecting specific agents unless the teams consisted of 2 agents. If each agent's contribution to task t is identifiable by the team members then each member of the team can have sense of each agent's relative performance in addition to the team's overall performance.

Let's revisit TeamInclined with considerations of Effect, which will be used in a simple learning technique. Recruiter agent will consider performance of known agents for choosing a teammate. From the recruitee's perspective, Effect is examined and if it is below its acceptable performance threshold, TeamInclined will return 0 and otherwise it will return 1. Another words, an agent may reject to be in a team due to its experience of poor prior performance.

Recruiter may not always decide based on prior experience but may choose to explore experiences with new teammates. This is generally known as exploitation versus exploration in machine learning. Typically, the recruiter will use consideration of Effect, say 90% of the time, along with a threshold of value of value of Effect, say 80%. For example, a recruiter will decide 90% of the time to consider prior experience and if Effect returns a value larger than 80% TeamInclined should return 1; otherwise, it should return 0. The remaining percentage of time is set aside for exploration, say 10%. While exploring, the agent will ignore Effect and decide to team without motivation. This exploration-based teaming will add to the agent's experience in Effect.

3. Beyond Efficiency

So far we have explained the efficiency motivation to join a team in terms of past performance. There are numerous efficiency considerations of teaming beyond past performance. Surely, in more complex situations such as having committed to handling multiple simultaneous tasks, an agent who would ordinarily seek teaming or join a team must consider the effects of new team commitments on tasks already committed. What if an agent has a unique ability for a task? What if the new task has a large intersection with the existing tasks? What if tasks had differing levels of priority?

There are many considerations that motivate agents toward cooperation, which can lead to decisions for teaming. One such consideration is trust. It is shown that agents that learn to trust one another are more likely to cooperate (Birk, 2000). It is intuitive with more trust among agents there will be more motivation for teamwork.

Trust is a mental stance. Autonomy as a decision to share work with others is also a mental stance. Cooperation as an attitude to share results with others is a mental stance. We believe a nontrivial combination of mental stances such as Autonomy, Cooperation, Trust are responsible for teamwork (Hexmoor and Beavers, 2001).

(Singh, 1998) present a team as <agents, social commitments, coordination relationships>. Social structure of teams are working conditions and this does not offer any clues about team formation. Since an outsider's viewpoint of whether a group of agents is a team is a mere judgment, Singh's exodeictic teams are meaningless.

4. Satellite Simulator and a Task

We have developed a simulator that allows placement of simulated satellites in orbit as well as identification of ground stations (Hexmoor and Duchscherer, 2000). Figures 1 shows six satellites in different orbits. In this Figure, a line connects the satellites that have line of sight to other satellites. For a simple task, assume that the ground station will need three independent images of a given longitude and latitude from a given altitude. Let's call the task 3Image.

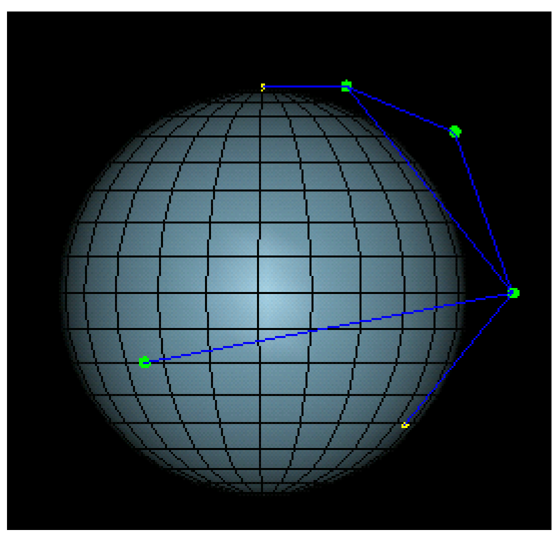

Figure 1. Satellite simulator

The ground station issues the command to the nearest satellite and that satellite will be responsible for performing the task by itself if no satellites are available. The satellite will complete the images itself taking one image in each orbit crossing the given location. If the satellite so decides it recruits other satellites to complete the task. Each of the recruited satellites may recruit another satellite. After recruiting one satellite, either satellite may decide to recruit a third teammate.

5. Experiments

The tests were performed using a collection of 15 agents. Seven ground station agents and 8 satellite agents. The system chooses a ground station at random and assigns a target for which three images are requested. This combination of ground station and target will be referred to as a task. The ground station reviews performance records of all satellites with which it currently has communication capability, and offers a leadership position to the satellite with the best performance record with respect to the current task. The contacted satellite can accept or refuse the offer based on its own performance beliefs. If it refuses, the ground station repeats the process, but excludes the previous satellite from the selection process.

Once a leader has accepted the ground station's request, it must decide whether to perform the task on its own, or form a team with at most two other satellite agents. The decision to form a team is based on the leaders database of known satellites, and their past performance when teamed with the leader on this task. Regardless of the team size, the team has at most three simulated earth days to complete the task. Failure to complete the mission results in the same task being assigned a maximum of three times. All team members, along with the ground station update their performance databases at the end of each task. Three sets of 2000 random tasks were performed with the satellite simulator.

The speed of the satellites relative to the earth is dependent on their altitude. The simulation contained the following satellite agents.

sphere satellite 70 0 600
sphere satellite 90 0 600
sphere satellite -20 0 1000
sphere satellite 0 0 5000
sphere satellite 60 180 2000
sphere satellite -30 70 500
sphere satellite -60 30 400
sphere satellite -70 100 450

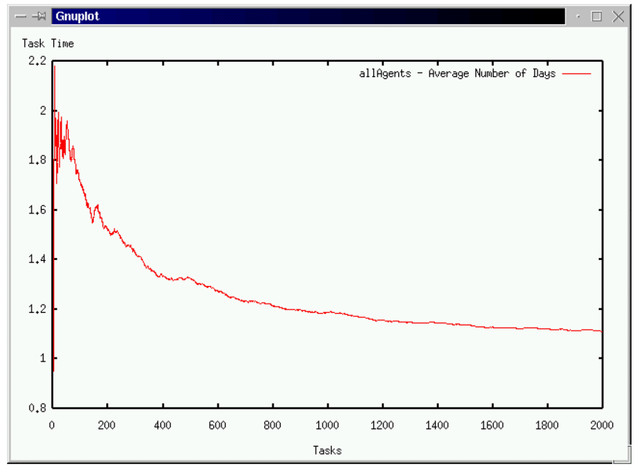

Figure 2

The last three values for each satellite indicates its orbital starting point (latitude, longitude, altitude). The following is the following approximate velocities for each satellite.

satellite 70 0 600 = 7573 m/s = 14.9 orbits/day
satellite 90 0 600 = 7573 m/s = 14.9 orbits/day
satellite -20 0 1000 = 7365 m/s = 13.7 orbits/day
satellite 0 0 5000 = 5934 m/s = 7.2 orbits/day
satellite 60 180 2000 = 6913 m/s = 11.3 orbits/day
satellite -30 70 500 = 7627 m /s = 15.2 orbits/day
satellite -60 30 400 = 7683 m/s = 15.5 orbits/day
satellite -70 100 450 = 7655 m/s = 15.4 orbits/day

Figure 2 shows the relationship between the average time required by all agent teams to complete an assigned task (y-axis) and the progression of task assignments given to the agent teams. (x-axis). The average task time required by a team of agents to complete a task decreases as the agents gain experience. At the start of task assignments, the average required time fluctuates considerably. This is due in part to the inexperience of the agent teams and to the fact that the average is based on very few tasks at this point. It can be seen that as the number of completed tasks increases, the average time to complete a given task fluctuates less and continues a gradual decrease in time.

If we can assume that all tasks are equally likely to be assigned and the agent teams are becoming more efficient in their execution of these tasks, then the average time required by a given team to complete a task should approach some optimal operational limit.

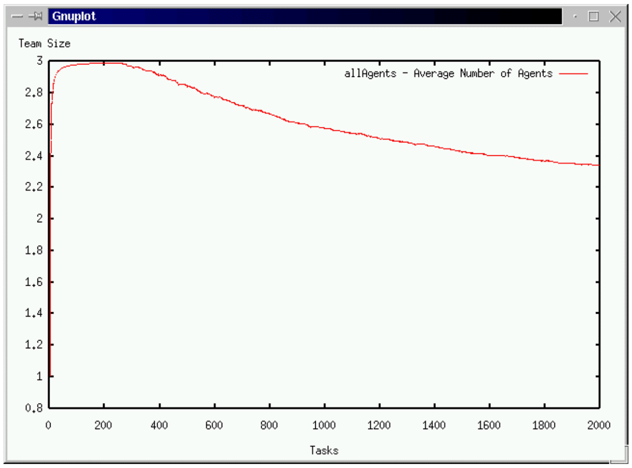

Figure 3

This limit would be dependent upon the orbital characteristics of each satellite agent and its orientation with respect to the ground station agents with which it must interact.

Figure 3 shows the relationship between the current task being performed by the agent teams and the average number of agents being used when forming these teams. As the agents gain experience, team leaders may decide, based on their assessment of other agent's capabilities, to attempt to complete the assigned task by themselves. The rational behind such a decision is an attempt to minimize the amount of resources required to complete a task and at the same time, continue to improve the time needed to complete any given task. If such a decision on the part of the team leader should result in poor task time completion, the resulting performance penalties assessed to the team leader will discourage such decisions in the future.

6. Conclusion and Future work

We have developed a simple algorithm for teaming based on reasoning about efficiency. This algorithm is demonstrated in the domain of a task shared among satellites. Our experiments clearly show basis for teaming decision.

In a more general analysis of teaming we must examine an agents psychogenetic needs and mental states that lead to motivations along with efficiency considerations.

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