

Bringing the Market to Level 4 Fusion: Investigation of Auction Methods for Sensor Resource Allocation

Tracy Mullen, PhD
Viswanath Avasarala
David L. Hall, PhD

The School of Information Sciences and Technology
The Pennsylvania State University

Abstract

Rapid evolution in sensor technology including distributed ground based sensors and devices such as smart dust have energized research efforts towards devising a theoretical foundation for sensor management and for multi-sensor data fusion. Features such as ubiquitous sensing, wide bandwidth communications and distributed processing provide both challenges and opportunities for sensor and process control and optimization. New sensors and wideband communications provide an information rich environment for users. However, limited sensor processing and resources and the heterogeneity of the contributing sensors make the utilization of such sensors a very challenging problem. Traditional optimization techniques used in level-4 fusion do not have the ability to address such an environment. This paper describes the results of a research study that investigated the potential of market-based resource allocation algorithms to improve the performance of multi-sensor network systems in complex observing environments.

Background and Problem Description

Recent developments in sensor technology such as distributed ground-based sensors and devices such as smart dust have energized research efforts towards devising a theoretical foundation for sensor management and multi-sensor data fusion [1,2]. Network-centric warfare and surveillance, with features such as ubiquitous sensing, wide bandwidth communications and distributed processing provide both opportunities and challenges for sensor and process control and optimization. On one hand, new sensors and wideband communications provide an information rich environment for users (shown conceptually in Figure 1). However, limited sensor processing and resources such as battery capacities and computational capabilities and the underlying heterogeneity of the contributing sensors make the utilization of such sensors a very challenging problem. Distributed sensor networks can be utilized by multiple users operating in a semi-cooperative environment with little/no

communication among the users. In addition, the sensor networks may include data collection entities that operate on very different timescales, from utilization of human inputs to real-time video-frame collection of images. Traditional optimization techniques do not have ability to simultaneously consider these wildly non-commensurate measures in a single optimization routine.

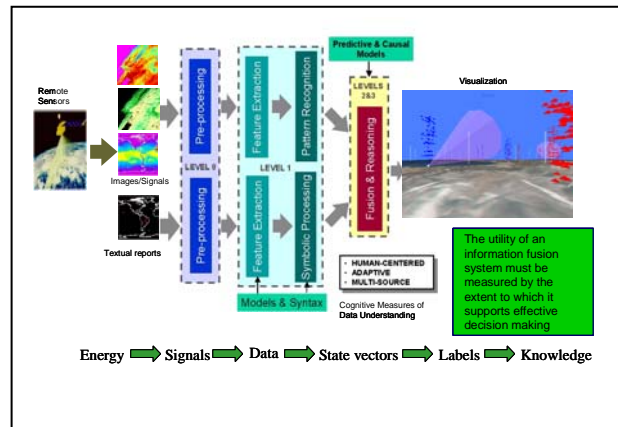


Figure 1: Energy to knowledge transformation

How can diverse sensing resources (including steerable sensors with high data rate access, human observers, unattended ground-based sensors, and others), be used effectively to support multiple users having different priorities and time horizons? How can such resources be used in situations in which the resources may be dynamically available (e.g., coming into and out of coverage, having widely different performance based on local environmental conditions, etc.) and may even be unknown to potential users? We believe that market-oriented programming [3] provides a valuable paradigm to address this distributed resource allocation problem. Recent years have seen significant developments in auction algorithms, particularly combinatorial auctions [4, 5, and 6]. Advances in market-based algorithms and the rapid evolution of data fusion service-based architectures, combine to motivate the exploration of such techniques for resource allocation.

As new collection capabilities are being developed to allow surveillance on a global scale and as new service-oriented architectures are implemented, the challenge is to use such capabilities effectively. Advances in new types of collection capability provide the promise for a new generation of data in support of situation and threat assessment. However, with new capabilities comes a continuing and even enhanced challenge of how to utilize these resources both individually as well as in collaboration with conventional sensors. This is the Level-4 process defined in the Joint Directors of Laboratories (JDL) data fusion processing model (Figure 2). Challenges include; utilization of persistent versus (and in conjunction with) non-persistent sensors, how to use collection resources to service multiple information consumers in a dynamic environment, tradeoffs of information quantity, quality, and timeliness, and how to use sensors having widely different reporting timescales.

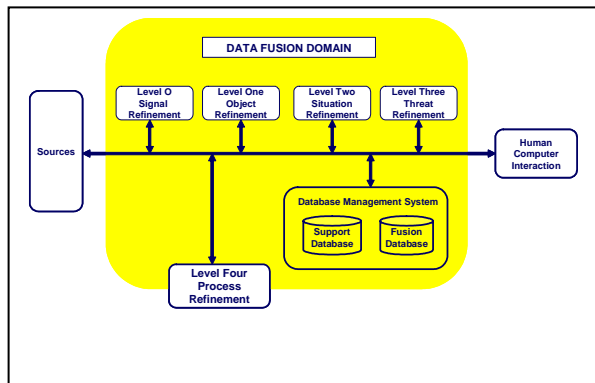


Figure 2: Joint Directors of Laboratories (JDL) Model

Sensor performance and sensor management are intimately linked—knowledge of sensor performance (e.g., resolution, fidelity, update rates) is required to improve data fusion results. Sensors provide information about the environment (e.g., environmental scans) and sensor management provides the optimum sensor configuration based on predicted system performance. This includes determining how best to deploy, configure, or reconfigure sensors subject to several constraints; in particular, sensors can be configured so that incoming targets are countered effectively.

Conventional approaches to solving the sensor management problem often employ exhaustive search methods, where all combinations of sensors and their performance are evaluated. As these combinatorial approaches must evaluate a large number of solutions, a real time implementation is often impossible. Novel methods for sensor management

will greatly aid in the complex problem of deciding which combination of sensors to deploy.

Summary of Approach

This project investigated the potential of market-based resource allocation algorithms to improve the performance of multi-sensor network systems in complex observing environments. We formulated the sensor management problem as a competitive market, in which a sensor manager holds a combinatorial auction to “sell” the various items produced by the sensors and the communication channels. Because standard auction mechanisms are not directly applicable to this particular problem, it was necessary to develop specialized auction protocols. Our approach has the capability to successfully deal with the strict real time considerations of the sensor network domain. Market based approaches require the explicit consideration of user-utility for the various resource allocations. Utility-based methods require that the relevance and importance of mission goals be explicitly defined. To study the effect of utility-based user modeling on sensor management, we conducted an initial comparative study of utility theory and information theoretic approaches to sensor management. The information theoretic approach models the sensor management problem as an optimization problem that involves sensor allocation to maximize information content about the environment. Direct information theoretic measures concentrate on maximization of quantity of information, neglecting the relevance of the information to the mission goals. The results of our current simulation vindicate the rationale of the proposed utility-based formulation.

Sensor Management Literature Review

The term *sensor management* refers to “the process which seeks to manage or coordinate the use of sensing resources in a manner that improves the process of data fusion and ultimately that of perception, synergistically” [7]. Typical sensor management tasks include sensor scheduling and determining the significance/criticality of any task to the overall mission. *Sensor scheduling* refers to the actual allocation of measurement tasks to specific sensors. Numerous papers on scheduling tasks exist in the literature of operations research and computer science research, which have served as starting points for a solution to the sensor scheduling problem (see [8]) for details. However, none of these solutions have been found to be directly applicable to the problem of sensor scheduling, and specialized algorithms have been sought. Hintz and Zhang

developed a specialized scheduling algorithm, called the on-line, greedy, urgency-driven, preemptive scheduling algorithm (OGUPSA), specifically for sensor scheduling [8]. OGUPSA uses a first-in-first-out (FIFO) queue structure for task allocation to a group of sensors based on the three main scheduling policies of Most-Urgent-First to pick a task, Earliest-Completed-First to select a sensor and least versatile first to resolve ties.

Another major task of sensor management system is determining the significance/criticality of any task to the overall mission. Several algorithms for different variants of this problem have been proposed in research including heuristics [9], expert systems [10], utility theory [11], automated control theory [12], cognition [13], decision-theoretic approaches [14], fuzzy logic [15], probability theory [16], stochastic dynamic programming [17], linear programming [18], neural networks [19], genetic algorithms [20] and information theory [21-25]. However none of these algorithms have been based on either robust mathematical frameworks or else a generic sensor management architecture, and thus at best, they serve as good “point solutions” to their respective domains.

Denton et al [26] have proposed a generic architecture and a hierarchical control methodology for the sensor manager problem. The proposed sensor management system consists of a mission manager, sensor manager and the sensor suite, forming a hierarchical control system. The mission manager is responsible for high level mission decisions and provides the primary direction to the sensor manager by sending information requests. The sensor manager consists of information instantiator, measurement scheduler and personality module. The *information instantiator* is responsible for converting the information level requests of the mission manager to measurement level requests that can be understood by the sensor suite. The *measurement scheduler* is responsible for allocating the various measurement tasks to the individual sensors. The *personality module* provides a common interface between the sensor manager and different kinds of sensors in the sensor suite.

Based on Denton et al’s architecture, Hintz and McIntyre have proposed a sensor management strategy that uses posnets/lattices in the mission manager to derive the high level priorities of various tasks. An information theoretic approach in the information manager for analyzing cost benefit analysis of the various information requests from the Mission Manager and OGUPSA algorithm and in the Sensor scheduler for scheduling actual sensor task.

Background on Computational Economies

Computational economies use the metaphor of market-pricing to provide a design paradigm for developing systems that can effectively engage in decentralized decision making with minimal communication overhead. The analytic framework is derived directly from economics in order to provide a principled and robust design methodology.

An initial model for our computational economy considers k goods (e.g., target tracks, environmental scans, etc.) and n agents who wish to buy or sell these goods. Agents can be either consumers or producers. *Consumers* specify their preferences over goods via a utility function (u_i) that also ranks their preferences over various bundles of goods. Further, consumers start with an initial endowment of goods, which acts as a budget. Let e_{ij} be agent i ’s endowment of good j , and x_{ij} agent i ’s final allocation of good j . The consumer’s objective is to choose a feasible bundle of goods, and can be defined as a constrained optimization problem

$$\max u(x_i) \text{ s.t. } \mathbf{p} \cdot \mathbf{x}_i \leq \mathbf{p} \cdot \mathbf{e}_i$$

where $\mathbf{p} = (p_1 \cdots p_k)$ is the set of prices for the k goods.

Producers can transform raw goods into finished product goods via their *technology*. A technology specifies the possible production set. In the special case, where there is one output good (e.g., $y_i = -x_{i,j}$), a *production function* specifies the maximum possible net output of y_i you can get from a given set of inputs as

$$y_i = -x_{i,j} = f(x_{i,1}, \dots, x_{i,j-1}, x_{i,j+1}, \dots, x_{i,k}).$$

A producer’s objective is to select a production plan that maximizes profits subject to its technology, while minimizing costs. Let $\mathbf{x}_{i,\bar{j}}$ be the input good consumption, and $\mathbf{p}_{\bar{j}}$ the input good prices. The producer has the constrained optimization problem

$$\max_{y_i} [p_j y_i - [\min_{\mathbf{x}_{i,\bar{j}}} \mathbf{p}_{\bar{j}} \cdot \mathbf{x}_{i,\bar{j}} \text{ s.t. } y_i \leq f_i(\mathbf{x}_{i,\bar{j}})]] ,$$

and since $y_i = -x_{i,j}$ we can rewrite the expression as

$$\min_{x_i} \mathbf{p} \cdot \mathbf{x}_i \text{ s.t. } \mathbf{x}_{i,\bar{j}} \leq f_i(\mathbf{x}_{i,\bar{j}}).$$

The price vector and demand vector pair, (\mathbf{p}, \mathbf{x}) , for each agent constitute a competitive equilibrium if and only if (1) \mathbf{x}_i for each agent i , given prices \mathbf{p} , is a

solution to its optimization problem, and (2) if the total amount of goods consumed equals the total amount of goods produced, plus the total amount with which the economy started.

Under certain conditions, competitive equilibrium exists, is unique, and is guaranteed to be *Pareto optimal* (no agent can do better without some other agent doing worse). Prices reflect how agents value these goods, and can be used to indicate when some sensor is in scarce supply (and thus perhaps more quantities should be acquired in the future). Finding these equilibrium solutions is done by one or more auctions. If the simplifying assumption that sensor management is a cooperative environment is made, optimality calculations are more straightforward.

Agents express their preferences, or willingness-to-pay, by submitting bids to auctions. These bids can range from simple point bids (\$5 for 1 good) to more complicated demand schedules. When there is more than one auction, agents face *exposure* problems, as they cannot express potential synergies. For example, if they have to bid for a left shoe in one auction, and a right shoe in another auction, they may end up with one left shoe, or one right shoe, where they would prefer to either have one of both or else no shoes at all. Combinatorial auctions address this problem by providing agents with a means of selling bundles, or combinations, of goods. An agent can now express that it would like a combination of one left and one right shoe, or nothing at all. However, combinatorial auctions can be computationally expensive. As we discuss in the next section, recent work has focused on various strategies for reducing the complexity as well as using anytime approaches to get near-optimal solutions in a reasonable time.

Initial Design

Our initial experiments in this area were very simple both in modeling the environment and in modeling the market-based sensor manager. For our current research direction, we are modeling a sensor management system as a computational economy, and testing it on more realistic environmental models (e.g., more realistic targets and target motion, sensor models, mission timeliness constraints, etc.). As shown in Figure 3, we will initially focus on the sensor management requirements of a single platform with multiple heterogeneous sensors. We plan to extend this model to multiple coordinating platforms.

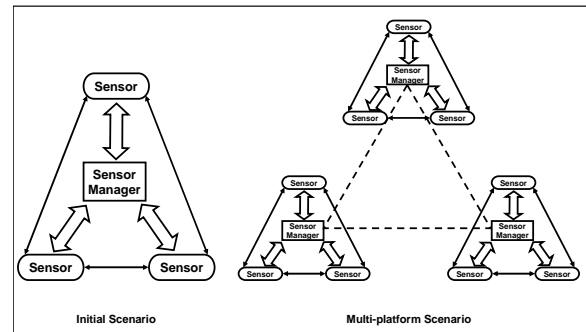


Figure 3: Market-based Platform Scenarios

The preliminary design we have been using is shown in Figure 4 below, where we have labeled the sensors to be those we are using in the continuing effort.

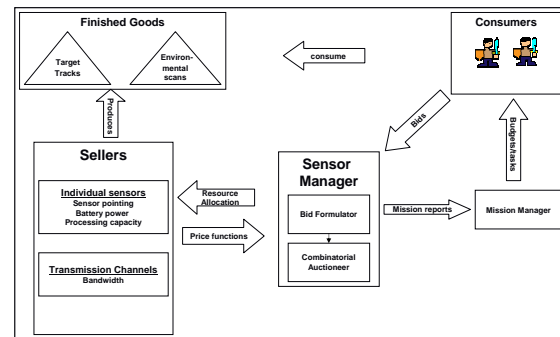


Figure 4: Single platform market-based architecture for sensor management

Consumers express their preferences on obtaining various sensor products (e.g., target tracks, environmental scans). Consumers may consist of information fusion processes that need to update situation data, or control processes (or even humans) who need to make a go/no-go decision. While consumers in a networked environment are interested in higher-end products (like target tracks), the producers (such as sensors, transmission channels, etc.) produce lower-end products (such as sensor parameter control and communication requirements). A mechanism for some kind of quality of service (QoS) mapping between buyers and sellers is essential to address these commensurability issues and create commodities that consumers are interested in and on which they can bid. Our mission manager is responsible for mapping consumer requests into terms of available sensors. Finally, the sensor manager conducts an auction to set prices and

allocate the available sensor products (target tracks, environmental scans) as needed.

Our sensor manager auction design will make use of recent research in more efficient and powerful auction algorithms. In particular, we will focus on anytime winner determination algorithms for combinatorial auctions [4, 6]. Combinatorial auctions are used to sell bundles of goods and can express synergies between goods. In the sensor management domain, a consumer may want to express that it is willing to pay a certain amount to buy a specific sensor with “excellent” applicability to the perceived threat, or pay a similar amount to buy two sensor tracks that together can provide “excellent” applicability, or else pay a lesser amount to get a sensor with just a “good” applicability to the perceived threat. A combinatorial auction can handle the evaluation of such synergistic resource allocation constraints. In the multi-platform case, it can also consider bundles of sensors for more complex problems.

Simulation Setup

For our initial research in this area, we designed and implemented a simple comparative study of information-theoretic and utility-based sensor resource allocation. Direct information-theoretic measures concentrate on maximizing the quantity of information, neglecting the value of information for mission goals. On the other hand, utility-based measures use the value of information for the mission goals in the sensor manager’s decision-making process. To conduct this comparative study, we developed a simulation environment consisting of a two dimensional search area involving multiple targets and multiple sensors for testing and comparing the performance of the various sensor management techniques. The search area is composed of rectangular cells within which stationary targets are randomly distributed. Targets are constrained to move only within a cell with a constant velocity corrupted with a white noise measurement. Each sensor’s capabilities and performance is modeled using a Kalman filter observation matrix (one for each sensor) and noise variance of their measurements. The sensor management scenario is modeled as a market-based system where the consumer agents bid for and purchase various sensor resources from the sensor manager. Consumer agents are assigned the responsibility of searching for and destroying targets. They are required to reduce the error covariance of the target estimates below a mission specified value before destroying them.

The flow chart of our simulation is shown in Figure 5, and details about the modeling parameters follow.

Target Modeling: Targets are randomly distributed throughout the search area. For this initial version, targets are constrained to move only within a cell with a constant velocity corrupted with a white noise. The target motion is simulated by the equation

$$x_k(t+1) = x_k(t) + w_k,$$

where $x_k(t+1)$ and $x_k(t)$ are positions of the target at time $t+1$ and t respectively, and w_k is the white noise with known constant covariance Q .

Sensor Modeling: For this simple scenario, sensors can be made to point in four different directions and have two modes of operation: high resolution and low resolution scan. In the low resolution scan mode, sensors can look at a larger area but with lower resolution and vice versa. Sensors are distributed throughout the simulation environment such that all the environment grids fall under the purview of at least one sensor. Each sensor’s capabilities and performance are modeled using a Kalman filter observation matrix (one for each sensor) and noise variance of their measurements. The measurement matrix for the i^{th} sensor is given by

$$z_i(k) = x_i(k) + v_k,$$

where $x_i(k)$ is the state vector and v_k is zero mean white noise with known variance R_i .

Consumer Agents: For our initial simulation, the environment is populated with a set of consumer agents, each of whom is assigned an area within which they are responsible to search and destroy targets. Consumers have a smaller area of influence, wherein they can directly pursue and destroy targets. After destroying targets within an influence area, the consumers move to the next unexplored area within their area of responsibility. Consumer agents send bids on various sensor services to the sensor manager and use the assigned services to update the target position information. They are allowed to destroy a target if they successfully reduce the error covariance of the target position measurement below a threshold value, P_{goal} .

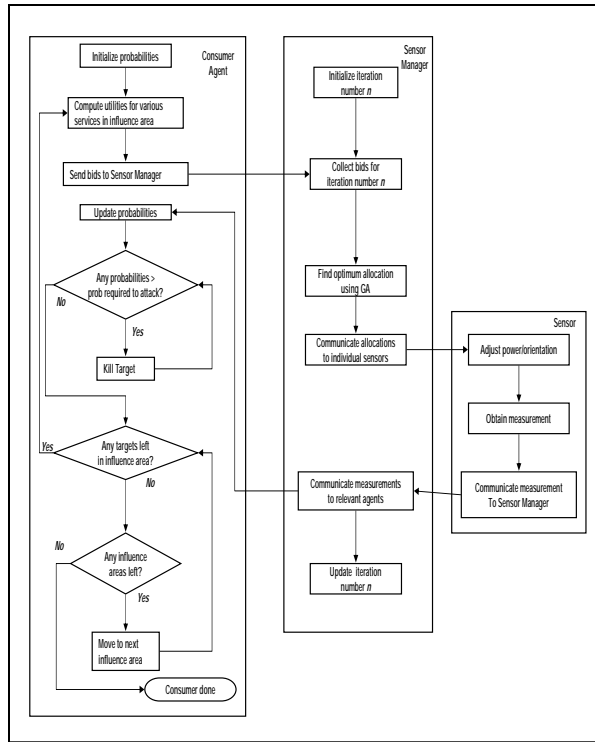


Figure 5: Simulation Flow Chart

Sensor Manager: The sensor manager collects bids on sensor services from various consumer agents and determines both the mode of operation and scan direction for each individual sensor. The sensor manager uses a genetic algorithm to find the optimum sensor allocation, given the consumer bids. It also maintains the target probability distributions for each cell, which are updated with every sensor measurement. This information is used to provide target state estimates to interested agents.

Information-Theoretic Bidding Formulation: For every cell in their area of influence, consumer agents bid the expected information gain for each possible sensor allocation. The amount of information gained can be measured by the change in entropy prior to and proceeding a sensor measurement. Assuming a normal distribution of target locations, the information gain (i.e., the difference between the a priori and a posteriori entropies) is calculated as

$$I = \log_2 \left(\frac{\sigma_s}{\sigma_b} \right)$$

where σ_s is the error covariance of the distribution and σ_b is the error covariance before the measurement.

Utility-Based Bidding Formulation: A sensor service S is defined as a set of sensor measurements on any particular cell. For each cell in its area of influence, a consumer computes the various possible sensor services possible and bids its utility for each service. When calculating service utility, we assume consumers specify a utility of U_d for each successful target destruction. For any given sensor service S , let n be the number of continuous such services required to bring the error covariance of the target estimate below P_{goal} . Hence, the consumer requires n consecutive allocations of service S , before it can destroy the target. In this simulation, we simplify the utility calculation for an individual scan as U_d/n . Thus if a particular target requires three consecutive low resolution scans before the error covariance of its state vector is reduced below the threshold value, then the utility of a consumer agent for a sensor service consisting of a single low resolution scan is $U_d/3$. In future versions, we plan to make this utility calculation more sophisticated. For example, one can imagine that if you have a heat seeking missile, the first scan imparts the most value (gets you to the right area) and then if you have time, more scans simply add incremental value. The overall detection utility in an unexplored cell for any service is obtained by multiplying U_d by the prior probability of target existence, as calculated by the consumer.

Results

We compared the performance of the information-theoretic sensor manager, utility-based sensor manager, and a randomly scheduling sensor manager. The random sensor manager serves as a baseline and randomly schedules scan directions and scan modes for various sensors. In the low resolution scan, a sensor can scan an area of four cells, whereas in a high resolution scan mode, it can scan only one cell. The measurement error covariance for a low resolution scan was chosen to be twice that of the high resolution scan, as shown below in Table 1.

When the threshold for the maximum error covariance of a target allowed before it can be attacked, P_{goal} is set relatively high (i.e., 3 or 4×10^{-3}), then fewer scans are needed to acquire enough information to successfully destroy a target. Under these circumstances, both information-theoretic and decision-theoretic approaches destroy targets at the same rate, which is much higher than that demonstrated by the random scheduler. However, when P_{goal} is relatively low (e.g., 1.8 or 2×10^{-3}) and

more scans/accuracy are necessary, the utility-based approach outperforms the other two techniques, as shown in Figure 6.

Our utility-based sensor manager takes the value of P_{goal} explicitly into consideration in the decision-making process. In contrast, entropy calculations that are used to formulate consumer bids in the information-theoretic sensor manager are independent of the value of P_{goal} . Instead, information-theoretic sensor manager concentrates only on maximization of information gain with every sensor resource allocation. This means that it can oscillate between targets without collecting enough information on one target long enough to successfully destroy it. From this study, we find that using both the information gain *and* the value of that information to the mission (i.e., its utility) to allocate sensor resources is the key to better performance.

No of Grids	64
No of targets	12
No of sensors	6
Measurement error covariance for High Resolution scan	$2 \cdot 10^{-3}$
Measurement error Covariance for low resolution scan	$4 \cdot 10^{-3}$
Process error covariance	10^{-3}

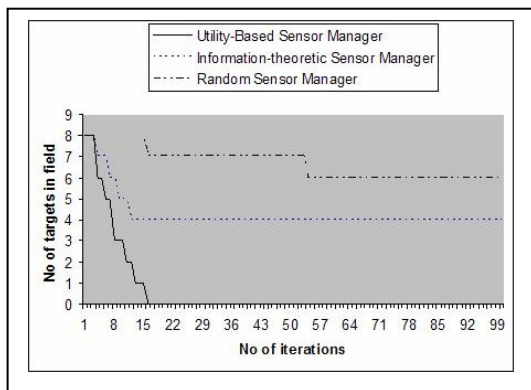


Figure 6: Sample results

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