A Bayesian Formulation for Auction Based Task Allocation in Heterogeneous, Multi-Agent Teams

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ABSTRACT

In distributed, heterogeneous, multi-agent teams, agents may have different capabilities and types of sensors. Agents in dynamic environments will need to cooperate in real-time to perform tasks with minimal costs. Some example scenarios include dynamic allocation of UAV and UGV robot teams to possible hurricane survivor locations, search and rescue and target detection.

Auction based algorithms scale well because agents generally only need to communicate bid information. In addition, the agents are able to perform their computations in parallel and can operate on local information. Furthermore, it is easy to integrate humans and other vehicle types and sensor combinations into an auction framework. However, standard auction mechanisms do not explicitly consider sensors with varying reliability.

The agents sensor qualities should be explicitly accounted. Consider a scenario with multiple agents, each carrying a single sensor. The tasks in this case are to simply visit a location and detect a target. The sensors are of varying quality, with some having a higher probability of target detection. The agents themselves may have different capabilities, as well. The agents use knowledge of their environment to submit cost-based bids for performing each task and an auction is used to perform the task allocation. This paper discusses techniques for including a Bayesian formulation of target detection likelihood into this auction based framework for performing task allocation across multi-agent heterogeneous teams. Analysis and results of experiments with multiple air systems performing distributed target detection are also included.

Keywords: multi agent systems, market-economy, decision theory

1. INTRODUCTION

As the use of unmanned platforms increases, it will be important for different platforms with varying sensors and capabilities to work together effectively in teams. Different platforms may have different sensor configurations, quality, costs, operational capabilities and bases of operation. Not only will it be important for different types of vehicles to work together, but also for these resources to be allocated efficiently, in dynamic and changing environments. Some example scenarios include dynamic allocation of UAV and UGV robot teams to disaster locations, search and rescue operations, and target detection. Allocation of transportation assets, and detection of forest fires or chemical spills are other examples. These scenarios are a specific type of the task allocation problem, in which there are multiple vehicles and multiple locations to be visited, with the goal being to allocate the team of vehicles to each of the locations while minimizing the overall team cost. Centralized approaches to the task allocation problem can be a source for communications and processing bottlenecks in the system and allow for a single point of failure. Furthermore, centralized approaches, while able to find optimal solutions, may not scale as easily as a distributed system and are less practical when changes in a dynamic environment require frequent re-planning. Market based methods (often referred to as ”auction” methods) are distributed algorithms that model tasks as goods that are to be sold in a market to the highest bidder. Auction based algorithms scale well because agents generally only need to communicate bid information. In addition, the agents are able to perform their computations in parallel and can operate on local information. Furthermore, it is easy to integrate humans and other vehicle types and sensor combinations into an auction framework. These methods are also robust to communication failures and dynamic team formation.

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This paper investigates the application of expected utility as part of task assignment in an auction framework on a multi-agent team. In addition, this paper presents an approach for including future observations by multiple sensors as part of the expected utility function and therefore allows for a more accurate estimate of utility when analyzing an agent’s bid.

1.1 Motivation

The need for assigning tasks to teams of agents with different capabilities applies to many domains; however, the search and rescue domain presents an interesting case in which multiple assets are combined. In a lost persons scenario, there are multiple assets that have different probabilities of detection of the victim, such as helicopters, searching dogs and people spaced out in a grid search.\(^1\) In many cases, the probability of detection by an asset increases with repeated visits to a probable target location. With helicopters, the victim might be obscured by vegetation and may later be visible. Searching dogs can be highly effective, but their effectiveness varies based on terrain, weather and other factors. Teams of people that are sweeping an area with a specific spacing may miss a victim on the first pass and still spot them on the second or third. Of course, combinations of assets and multiple assets are possible. Search organizers can use known probabilities of detection (POD) for assets and asset combinations and consider the effect of multiple passes by sets of assets. For instance, a team of searchers spread out with only 20 feet between them, performing a single pass, are about as effective as a smaller team of searchers that is spread out at 60 feet, but that performs two passes.\(^1\) The problem for search organizers then, is to consider the search assets available, the probabilities of detection for each of those assets and the probabilities that a target will exist in a given location. However, in such a search and rescue setup, there may be only a few victims and therefore detection of false positives are not a big concern, as victims can easily be identified once detected. Furthermore, these assets are suited to a centralized organization model.

In robotics and unmanned systems domains, events may happen more quickly and the environment may be more dynamic in nature. As such, task allocation is better suited for a decentralized and dynamic strategy. Yet, the problem is similar in many ways; the ideal team would leverage all assets available, even if some are more accurate than others. This may mean that some assets make multiple passes of a target to attain the same detection confidence that another might make in only one pass. In the search and rescue domain, false negatives are very important. That is, searchers do not want to miss a target that exists due to sensor error. In other domains, false positives are more of a concern. In a target detection scenario, it is important that a target’s existence be verified with confidence, before additional (perhaps more expensive and dangerous) assets are deployed. While search and rescue robots are an active research area,\(^2,3\) the rest of this paper will consider a target detection scenario, in which a requirement is that targets are detected with a given confidence level.

The Georgia Tech Research Institute (GTRI) has developed a system for performing cooperative autonomy research using multiple unmanned vehicle platforms. The system consists of multiple small, Unmanned Aerial Vehicles (UAVs) and an Unmanned Ground Vehicle (UGV), as shown in Figure 1. The vehicles operate autonomously and communicate with each other in a distributed manner. In a target detection task, the team of vehicles could respond to ground sensor notifications of possible intruders. Each vehicle may carry a different sensor and encodes the local cost to visit a location via their bid value. This will serve as a motivating scenario for this work. The remaining discussion only considers experiments with multiple UAVs, although the framework allows for UGV participation as well.

1.2 Related Work

Cameron and Durrant-Whyte\(^4\) investigated the use of statistical decision theory to determine optimal sensing locations for performing localization and recognition tasks. Their work investigated the use of decision theory for a single robot with a manipulator to more effectively manage sensor placement. Bourgalt, Furukawa and Durrant-Whyte\(^5\) investigated the use of decentralized Bayesian methods for allocating a team of UAVs in a search mission. The agents in this system exchanged target probability information, and each agent sought to maximize their utility. Similarly, in the work by Tisdale et. al.,\(^6\) multiple UAVs exchanged PDFs to update a target location estimate.

Xiong, Christensen and Svensson\(^7\) described a multi-agent negotiation mechanism using a sub-game perfect equilibrium strategy for performing target distribution. Each sensor was represented by an agent that negotiated
on behalf of the sensor and interacted with opponents to receive more assignments and achieve better payoffs. Strategy profiles were created to allow agents to come to agreement with minimal delay. Kraus\textsuperscript{8, 9} provides an excellent review of strategic, competitive negotiation mechanisms for multi-agent systems and discusses approaches from game theory and economics. The choice of negotiation mechanism can depend on many factors, but auction mechanisms are useful when agents are mainly interested in their local cost factors rather than factors that affect other agents. For the purposes of this paper, the agents cooperate and are not competitive, and bid their true valuations.

Zlot and Stentz, et. al, implemented a market based mechanism on a team of indoor robots to perform a multi-robot exploration task\textsuperscript{10}. The robots negotiated new areas available for exploration and revenue was exchanged for information. The multi-robot team showed a significant performance improvement over teams that did not negotiate. The multi-robot routing problem consists of a set of robots, a set of target locations and a cost function. The objective of this problem is to assign each robot to a target and compute the plan for each robot to visit each of their locations such that the overall team cost is minimized. Lagoudakis\textsuperscript{11} provides a theoretical analysis of auction methods applied to the multi-robot routing problem and investigates the performance of several bidding rules.

Several other researchers have investigated the use of market-based mechanisms for multi-robot coordination. In market-based approaches, self-interested robots operate in a virtual economy and exchange goods (information, task performance, etc.) for virtual revenue. While each agent seeks to improve their own situation, the entire team benefits from the cooperation. An excellent survey of market-based multi robot coordination is provided by Kalra and Zlot, et. al.\textsuperscript{12} Market based methods have been used in a number of domains, including simulated UUVs,\textsuperscript{13} simulated rovers,\textsuperscript{14} UAVs,\textsuperscript{15} and ground robots.\textsuperscript{10, 16}

The main contribution of this work is the integration of an auction based algorithm for performing multi-robot task assignment, combined with an expected utility based task assignment function. The use of expected utility allows for the combination of the platform’s cost for visiting a target location, along with a consideration of the sensor characteristics. The inclusion of sequential analysis methods from decision theory allows for a more accurate expected utility evaluation when multiple sensor observations may be required. Simulated experiments show that this approach will perform better than auction based methods that do not explicitly account for sensor characteristics.

2. PROBLEM STATEMENT

In the basic problem setup there are multiple agents, each carrying a single sensor, varying in quality of detection. An auction mechanism is used to divide tasks among the agents, and the tasks in this case are to simply visit a location and perform an observation with the sensor. Targets are static (non-moving) and will be present only at some of the locations. Also, targets are assumed to be independent of each other. The auctioneer could in principle be any of the agents, but this work will assume a static, external auctioneer that periodically auctions
Table 1. Probabilities of detection for example sensors

<table>
<thead>
<tr>
<th>Sensor</th>
<th>Target Present</th>
<th>No Target</th>
</tr>
</thead>
<tbody>
<tr>
<td>S₁</td>
<td>0.80</td>
<td>0.10</td>
</tr>
<tr>
<td></td>
<td>not_found</td>
<td>0.20</td>
</tr>
<tr>
<td>S₂</td>
<td>0.70</td>
<td>0.20</td>
</tr>
<tr>
<td></td>
<td>not_found</td>
<td>0.30</td>
</tr>
<tr>
<td>S₃</td>
<td>0.95</td>
<td>0.01</td>
</tr>
<tr>
<td></td>
<td>not_found</td>
<td>0.05</td>
</tr>
</tbody>
</table>

new tasks (locations to visit.) This work also assumes perfect communications between the agents and the agents will exchange bid information with the auctioneer.

A basic auction mechanism that performs distributed task allocation might only consider the cost of executing a chosen task (i.e., visit a location and acquire a sensor reading). In such a model it is implicitly assumed that tasks execute and acquire perfect information. Thus there is no integration of sensor characteristics.

In the target detection task, there are two cases that need to be predicted with reasonable certainty: whether a target exists at a given location, and whether it does not exist at the location. When noisy sensors are considered, these cases correspond to the true positive case (the case that a target exists and is sensed) and the true negative case (the case that a target does not exist and is not sensed). Expressed as prior probabilities, these are \( P(T|S) \), the probability that a target exists given that it was sensed, and \( P(\neg T|\neg S) \), the probability that a target does not exist, given that it was not sensed.

This work assumes that sensors have prior estimates for probability of detection and that these estimates are known in advance. Consider for example, a multi-agent team that consists of three different sensor types, (\( S₁ \), \( S₂ \), \( S₃ \)). These sensors return a binary detection value (positive, negative). Also, assume that the probability that a target will exist at a given search location is \( P(\text{Target}) = 0.25 \). The Sensor-Target Probabilities for \( P(S) \) are given in Table 1, and the probabilities vary for each of the 3 sensor types. \( S₁ \) is considered reasonably accurate, \( S₂ \) has the least accuracy, with a high false-positive rate, and \( S₃ \) is very accurate. Given the prior probabilities, \( P(T) \) and \( P(S) \), Bayes’ rule can be used to find the posterior, \( P(T|S) \) as shown in Equation 1. As one might expect, using Sensor \( S₃ \) leads to a very high probability (or confidence) that a target exists if the sensor returns a positive detection.

\[
P(T|S) = \frac{P(S|T)P(T)}{P(S)}
\]

\[
P(T|S₁) = \frac{(0.80)(0.25)}{(0.80)(0.25) + (0.10)(0.75)} = 0.727
\]

\[
P(T|S₂) = \frac{(0.70)(0.25)}{(0.70)(0.25) + (0.20)(0.75)} = 0.538
\]

\[
P(T|S₃) = \frac{(0.95)(0.25)}{(0.95)(0.25) + (0.01)(0.75)} = 0.969
\]

3. APPROACH

3.1 Auction-Based Task Allocation

There are many different methods for performing distributed cooperation, including optimization algorithms and game theoretic techniques. However, auction based approaches have the benefits of being simple to implement and understand, and can easily be modified as mission requirements dictate. In addition, auction based algorithms generally have low communication requirements (agents coordinate tasks through bid messages), and therefore, are well suited to environments with communication constraints. Finally, auctions can perform computations in parallel and the methods take advantage of the local information known to each agent. For instance, a UAV would not need to communicate a low fuel state to the entire team for allocating tasks, but could implicitly include this knowledge in their own task selection through cost-based bidding.
3.1.1 Basic Auction Approach

In the basic auction algorithm, the problem is to assign a number of tasks to agents (ex., UAVs with different sensor characteristics). The tasks in this case are to visit a target location and perform a sensor reading, resulting in a binary detection result (detection, no detection). In the auction framework, each robot is a bidder and the items to be auctioned are the visit tasks. For ease of analysis, this work assumes that a central auctioneer exists to allocate the task, however; any of the agents in the system could serve as an auctioneer in a fully distributed implementation. This approach can easily be used on teams with different robot characteristics: each robot knows their own location and cost function and submits cost based bids to the auctioneer. While costs and rewards use the same basis for calculation, no revenue is actually exchanged.

In the auction mechanism, the auctioneer periodically auctions new tasks to each member of team. The agents each maintain a current task list and compute the incremental cost to complete a proposed task. This incremental cost is known as the cheapest insertion heuristic: for each pair of tasks in the current task list, the agent compares the additional Euclidian distance based cost for inserting the new task, and selects the insertion that minimizes that cost. This insertion cost forms the agent’s bid. The auctioneer selects the lowest cost bid as the winner of that auction and performs the task assignment. When an agent wins and is assigned a new task, the task is inserted into the agent’s task list, again using the cheapest insertion heuristic. Auctions that proceed with a single item being auctioned at a time in this manner are referred to as Sequential Single-Item (SSI) Auctions. SSI Auctions provide reasonable theoretical performance guarantees for the sum of travel distances and communications, even when using the cheapest insertion heuristic.11

3.2 Multiple Sensor Observations

After an observation has been performed and the posterior probability of the target, $P(T|S)$, is calculated, the auctioneer can determine if the confidence threshold has been met. If the threshold is not met, then the system will require another observation to verify the target, increasing the overall team cost. However, additional observations would lead to increasingly more accurate estimates for $P(T|S)$. For instance, it may be worthwhile to request a sensor to sweep a target location multiple times, or perhaps send separate platforms, each with less accurate sensors if the platform with the more reliable sensor is not available or too costly. The equation for binomial probabilities, shown in Equation 2, can be used to compute the probability that a sensor returned $k$ detections out of $n$ target visits. Joint observations from different sensors are combined using Bayes’ rule to get the probability that the target exists, given one or more detections from one or more sensors. This provides a framework for evaluating the probability that a target exists by combining sensor readings from multiple, different sensor visits of a target location. The system designer can place an acceptable detection threshold to determine the number of times a location should be visited.

$$p(k) = \binom{n}{k} p^k (1-p)^{n-k}; k = 0,1, ..., n$$ (2)

As an example, the probability of $S_2$ returning 1 true detection out of 2 trials as well as the probability of 1 false detection out of 2 trials is given by:

$$p(k = 1)_{S_2true} = \binom{2}{1} (0.7)^1 (1-0.7)^1 = 0.42$$

$$p(k = 1)_{S_2false} = \binom{2}{1} (0.2)^1 (1-0.2)^1 = 0.32$$ (3)

Also, the probabilities of $S_1$ returning 1 true detection out of 1 trial, as well as 1 false detection is given by:
\[
p(k = 1)_{S_{true\oplus}} = \left(\frac{1}{1}\right)(0.8)^1(1 - 0.8)^1 = 0.8
\]
\[
p(k = 1)_{S_{false\oplus}} = \left(\frac{1}{1}\right)(0.1)^1(1 - 0.1)^1 = 0.1
\]

Finally, assume that each of the observations are independent and combine their joint probabilities using Bayes’ rule to evaluate the probability that the target exists, given 2 positive detections out of 3 target visits from 2 different sensors in (5):

\[
P(T|S_1^n, ..., S_m^n) = \frac{P(S_1^n, ..., S_m^n|T)P(T)}{P(S_1^n, ..., S_m^n)} = \frac{(0.80)(0.42)(0.25)(0.80)(0.25) + (0.10)(0.32)(0.75)}{(0.80)(0.42)(0.25)} = 0.778
\]

3.3 Expected Utility

A detailed discussion of statistical decision theory applied to analyzing decisions under uncertainty is given by Raiffa. In particular, the notion of expected utility, \( Eu \), is useful for estimating future reward in an uncertain environment. Expected utilities of dynamic, uncertain environments can be modeled as a decision tree, as shown in Figure 2. Each circular node is a chance node, and the possible outcomes or branches of that node are show along with the probabilities. The expected utility is the sum of the probabilities times the reward of each branch. An example using the decision tree in Figure 2 is shown below. For each target location, a target will exist with probability \( P(T) \). Upon successful completion, each task delivers a reward, \( R \), and each agent’s bid consists of a cost, \( C \), to perform the task. A sensor detection is correct if the target exists and is reported by the sensor or if it does not exist and is not reported by the sensor. Rewards are assigned when the sensor detection is correct for the task and the detection likelihood is greater than the target detection threshold, \( \alpha \).

\[
Eu(Sn) = P(T)(P(S|T)(R - C) + P(\bar{S}|T)(0 - C)) + P(\bar{T})(P(S|\bar{T})(0 - C) + P(\bar{S}|\bar{T})(R - C)) \tag{6}
\]

This reflects the probabilities at each decision point and the awarded utilities. As an example, assume that a constant Utility of 100 units is awarded whenever an agent successfully detects a target and that 0 units are awarded otherwise. Now, assume that each sensor’s agent calculated their individual cost, per the basic auction framework, to deliver the associated sensor to the target location as: \( S_1 = 20 \) units; \( S_2 = 10 \) units; \( S_3 = 30 \) units. Following each path in this tree, the expected utility, \( Eu \), is calculated as shown in Equation 7. In this example, even though the more accurate sensor has a higher POD, the less accurate sensors are closer to the target location, having lower cost, and therefore the Eu values are approximately equivalent.

\[
Eu(a_1) = (0.75)((0.90)(80) + (0.10)(-20)) + (0.25)((0.80)(80) + (0.20)(-20)) = 67.5
\]
\[
Eu(a_2) = (0.75)((0.80)(90) + (0.20)(-10)) + (0.25)((0.70)(90) + (0.30)(-10)) = 67.5 \tag{7}
\]
\[
Eu(a_3) = (0.75)((0.99)(70) + (0.01)(-30)) + (0.25)((0.95)(70) + (0.05)(-30)) = 68
\]

This expression of cost, incorporating Expected Utility, could be used to inform a bid in the auction framework. As such, the auctioneer selects as the winning bid the agent sensor combination with the maximum expected utility for performing that task. The cost for the agent to perform the task is propagated through each branch of the tree to determine the expected utility, \( Eu \). In selecting the best sensor for performing the task, the auctioneer can apply the above \( Eu \) calculation to the agent’s cost bid, using the known sensor model, to arrive at the \( Eu \) of assigning the task to that agent. The auctioneer then simply assigns the task to the sensor that maximizes the \( Eu \) for performing the task.
3.4 Sequential Analysis

In addition to modeling the expected utility the decision tree can also model the effect of multiple, sequential sensor visits. This can be used to calculate a more accurate expectation in the case of multiple observations. The expected utility as described above can result in infinite recursion if the depth of the decision tree is not limited. In those situations in which sensors oscillate between correct and incorrect detections (albeit with decreasing probabilities), the likelihood of a target may not reach the desired threshold and the expectation can be analyzed further in the future. Rather than setting an arbitrary depth on the expectation, it would be better to inform the decision process with an understanding of the amount of utility that additional information would provide.

Sequential Analysis, as described by Wald,\textsuperscript{19} is a technique from decision theory that provides a framework for analyzing the expected utility of repeated decisions. Sequential Analysis is often used by decision makers in business to determine whether to seek more information about a process or to stop sampling and make a decision. In the distributed task allocation problem, it is important for the auction algorithm to assign the most effective sensor combinations to each task by predicting those assignments in advance, with consideration that some sensors may perform multiple target visits if the detection threshold is sufficiently high. However, in practice, the system will observe the outcome of each trial (sensor task) and decide whether that task is complete (stop sampling) or if more information is needed (continue sampling by assigning the task to another sensor.)

In this framework the expected utility tree is performing an estimate of the expected cost for performing the task, including the cost for additional sensor visits if the detection likelihood threshold is not met. The task of visiting a target and performing a sensor detection is viewed as testing the hypothesis that the target exists, given the sensor observations. Each time that a sensor task is complete, a decision is to be made. The choices are to accept the hypothesis and stop the decision process, reject the hypothesis and stop the decision process or perform additional observations. The approach using sequential analysis allows for the hypothesis to be accepted or rejected when the likelihood falls above or below stated thresholds. In the last case, the decision whether to keep sampling is determined by the additional expected utility that further sampling would gain, noted the Expected Net Gain from Sampling (ENGS).\textsuperscript{20}

The ENGS is simply the difference between the expected utility with the current observations and the
expected utility if an additional sample was to be taken. With this approach, the sequential decision process continues, calculating the likelihoods and ENGS for different sample sizes of \( n \), until the value for \( n \) that maximizes the ENGS is found. This is the value that will be used to approximate the Eu for task assignment. For example, with reward and cost values of \( R = 100 \) and \( C = 20 \), the related sequential decision trees are shown in Figure 3. After all payoffs are considered (using the Eu), the ENGS of the additional sample is computed as shown in Equation 8.

\[
\begin{align*}
\text{ENGS}_1 &= \text{Eu}(S_1)_{1\text{sample}} - \text{Eu}(S_1)_{0\text{samples}} = 47.5 - 0 = 47.5 \\
\text{ENGS}_2 &= \text{Eu}(S_1)_{2\text{samples}} - \text{Eu}(S_1)_{1\text{sample}} = 58 - 47.5 = 10.5 
\end{align*}
\]

In the above example, the Eu is greater with \( n = 2 \), but the ENGS is maximized with \( n = 1 \). Therefore, the appropriate sample depth for the Eu tree is 1. Intuitively, this reflects that it is not worth the resources to continue sampling for little added gain. In other cases, the value for \( n \) that maximizes the ENGS value leads to a deeper Eu tree, as shown in Figure 4(c). With the sequential analysis approach, reward values are only granted to the leaf nodes if the detection threshold, \( \alpha \) is met. For instance, if an initial sensor visit did not provide the desired confidence, then another observation would be required. If sequential analysis is not used, then the expected utility tree can either be optimistic (often over-estimating the utility) as shown in Figure 4(a) or pessimistic, possibly resulting in negative utilities. The sequential analysis approach therefore provides for a more refined estimated utility.

![Sequential Analysis: different sample sizes can result in varying estimates for the expected utility for the task assignment. Final leaf nodes are outcomes that met the given probability threshold and are shown as diamond shapes. The cost is propagated to all leaf nodes and rewards are applied at final leaf nodes only.](image)

4. EXPERIMENTS AND RESULTS

4.1 Discounted Reward and Cost Factor

An issue with relying too heavily on the expected utility approach alone is that it tends to favor the vehicles with the more accurate sensors. This would cause the other sensors to be underutilized. To address this issue, a discounted reward can be used to perform task assignment, as described in. A discount factor, \( \gamma \), between 0 and 1, is applied to the reward \( t \) time steps into the future, \( \gamma^t R \). This results in a more even distribution of tasks. The discounted reward factor rewards tasks that are performed sooner, rather than later. Furthermore, this forces some tasks to be re-bid later when the vehicles have fewer tasks in their schedules. This results in a more equitable distribution of tasks as the items are re-auctioned until they are won (only bids resulting in \( \text{Eu} > 0 \) will be awarded). At the time they are awarded and assigned, the agents may be closer or have a smaller task list. All of the auction methods in these experiments used the discounted reward factor to ensure that any one agent was not overloaded with tasks.
Figure 4. Sequential Analysis vs Optimistic Look-ahead: a) If sequential analysis (SA) is not used, the expected utility can be overly optimistic. b) The sequential sampling approach provides for a more refined estimate of $E_u$. c) In this example, when using the SA method, the ENGS is maximized when $n=2$.

4.2 Experimental Setup

The MASON multi-agent simulation framework is used to perform simulations of multiple UAVs performing distributed task allocation using an auction based mechanism. The simulation consists of multiple simulated UAVs, modeled as points in a 2D plane. Vehicle dynamics and attitude are not modeled in these simulations. The simulation environment was 600x600 units, with target locations randomly distributed. During an experiment, the simulation engine executes for a number of time steps until all tasks are complete. The simulation also includes a centrally located auctioneer which introduces new tasks to the system every $n$ time steps by announcing a new auction. At each time step, each UAV evaluates their position and adjusts their heading toward the next task. The vehicles’ velocities are held constant at 1 unit per time step. The UAVs also evaluate their current task list and respond to auction messages with bids.

A UAV’s task is considered complete when the UAV visits the task location and notifies the auctioneer. The auctioneer calculates the posterior probability that each task was successfully completed by comparing the target detection likelihood, given all sensor visits, $P(d|S)$. If the threshold is not yet met, the task is re-auctioned after $r$ steps for assignment to UAV. Rewards are only granted to the UAVs that successfully complete a task. The simulation keeps a running count of each UAVs cost (expressed as the number of time steps) and reward. UAVs that have no task still accumulate cost at a constant rate.

4.3 Detection Threshold Experiments

Experiments were performed in which the following three auction methods were compared against each other while varying the required detection threshold for each task. In the Basic Auction method, the cost function considers only the cost for the UAV to visit the target location and does not consider the sensor qualities. The Expected Utility method applied the $E_u$ to the agents bid with the expected utility tree pruned at the first level with optimistic look-ahead. The Expected Utility SA method used the ENGS stopping rule to prune the $E_u$ tree.

In the Expected Utility SA method, the sequential analysis for multiple sensor visits to a single target models a future visit to the target location, re-using the same sensor type in the decision tree. In theory, any of the sensors could be assigned the visit task and the expectation could be taken over all available sensors. Another option is to cluster each sensor’s task locations and assign the closest sensor. The cost bid for future visits could be modeled similarly, or by taking an even distribution of sensors. However, in practice these assumptions work well and can be though of as placeholders for a sensor with similar characteristics and costs.

Sets of experiments were performed using teams of 2 and 6 UAVs. The 2-UAV team consisted only of the first two, less accurate, sensor types in Table 1 and the 6-UAV team consisted of two of each sensor type in Table 1. For each target probability threshold value the experiments were performed 30 times with random UAV starting locations. In each experiment, the auctioneer allocated 200 tasks, using SSI auctions. Tasks that did not meet
the detection threshold upon completion were later re-auctioned, resulting in additional team cost. The results of each experiment were averaged over all of the runs.

4.4 Discussion

The results of these experiments are plotted in Figure 5. In both sets of experiments, the global team cost for the Expected Utility methods performed better than when using the Basic Auction algorithm. The Eu methods are able to more efficiently allocate sensors to tasks because they explicitly consider the sensor detection probabilities as part of the task assignment. The Expected Utility SA method performed slightly better than the Expected Utility method with optimistic lookahead. The additional expectation provided by the sequential analysis likely resulted in a more efficient allocation of sensors to tasks by performing a more efficient lookahead into the expected utility of the task assignments.

![Figure 5. Experimental Results: The results of multiple experiments with different values for the target detection threshold, $\alpha$. The unit score is the total team’s reward/cost over the entire experiment. The Eu methods for task assignment perform better than the Basic Auction method which does not explicitly account for sensor characteristics. The Expected Utility SA method using sequential analysis performs better than the Expected Utility method using optimistic look-ahead.](image)

5. CONCLUSIONS AND FUTURE WORK

Multi-agent teams may consist of agents with different sensor qualities and characteristics. In many domains, multi-agent teams may need to perform cooperatively assign tasks across the team in order to maximize the overall team efficiency. In teams with different sensor capabilities, the sensor characteristics should be accounted for explicitly in when performing the task assignment. When the quality of the sensors on the team varies, it may be better in some cases to assign multiple, less accurate sensors to the detection task, rather than overload a more accurate sensor. In adopting this approach, the auctioneer will sequentially re-auction tasks until the detection threshold is met.

This paper described an approach for applying an estimated utility to the task assignment function, along with an approach for calculating the number of future samples to consider when performing an estimate. The experiments show that when expected utility for performing a task is applied to the agent’s bid, the overall performance of the team is improved over a basic auction mechanism. Furthermore, the authors showed that using sequential analysis to maximize the expected gain of additional samples could be used to approximate the appropriate expected utility tree depth when calculating the expected utility. Experiments with this approach results in slight performance improvements over an optimistic expected utility calculation, when detection confidence requirements are high.
Future work will investigate the use of these methods when the sensors’ prior probabilities are not known in advance and must be learned. In addition the authors hope to perform similar experiments on both UAVs and a UGV, using the Georgia Tech Research Institute’s Unmanned Systems research platform, shown in Figure 1.

REFERENCES


