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Market-Based Optimization for Detection and Tracking of Resident Space Objects

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Future space-based sensors have more complex data processing requirements and thus need more efficient sensor management tools to ensure their effective operation. Moreover, the dynamic, real-time nature of the domain requires a solution capable of adaptive scheduling. Here, we propose a market based approach to optimize the detection and tracking of resident space objects that encompasses the sensor system as a whole, including the network resources and computational power that support sensor tasks. Our market-based optimization approach applies solutions from economic theory, particularly game theory, to the resource allocation problem by creating an artificial market for sensor information and computational resources. Intelligent agents are the buyers and sellers in this market, and they represent all the elements of the sensor network, from sensors to sensor platforms to computational resources. These agents interact based on a negotiation mechanism that determines their bidding strategies. This negotiation mechanism and the agents bidding strategies are based on game theory, and they are designed so that the aggregate result of the multi-agent negotiation process is a market in competitive equilibrium, which guarantees an optimal allocation of resources throughout the sensor network. This approach was chosen in large part for its superior computational efficiency, based on the mathematical foundations of economic theory.

I. Introduction

The Air Force is currently developing Space Radar capable of tracking resident space objects (RSOs) and searching space for unknown objects and activity. The main challenge there is to develop more effective tasking algorithms that can perform mission objectives in such a dynamic, complex domain with multiple constraints. The communications and resource constraints present in this domain will increase as space systems and missions evolve.

Two characteristics distinguish all of these systems from the ground- and air-based platforms they supplement: first, they contain far more components and subcomponents that must be coordinated in order to function properly; and second, this added complexity adds a great deal of new data processing requirements, just as network bandwidth and computational power is becoming relatively more scarce due to limited satellite payloads. These challenges will only become more difficult as large constellations of microsatellites are deployed as part of future sensor systems.

Many current approaches to dynamic sensor management simply repackage traditional optimization tools such as linear programming and apply them to the real-time domain. These approaches have two main problems. First, they perform poorly in dynamic environments, because they lack true adaptive capabilities. Extensions and modifications of these algorithms have attempted to deal with this, but such a patchwork approach is inferior to an algorithm designed specifically for adaptation. Second, current approaches are computationally inefficient, so even if they have the algorithmic capability to adapt to changing conditions, they are not fast enough to do so effectively.

Our approach, a market-based optimization protocol that we describe below, treats sensor systems as true *systems*, looking not just at individual sensor assignments but also at the underlying resources such as network bandwidth and signal processing power that are necessary to support the increased data processing loads of newly-developed space-based sensor systems. Ours is a holistic approach that goes beyond mere task assignment and takes account of all resources and assets in a sensor system. Only by simultaneously optimizing all parts of the sensor system can resources be used efficiently, particular with the growth of distributed sensor systems with many nodes. Our approach develops a *computationally adaptive* approach to both optimization and the sensor modeling that supports it, to ensure that optimization maximizes the use of available computational resources.

Our approach applies solutions from economic theory, particularly game theory, to the resource allocation problem by creating an artificial market for sensor information, computational resources, and communications bandwidth. Intelligent agents are the buyers and sellers in this market, and they represent all the elements of the sensor network, from sensors to sensor platforms to computational resources. They provide support for heterogeneous sensors, modes, and search patterns, and their goal is to distribute resources in a way that minimizes the sum of target objects' covariances, weighted by object priority. These market agents interact based on a negotiation mechanism that determines their bidding strategies. This negotiation mechanism and the agents' bidding strategies are based on game theory, and they are designed so that the aggregate result of the multi-agent negotiation process is a market in competitive equilibrium, which guarantees an optimal allocation of resources throughout the sensor network. Negotiation works continuously, providing dynamic adaptation to changes in the mission environment. Negotiation is designed to minimize communication resource requirements, ensuring that the system scales well to more complex sensor networks. Economic theory provides a mathematical infrastructure that can be used to prove the computational efficiency of our approach, and we assess this efficiency using both formal mathematical methods and computational testing.

II. Market Based Optimization

The application of economic theory, and game theory in particular, to computer science problems such as resource allocation has grown into a mature field of research over the past two decades.[1] The problem of allocating scarce resources among a set of distributed agents is the very problem faced by a market economy. A very large body of economic research exists on the functioning of markets, so they are well understood. A central result of economic theory is that, given proper conditions, a market will produce an optimal distribution of resources with a minimum of transaction costs, which are analogous to communication resources in the computational problem.[2]

In adapting this work to the problem of optimizing resources in a sensor network, we can exploit the results of economic theory in order to design multi-agent systems that produce optimal resource allocations. Markets have buyers and sellers of goods and services, so we must formulate the sensor resource optimization problem in these terms in order to take advantage of market-based solutions. This is easily done using the multi-agent framework described in the previous section. Agents represent both the buyers and the sellers in our artificial economy, and the goods and services for sale are the assets controlled by those agents, which include computational resources and information collected by sensors. Our multi-agent system simulates a marketplace where these agents exchange their services. By finding the competitive equilibrium of this artificial economy, we can solve the resource allocation problem and ensure optimal usage of our sensor resource system.

Market-based optimization, using a particular negotiation/bidding mechanism, allows the agents to reach this equilibrium. The negotiation mechanism, or protocol, defines the rules used by agents in conducting transactions. It determines how agents make bids for the services of other agents as well as how agents communicate with one another. In addition to following these rules for negotiation, each agent uses a negotiation strategy that determines how that agent bids. Negotiation strategies are based on the results of game theory. Game theory examines how individuals make decisions when they know that their actions affect other individuals and when they assume that other individuals also take this into account. For example, if two agents are bidding on the use of a shared antenna, they will formulate their bids not only based on how they value that antenna but also on how they think the other agent values that antenna. They do this because, in order to win the bidding war, they do not necessarily have to bid as high as they believe use of the antenna is worth; they must only bid higher than the other agent who is also bidding. The results of game theory allow bidders to maximize their own utility in a competitive marketplace; when everyone follows these strategies, the market as a whole is optimized.[2,3]

In our implementation, each agent has the ability to calculate the utility [a] of its possible actions. System agents can calculate the utility of buying information from sensors, sensor agents can calculate the utility of buying computational resources and of selling sensor information, and resource agents can calculate the utility of selling computational resources. Using these utility calculations, agents carry out strategies for

[a]"Utility" is the economic term for the value of an action or situation.

formulating and accepting bids. By using the results of game theory, these strategies can be optimized in order to produce the best possible aggregate outcome. Charles River's in-house GRADE tool for building intelligent, multi-agent systems provides every agent with capabilities for reasoning based on Bayesian belief networks and on rule-based expert systems. Both of these approaches are appropriate for encoding optimal negotiation strategies, so one task of future work will be to determine which of these options is better suited to reasoning in negotiation.

Market-based mechanisms using negotiation for resource allocation have been used to solve problems in a variety of domains. A number of efforts have used this approach to allocate computational resources for distributed computing.[4–7] Others have used the method for information retrieval from digital networks.[1,8,9] More recently, the technique has become widespread in solving just-in-time manufacturing control problems.[10] Finally, negotiation has been successfully applied to the military collection management domain for multi-sensor multi-target tracking.[11] The success of negotiation in these fields, all of which share significant similarities with the real-time sensor optimization problem under examination here, leads us to believe that we can achieve the same degree of success in the detection and tracking of RSOs.

As mentioned above, if the negotiation mechanism is designed properly, it will produce optimal resource allocations. One major assumption on which this rests is that agents can accurately calculate the utility of their actions. In the case of sensor network optimization, this means accurately calculating the value of the information that sensors can provide. In a way, this is a question of properly prioritizing sensor tasks, because the greater a tasks priority, the greater should be its utility. The promise of negotiation as a means of optimization is that, as long as this step is correct, it guarantees that the results will be optimal. Utility functions may be as simple or complex as is necessary in order to be accurate. Thus, they could range from simple mathematical functions to complex chains of reasoning. Again, GRADE agent technology is helpful here, because it provides both Bayesian belief networks and rule-based expert systems that can be used for more complex modeling of utility functions. Moreover, the communication interface available to each agent allows it to obtain feedback from signal processing algorithms to aid in calculating the value of various sensor tasks. Another important part of our future work will thus be to examine alternative methods of augmenting utility calculations and determining which provides the best way of calculating the value of the available sensor information. This includes exploring the use of libraries of utility functions that use situation assessment (guided by belief networks and/or expert systems) to dynamically select appropriate methods of utility evaluation, based on the current situation and particular information requirements.

The other major assumption of the negotiation mechanism is that, in order to generate an optimal allocation of resources, the mechanism itself must have sufficient computational resources with which to execute in order to maintain competitive equilibrium in the face of real-time changes in the mission environment. In order to accomplish this, our negotiation algorithm must be as efficient as possible. Game theory allows us to minimize the communication overhead needed for negotiation by designing bidding protocols that resolve the negotiation in as few steps as possible. A variety of such protocols already exist and have been tested in a number of application areas.[12] We have tried to design algorithms that maximize the efficiency with which they use available computational resources so that the system is fast enough to maintain optimal allocation in real-time.

There are a number of alternative methods of implementing this multi-agent negotiation system across the sensor network. Choosing among these options is important for realistically simulating the deployment of our optimization strategies. There are two obvious alternatives: One is to implement it as a truly distributed system, where the agents reside with and directly control the physical entities they represent. The other is to maintain the agents on a centralized system that sends tasking orders out to the sensor network itself. The first approach relies more heavily on on-board processing, while the second relies more heavily on communication, so there are certainly tradeoffs in these approaches. The best approach might be a hybrid combination of these two methods. However, regardless of what type of implementation is ultimately required for deployment, the flexible, modular nature of market based optimization and its ability to function over networks of sensors allow it to work without modification in any of these contexts. This is a major source of value in our distributed approach to optimization.

II.A. Agent Roles Within the Market

Charles River's market based solution constructs a set of agents that represent all the elements of a sensor network, using three different agent types:

- Sensor agents represent sensors themselves as well as the platforms that carry them. Examples include passive sensors such as IR and UV sensors, active sensors such as LADAR, and sensor platforms such as satellites. The main purpose of sensor agents is to collect information. In order to do this, they must obtain access to the computational resources needed to carry out their tasks and in some cases they must cooperate with the agents representing the platforms on which they reside. They respond to requests for information from engagement systems (e.g. command and control) and other external systems.
- Resource agents represent computational resources including processing nodes and communication resources such as network bandwidth. Resource agents provide the computational power that sensors and other components in the sensor network need to complete their tasks. They respond to requests from sensor and system agents and at times they must also coordinate among themselves in order to ensure optimal resource allocation.
- System agents represent engagement systems as well as other external systems that might require data from the sensor network. System agents work on behalf of these systems to obtain the requested information from sensor agents. They must also interact with resource agents when they need to carry out tasks such as signal processing.

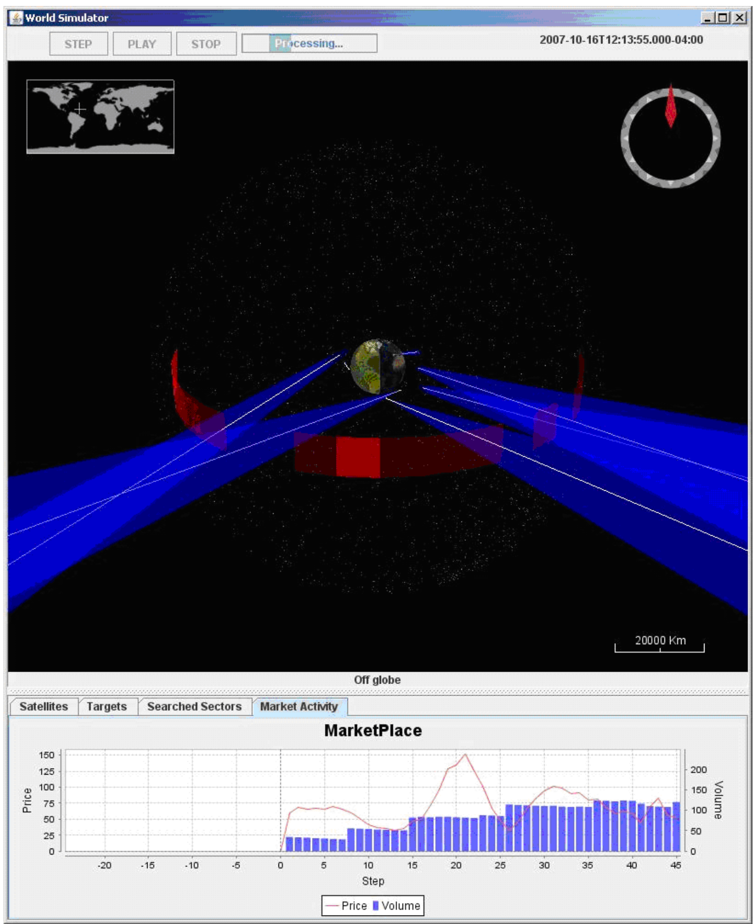

Figure 1: *Screenshot of our prototype executing an RSO tracking mission. The display provides a 3D view of the mission space, along with a variety of market diagnostics to monitor performance.*

As an example to illustrate our approach, take the situation where a resident space object (RSO) maneuver has been detected by space-based surveillance (see Figure 1). This RSO, which previously was a relatively low priority, is categorized by the 1st Space Control Squadron (1SPCS) as a category 3 RSO which means that it has recently maneuvered and can no longer be associated with its cataloged position. This update from 1SPCS is sent to ground-based operations in the form of tasking. This tasking is used by buyer agents to update their utility calculations which determine the price they will pay for satellite operations within the market. In this case, a notional agent representing the recategorized RSO will negotiate within the market for self-observations and pay a higher price than lower categorized RSOs or other buyer agents. In the context of our approach, these are called *system agents* and they represent the initiating agents which trigger top-level purchases in the market.

Sensors on the satellite platform are represented by *sensor agents*, which sell their product (observations) within the market. Satellites have limited communication capacity and opportunities so time and bandwidth must be managed. In some cases, the satellite capable of performing the final surveillance task may be unable to communicate directly with ground control. Agents representing computational resources such as processing nodes and network communication resources are represented by resource agents. Here, a *resource agent* might provide relay services between ground control and the ultimate observing agent. Computational resources such as processing nodes or relay operations are more resource intensive than direct ground control to satellite tasking but this may be desirable for emergent tactical situations. Indeed, the shared and cooperative behaviors provided by agent based negotiation provides multiple benefits. Satellite assets can share resources and distribute operational load as system resources (communications, sensors, satellite platforms) malfunction, become upgraded, or are simply added by operators.

The technology here is innovative for three reasons. First, it takes a holistic approach to sensor management, optimizing not just sensor tasking but also the resources (network communications and processing power) needed to support those tasks. Second, it relies on our past work that extended market-based optimization to work with heterogeneous assets, in a way uniquely suited to the dynamic environment found in the sensor management domain. Third, our approach is computationally adaptive, both in optimization and sensor modeling, meaning that it adapts its mechanism to the complexity of the given problem, to ensure maximum computational efficiency.

The scenario presented above is only one (simplistic) example of a chain of transactions within the multi-agent sensor network, but game theory guarantees that, with properly designed negotiation mechanisms, the result for the system as a whole will be an optimal allocation of resources. Moreover, the negotiation process happens continuously, even as conditions change, which makes the approach perfectly suited for solving the real-time allocation problem unique to sensor planning. New objects might be detected, new sensor information might be needed, or sensor resources and computational resources might fail. The sensor network using this scheme seamlessly adapts to all of these kinds of circumstances. Moreover, because the system takes a multi-agent approach, it is highly flexible and extensible, so it can maintain optimal resource allocation under any configuration of sensors and network interfaces, including the addition of new sensor types.

III. Mapping a Market to the Space Search Domain

Integrating Charles River's market framework with the space search simulation was a straightforward process. Search sectors and RSOs are represented by notional buyer agents submit self-search tasks to the market. Satellite sensors are represented by seller agents that maximize profit by competing for search tasks.

III.A. Search Sectors as Buyer Agents

A buyer agent is created for each search sector in the geo-synchronous belt. This agent calculates a reserve price based upon its last search time. A recently searched sector agent has a lower reserve price than a not-recently searched sector. Each search sector buyer creates a task within the market to compete for searches against other search sectors and possibly RSOs.

III.B. RSOs as Buyer Agents

A buyer agent is created for each RSO within the simulation. RSO buyer agents purchase observations of its constituent domain object. The reserved price is a function of its category (see Table 1), which in an operational setting would be established by the 1st Command and Control Squadron (1CACS) in Cheyenne Mountain Colorado. RSO observation tasks with a lower category have a higher reserve prices, thus 'Attention' categorized buyer agents will pay more for observations than 'Corrupted' ones.

Table 1: *Resident Space Objects are prioritized according to the following categories. A lower number indicates a higher priority.*

Category	Name	Definition
1	Lost	An RSO that has not been tracked by an SSN within the last thirty days.
2	Attention	An RSO that has not been tracked within at least five days, but is not officially a Lost object.
3	Maneuvered	An RSO that has recently maneuvered and can no longer be associated with its cataloged position.
4	New Launch	An RSO that was recently placed into orbit but for which no element set has been established
5	Corrupted	An element set in the catalog that is seemingly miss associated with another object.
6	Uncataloged	An RSO that has never been previously cataloged

III.C. Satellite Assets as Seller Agents

A seller agent is created for each satellite asset. This seller agent knows its constituent satellite's current state, capabilities, operating parameters and task queue. The satellite's capabilities for a given resource period are a function of:

- Location
- Attitude
- Slew Rate
- Field of View (FOV)
- Committed Tasks - tasks it has begun executing

Sector search and RSO observation tasks which can be accomplished are bid on by the satellite's seller agent. The Seller's reserve price is a function of any intersecting tasks or task bundles under contract, but not yet committed.

III.D. Description of Tracking and Detection Scenarios

Multiple scenarios were generated to validate our general approach of using the market algorithm to task space based sensors. The scenarios ranged from a single LEO satellite searching geo-synchronous space to multiple LEO satellites searching the geo-synchronous space and tracking multiple RSOs. On any given run of a scenario, users can select which algorithm to perform the tasking optimizations. This allowed for easy comparison between identical scenarios. During execution all data would be routed to a data collection point (in our case, a database) for later retrieval to perform comparison calculations.

For each scenario, satellites were positioned in LEO where they could search the geosynchronous space and track RSOs. The MSX[13] satellite, part of the SBV project, provided a model for our satellites and their operational characteristics. The MSX satellite is equipped with passive visible sensors with a field of view that is 6.6 by 1.4 degrees. It has attitude rates of up to 1.6 deg/sec with accelerations of 0.03 deg/sec. The scenarios were run with increasing numbers of satellite assets starting with one and ending at seven. The Global Star satellite ephemerids, the orbits of a constellation of actual LEO satellites, were used as the orbits for our simulated MSX-like satellites.

Our prototype implementation models real satellites using RSO data from NASA's Navigation and Ancillary Information Facility (NAIF), using their SPICE toolkit. We demonstrate the performance of our approach in a variety of RSO tracking and detection scenarios.

III.D.1. Geo-sync Search Only

The geo-sync only scenario tasked the satellite assets to search the geo-synchronous space. No RSOs were part of this scenario and the only measure was search coverage. The geosynchronous search space was arbitrarily divided into 1080 search sectors of 10 by 10 degrees each (longitude and latitude). Notional buyer agents were created for each search sector which competed against one another within the market for self-observations. The utility of self-searches increased as search sectors were unobserved. Satellite agents, who were sellers in the market, calculated their reserve price based on their capability constraints.

III.D.2. Geo-sync Search with Resident Space Objects (RSO)

The second scenario adds resident space object tracking. Notional buyer agents were created for 500 randomly placed RSOs which compete in the market for self-observations. RSO buyer utilities were based on randomly assigned priorities which match the categories established by 1CACS. See Table 1 for details.

IV. Results

An efficient optimization algorithm for satellites performing detection and tracking should be able to search more sectors and track more RSOs as more assets come online. Managing satellite assets inefficiently increases the likelyhood of overlapped observations or uncoordinated slews, i.e., two satellites leap-frogging to perform sector search tasks as satellite assets are added to the domain. Mapping space-search domain assets to buyer and seller agents as participants in Charles River's market based solution was relatively straight forward. Given that they are properly incentivized and that they correctly calculate their respective costs and utilities we should see near linear increases in observation and tracking times as we add assets to the system.

To test our approach, the geo-synch search scenario was simulated multiple times to record the average duration that each of the 1080 search sectors was observed. For a satellite to observe a sector of the geosynchronous space it could not be slewing. Overlapping observations would not double the observation time. Our market driven algorithm scales linearly within this basic search scenario as satellites are added. Figure 2 shows that satellites competing within the market are coordinated.

To vet our approach within a more dynamic scenario we added RSOs of various priorities at random spots within the geosynchronous search space. Observation durations were recorded as before, however, a satellite asset observing an RSO would not contribute observation time to the RSOs surrounding search sector. This allowed us to measure the tasking trade-offs made between RSO tracking tasks vs. routine search tasks. Again, running the scenario with one satellite asset establishes the near optimal performance. One satellite will never overlap another satellite's observations. Nor will one satellite be forced to slew excessively or leap-frog another satellite's observations to avoid overlap. The results in Figure 3 indicate that a single satellite observed RSOs for roughly three times the duration that it spent observing search sectors. Also, we can see that the total coverage for this more complex dynamic scenario was below that of the coverage from the simpler, search only scenario. This is due to increased slew activity between randomly placed RSOs. Search sector to search sector slews are never more than 10 degrees whereas RSOs may be further apart.

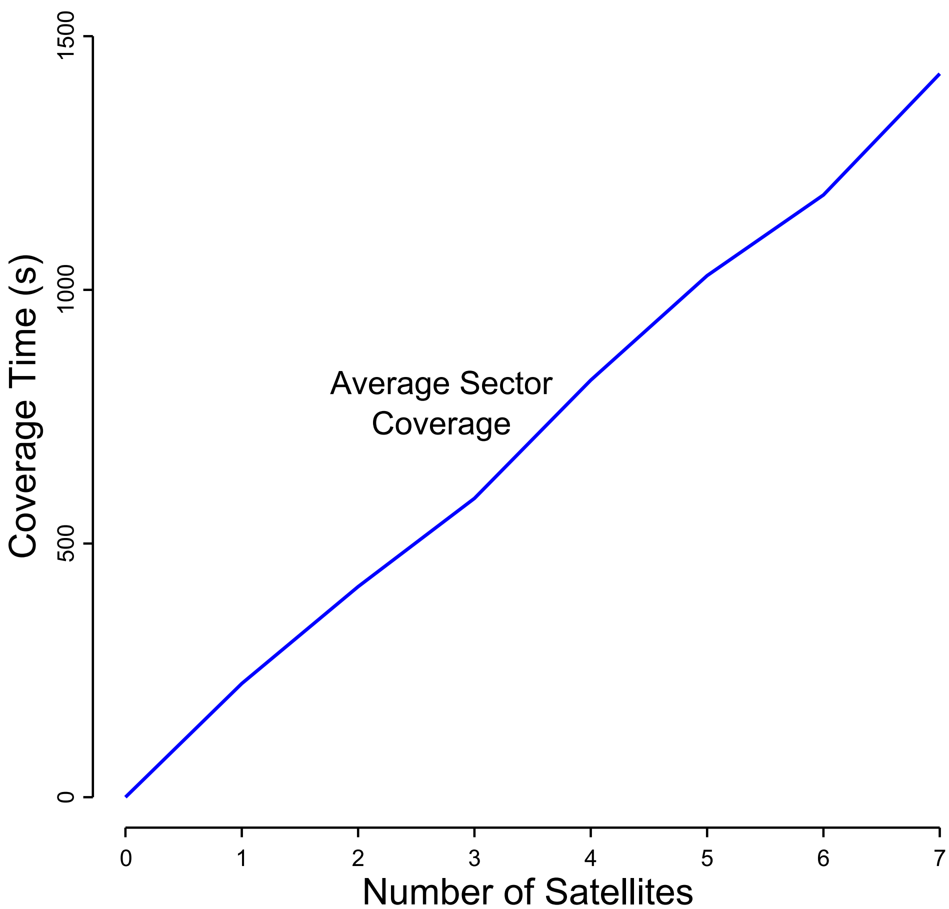

Figure 2: *Near-perfect scaling of searching coordination as more satellites are added. Perfect scaling here would show up as exact linear increases in coverage time, mirroring those that appear when the first satellite is added, suggesting that there is no duplication of effort across satellites. Here the results scale almost exactly linearly, suggesting our approach provides optimal coordination for detection with a number of satellites.*

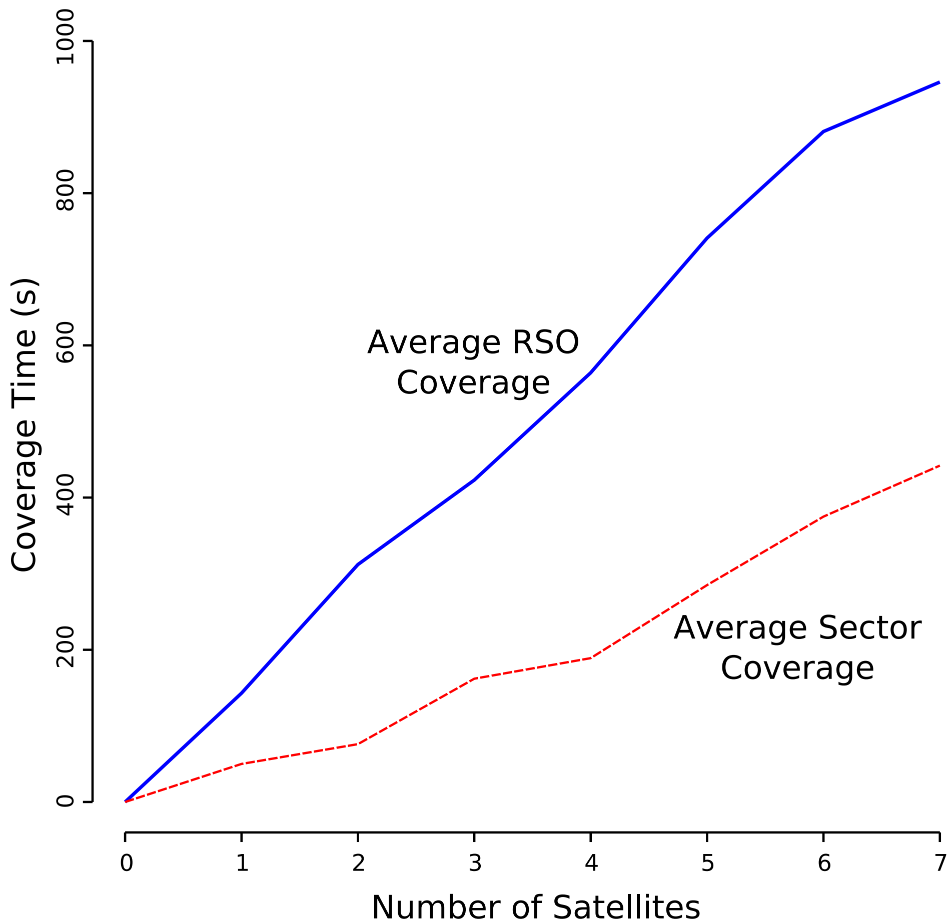

Figure 3: *Near-perfect scaling of tracking coordination as more satellites are added. Perfect scaling here would show up as exact linear increases in coverage time, mirroring those that appear when the first satellite is added, suggesting that there is no duplication of effort across satellites. Here the results scale almost exactly linearly, suggesting our approach provides optimal coordination for tracking with a number of satellites. Because RSO tracking has a higher priority than detection, sector search tasks were degraded in order to service RSO track tasks.*

V. Conclusion

In this paper we have applied Charles River's market based approach to detection and tracking of RSOs within a high-level simulation that assumes a future detection and tracking capability employing multiple LEO MSX-like satellites. We tested our assumption, that a market based approach provides efficient, robust, multi-objective search and track plans at both an individual satellite and global level and achieved near linear scaling in both simple and dynamic scenarios. Market based algorithms are robust and combine the best characteristics of both distributed and centralized solutions. These qualities suit future space-based space-search detection and tracking missions which, by their very nature, takes place in a distributed, constrained, and dynamic environment.

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