Agent Negotiation of Target Distribution Enhancing System Survivability

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This article proposes an agent negotiation model for target distribution across a set of geographically dispersed sensors. The key idea is to consider sensors as autonomous agents that negotiate over the division of tasks among them for obtaining better payoffs. The negotiation strategies for agents are established based upon the concept of subgame perfect equilibrium from game theory. Using such negotiation leads to not only superior measuring performance from a global perspective but also possibly balanced allocations of tasks to sensors, benefiting system robustness and survivability. A simulation test and results are given to demonstrate the ability of our approach in improving system security while keeping overall measuring performance near optimal. © 2007 Wiley Periodicals, Inc.

1. INTRODUCTION

Sensor management has great significance for modern tracking systems.[1,2] The sophistication of multisensor and multitarget scenarios entails controlling sensing resources against the entire target complex. Sensor management fits into this purpose in efficiently directing the usage of available sensors to increase the overall system performance.[3] Among typical factors of concern within a practical sensor management design for performance improvement are probability of target detection, track/identification accuracy, probability of loss-of-track, probability of survival, probability of target kill, and so forth.[4]

To date, a profusion of information theoretic methods has been proposed to deal with sensor management in multitarget environments; see Refs. 5–10 as examples. The main idea therein is to evaluate the potential contribution of a sensing plan in terms of uncertainty reduction using entropy-based information metrics.

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This is advantageous in shifting the emphasis of the problem from manipulating sensing devices to optimizing information gain. On the other side, these approaches are typically based on a global optimization method, which challenges the need for robustness and graceful degradation in the presence of communication noise and breakdown of individual sensors.

Indeed, optimization of immediate information achievement might not be the unique criterion in sensor management. As stated by Musick and Malhotra,[11] a sensor manager has to value long-term goals of survival and success rather than just accuracy and identity. This tenet merits particular attention in defense applications, where active sensors betray their existence by emitting signals. It is crucial in such cases to have a sensor utilized at a low frequency to reduce its exposure to adversaries as well as the risks of its being attacked. Unfortunately, the sensors' need to remain covert often conflicts with the need for optimal measuring effectiveness. Resolving conflicting demands on sensor suites presents a serious dilemma in sensor management.

This article investigates task distribution across geographically dispersed sensors (e.g., radars) in a network to track multiple targets at the same time. As the number of targets assigned to a sensor affects its exposure and the probability of being detected, excessive usage of certain competent sensors in tracking is undesirable because it makes them vulnerable to enemy threat. Biased distribution of tasks to particular sensors has thus to be curtailed whenever possible to benefit system survivability. However, this request should be considered as a soft goal with imprecise, variable valuations during situation development, making adaptive handling of it hardly possible within an optimization framework. We try to solve this problem by resorting to an agent-based negotiation paradigm. We consider sensors in this context as autonomous agents that negotiate with each other about task distribution. A negotiation model for target distribution is established based on the concept of subgame perfect equilibrium (SPE)[12] in game theory. A significant advantage of doing this is that every agent is competing for a portion of targets for its own measuring performance such that possibly balanced sensor–target assignments can be achieved for mission completion. On the other hand, because each local agent attempts to be better off in the negotiation, we can still ensure (at least) near optimal measuring performance from a global perspective.

The work presented herein describes part of our project to investigate the potential utility of game theory to overcome certain drawbacks of traditional sensor management methods (usually centralized upon global optimization) employed in multisensor and multitarget tracking. This article indicates how a distributed assignment strategy based on game theory helps to enhance the robustness of a sensor network. Another recently published paper[13] deals with target-specific requests for reactive resource allocation using game theoretic negotiation.

This article is organized as follows. Section 2 gives a general description of the underlying problem. Section 3 constructs sensor performance against assigned targets as a basis for (sensor) agent negotiation. The detailed negotiation model on target division is presented in Section 4, followed by simulation results and analysis in Section 5. Finally, we conclude the article and suggest further investigation issues in Section 6.

2. THE UNDERLYING PROBLEM

We consider a sensor network consisting of remotely located sensing resources that are expected to work together to monitor an underlying territory, that is, to keep track of all targets within that region. Measurements have to be made on all these targets in every time step to update their state estimates. We require coordinated sensing actions among sensors to cover the whole target complex without any redundant observation. Solving this problem implies dividing the whole set of targets into disjoint subsets to be assigned to different sensors, as exemplified in Figure 1 in which the numerous targets, indicated as solid squares, need to be covered by the three available sensors. The whole target complex is thus divided into nonoverlapping groups D_1, D_2, and D_3, as allocated tasks for sensors 1, 2, and 3, respectively.

At a first glance, one would intuitively propose a solution commanding sensors to take charge of targets in their local areas, and then target handing off could be arranged when a target is moving from the area of one sensor's jurisdiction to that of another. However, serious questions will arise in doing this as to where the switching boundaries should be and how such boundaries vary with environment changes when, say, new targets are entering into the area. This problem is further complicated by many other practical factors, such as limited sensor capability, sensor accuracy in measurement, terrain conditions, effects of sensor–target relative positions, sensor emission and security, and so forth. Perplexing diversity in multitarget scenarios makes empirical ad hoc procedures[14] for sensor cueing unrealistic or hardly feasible. We desire dynamic target distribution schemes amenable to a sound, theoretically well-founded framework.

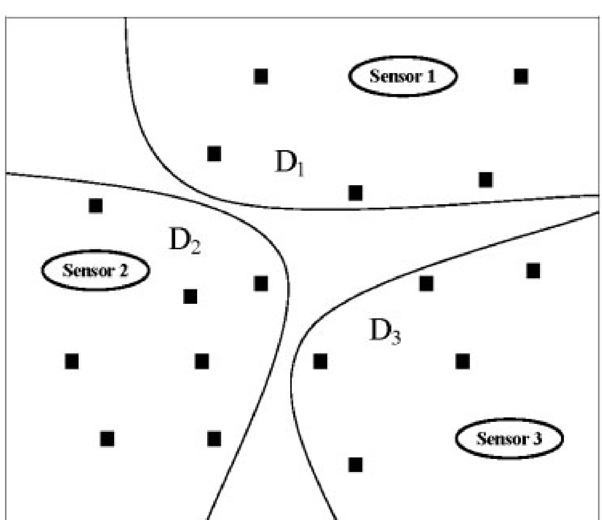

Figure 1. Distribution of targets among three sensors.

From the viewpoint of global measuring effectiveness, target distribution can be formulated as a constrained optimization problem. Let the sensors be indexed from 1 to n and the targets from 1 to m. By c_{ij} we denote the value or effectiveness of applying sensor i to measure target j. Target division among sensors would be to choose decision variables $x_{ij} \in \{0,1\}$ for a sampling period to maximize the objective function

$$G = \sum_{i=1}^{n} \sum_{j=1}^{m} c_{ij} x_{ij} \tag{1}$$

subject to a maximum track capacity constraint (a_i representing the maximum number of targets that can be sensed by sensor i in a sampling period)

$$\sum_{j=1}^{m} x_{ij} \leq a_i \quad i = 1 \ldots n \tag{2}$$

and a minimum target coverage requirement

$$\sum_{i=1}^{n} x_{ij} = 1 \quad j = 1 \ldots m \tag{3}$$

Obviously, we have a lot of optimization tools like linear programming and its variations at hand to find such a constrained solution achieving the maximum of (1).

However, an optimal solution to the above problem is not always what we desire. In some cases, we may prefer a target division that is not strictly optimal in the sense of global estimation effectiveness but is superior in terms of meeting the robustness requirement in target monitoring. Unduly stressing the role of optimization may occasionally cause overloading of a small portion of sensors in the network with merely trivial benefit but imposing higher risks on them in face of opponent countermeasures (i.e., detection and attacks) and resulting in greater loss of tracks if failure really happens to these sensors. We believe that a possibly balanced distribution of targets among sensors is valuable for yielding robust performance of the network, as is explained in the Appendix according to the overall probability of being detected and the expected number of losses of tracks. A comprehensive sensor manager has to consider long-term interest and contrive to find a good balance between measuring performance and system survivability. This is the point of departure of this article.

3. SENSOR PERFORMANCE AGAINST ASSIGNED TARGETS

Given a target distribution profile, an invoked sensor is requested to perform measurements on all targets assigned to it within a sampling period. The contribution of this sensor to information gathering is determined by its associated subset of targets. As a preparation for the following discussion of sensor negotiation, this section is dedicated to establishing an assessment of performance of sensors in accomplishing their appointed tasks. We elicit the so-called *sensor performance* index based upon the assumption of utilizing the Kalman filter as the principal tracking algorithm.

We start from considering state estimation of one target, say target j, which has the following system equation:

$$x_j(k) = F_j x_j(k-1) + w_j(k-1) \tag{4}$$

This target is supposed to be tracked by sensor i, with the corresponding measurement equation being written as

$$y_{ij}(k) = H_{ij} x_j(k) + v_{ij}(k) \tag{5}$$

Notice that y_{ij} refers to the measurement variables of the target by sensor i. As applying different sensors to the same target might produce different properties of observation models, it is beneficial here to emphasize the sensor–target pair in the subscripts of some variables like y, H, and v in Equation (5).

The tracking algorithm is composed of two stages: prediction and update. The prediction stage uses the system model to forecast target states at the next time step, and later the predicted state estimates are modified in the update stage in light of new measurements. We will not reiterate here the details of how such estimates evolve but focus on the error covariance of the target to examine the role of the sensor applied in uncertainty reduction.

The prediction alone enlarges the uncertainty of the state estimate due to system noise. The a priori error covariance for target j is given by

$$P_{ij}(k|k-1) = F_j P_{ij}(k-1|k-1) F_j^T + Q_j(k-1) \tag{6}$$

with Q_j denoting the system noise covariance of the underlying target. Sensor i is then activated to make measurement on target j to provide new evidence for belief revision. We get the updated error covariance after the measurement by

$$P_{ij}(k|k) = P_{ij}(k|k-1) - K_{ij}(k) H_{ij} P_{ij}(k|k-1) \tag{7}$$

where

$$K_{ij}(k) = P_{ij}(k|k-1) H_{ij}^{\mathrm{T}} [H_{ij} P_{ij}(k|k-1) H_{ij}^{\mathrm{T}} + R_{ij}]^{-1} \tag{8}$$

It is apparent that the a posteriori error covariance $P_{ij}(k|k)$ is largely affected by the measurement noise covariance R_{ij}. Larger measurement noise leads to bigger updated covariance of state estimate and vice versa. An extreme case is the one without measurement or, equivalently, with infinite measurement noise covariance, then we get to $P_{ij}(k|k) = P_{ij}(k|k-1)$ from the above two equations.

The role of the applied sensor in reducing target uncertainty can be seen more clearly from an alternative formulation[15] for updating covariance of states. According to this alternative method, we have

$$P_{ij}(k|k)^{-1} = P_{ij}(k|k-1)^{-1} + H_{ij}^{\mathrm{T}} R_{ij}^{-1} H_{ij} \tag{9}$$

We see here $H_{ij}^{\mathrm{T}} R_{ij}^{-1} H_{ij}$ as an important matrix for discerning the difference of covariances of state estimates before and after the measurement. The achieved reduction of uncertainty is enabled by sensor i through its measurement. In view of this, we define the norm of this matrix as *sensor information gain*, $g(i, j)$, contributed by sensor i on target j. So we write

$$g(i, j) = \|H_{ij}^{\mathrm{T}} R_{ij}^{-1} H_{ij}\| \tag{10}$$

In reality, the measurement noise of sensor i on target j is not a simple entity but reflects a composite effect of the sensor's inherent property, sensor–target relative position, terrain conditions, enemy countermeasures, and so forth. The covariance of such noise varies with time and is dependent on factors like

- sensor quality (accuracy and reliability)
- distance from sensor to target (accuracy declines with increase in distance)
- viewing angle from sensor to target (sometimes better with larger angle)
- transparency along the path between sensor and target
- opponent interference on sensor signals.

A competent sensor with respect to a target is the one that exhibits a small noise covariance R_{ij} when measuring that target. Competent sensors are more valuable to target uncertainty reduction as expressed by their *sensor information gains* defined in (10).

Finally, we establish the measure of performance of a sensor in accomplishing all tasks appointed to it. Suppose sensor i is in charge of target group D_i; its contribution to the global picture is accrued by measuring all assigned targets within a sampling period. As information gains are elicited by the sensor for uncertainty reduction on respective targets assigned, the performance of sensor i is defined to be the sum of these information gains effective for state estimates of the targets in D_i. Thus, we express *sensor performance* in face of assigned targets as

$$P_i(D_i) = \sum_{j \in D_i} g(i, j) \tag{11}$$

In the following, *sensor performance* will be used as a basic quantity for (sensor) agent negotiation on target distribution. The assumption made is that every sensor hopes to be "excellent" in its own performance by taking over more jobs. Such demands and emerging conflicts are resolved through game theoretic negotiation, resulting in a possibly balanced distribution of tasks.

4. AGENT NEGOTIATION ON TARGET DISTRIBUTION

In this section we study the negotiation issue for target distribution on the basis of game theory. Our motivation is to enable interactions among agents in decision making and to achieve a final outcome that is dependent on everyone's choice and acceptable for all parties. Considering interplay of agents is useful to distribute tasks to possibly more sensors, enhancing measurement robustness and system survivability. In addition, we want to achieve task allocation in a distributed fashion, that is, without a centralized supervisor. Each agent makes a selection considering the characteristics of its opponents apart from its own preference.

4.1. Agents and Their Utility Functions

We consider sensors as autonomous agents that bargain over redistribution of targets for every fixed time interval. Such a time interval usually consists of a given number of sampling periods and is termed an *R-interval* in this article. The involved agents are assumed to exhibit the following behaviors in the whole tracking process:

- Rationality. Agents are self-interested and rational; they try to maximize their own sensor performance and payoffs in negotiations.
- Cyclicity. Negotiation is launched among agents at the beginning of an R-interval but cannot continue beyond the end of it. In the next R-interval, another round of negotiation is needed to update decisions in the possibly new situation. Such processes are repeated for the whole interesting time span.
- Initial quiescence. After negotiation begins, agents will not make any measurements until an agreement is reached. Certainly this is not a desideratum from an operational point of view. Here we postulate it just to create a setting of the game under which agents can interact productively and fairly. Such an introduced rule (of the game) fosters the same attitude toward time by all agents and motivates them to become more cooperative in accepting offers. Later we will show that, under our negotiation strategy, agreement will be reached in the first time step, thus making quiescence in sensing never really happen.
- Temporary commitment. Once an agreement is reached, all parties will follow it until the end of the underlying R-interval. Subsequently, the agents will start another round of negotiation.

There are two kinds of consequences if a negotiation is performed: either disagreement or agreement. Disagreement means that no solution acceptable for all parties can be reached in a limited duration for negotiation, that is, R-interval. The other case is arrival at an agreement within the underlying R-interval. Every agent has its own preference about whether and when an agreement is reached and what portion it obtains from the agreement. We assume that agent $i \in$ **Agents** has a utility function, U_i, over all possible outcomes: $\{A \times \{0, 1, \ldots, K\}\} \cup \{Disagreement\}$, where A is the set of possible offers and K refers to the last period of the R-interval in which the negotiation is conducted. Specification of utility functions for all agents is a prerequisite for developing efficient negotiation strategies.

As agents negotiate in order to realize cooperative behaviors among them in multitarget tracking, finding agreement is in line with the interests of everybody, and no one can benefit from bargaining without fruit. This leads to the preference of agreement over disagreement by any agent and in any circumstance, as stated in C1 (the first characteristic of agent preferences).

C1. Disagreement is the worst outcome. For any agent $i \in$ **Agents** and any outcome $x \in \{A \times \{0, 1, \ldots, K\}\} \cup \{Disagreement\}$, $U_i(Disagreement) < U_i(x)$.

Now we turn to discussing the utility of reaching agreement D, as a target division profile, at time $t \in \{0, 1, \ldots, K\}$. By D_i we denote the allocation to sensor i in the agreement that causes the performance of sensor i to be

$$P_i(D_i) = \sum_{j \in D_i} \| H_{ij}^{\mathrm{T}} R_{ij}^{-1} H_{ij} \| \tag{12}$$

Moreover, the agent is assumed to receive a reward not more than unity in terms of its performance contributed. The purpose of doing so is to normalize the sensor performance index for easy handling and to allow for nonzero assessment for a sensor's quiescence in complying with the agreement. The reward to sensor i, under appointed target group D_i, is given by

$$r_i(D_i) = \alpha + (1 - \alpha)(1 - e^{-\beta \cdot P_i(D_i)}), \quad 0 \leq \alpha < 1 \text{ and } \beta > 0 \tag{13}$$

such that $P_i \in R^+$ is converted into a regular interval $[\alpha, 1)$. Here α is a user-defined coefficient representing the agent's attitude toward measurements versus quiescence. It can also reflect the emotion of an agent to get a nonempty portion of targets in the negotiation. A typical dependence between sensor performance and sensor reward is depicted in Figure 2.

Further, because the sensors keep commitments once a treaty is reached until the end of the R-interval, rewards are received in the duration from period t to period K, and they have to be accumulated to indicate the overall payoff engendered. Herein we also take for granted that the R-interval is properly specified as short enough to assure approximately constant covariance of measurement noises within it. This suggests and justifies the calculation of the utility of sensor i, from outcome (D, t), by

$$U_i(D, t) = (K - t + 1) r_i(D_i) \tag{14}$$

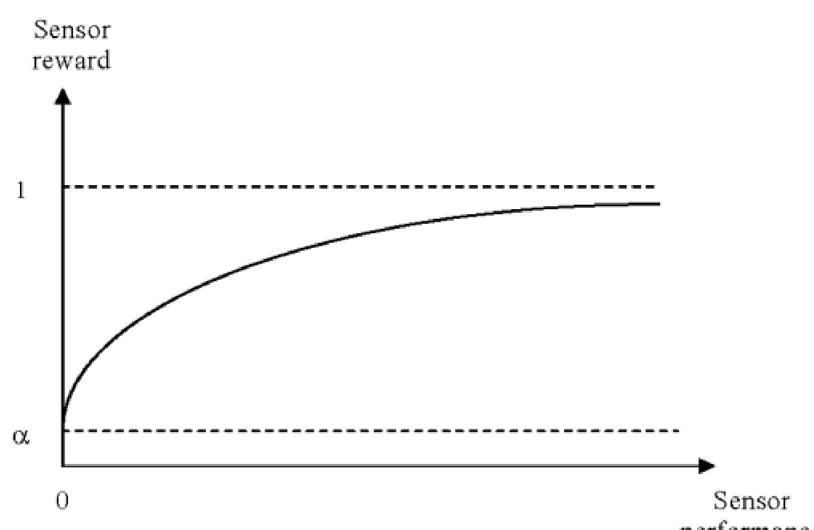

Figure 2. Sensor reward derived from sensor performance.

The above defined (sensor) reward and utility function manifest the other two characteristics of agent preferences in the negotiation.

C2. Sensor performance is valuable. For any $t \in \{0, 1, \ldots, K\}$, $D, Q \in A$, and $i \in$ **Agents**: $U_i(D, t) < U_i(Q, t) \Leftrightarrow P_i(D) < P_i(Q)$. For agreements that are reached at the same time, each agent prefers an allocation leading to greater sensor performance.

C3. Benefit is lost with time. For any $t_1, t_2 \in \{0, 1, \ldots, K\}$, $D \in A$, and $i \in$ **Agents:** $U_i(D, t_1) > U_i(D, t_2) \Leftrightarrow t_1 < t_2$. For the same agreement that is reached at different times, each agent desires the earlier rather than the later.

4.2. Negotiation Game

We model the negotiation for target division among sensors as an extensive game characterized by a 5-tuple $\langle Agents, A, H, P(H), U_i \rangle$, where

- Agents = {Sensor 1, Sensor 2, Sensor 3, ..., Sensor n}
- A is the set of possible divisions of targets among sensors
- H is the set of sequences of offers and responses
- $P(h)$ determines which agent has the turn to make an offer after a nonterminal history h
- U_i is the utility functions of agents on $x \in \{A \times \{0, 1, \ldots, K\}\} \cup \{Disagreement\}$.

It is assumed that at a particular time period one of the agents makes an offer and the other agents respond to it by acceptance or rejection. The order in which the agents make their proposals is specified before the negotiation begins. The first action in the game occurs in period 0 when one agent makes the first offer and the other agents accept or reject it. Acceptance by all other agents ends the game with agreement whereas rejection by one other participant pushes the game into period 1. Subsequently, another agent proposes something in period 1 that is then accepted or rejected by its opponents. The game continues in this manner as long as no agreement has been reached until the last period K of the R-interval. If still no agreement is achieved at time K, we say that the game ends with disagreement.

4.3. Negotiation Strategies

Negotiation strategies, as a key element in our bargaining game, are utilized by participants to maximize the expected values of their respective payoffs. A strategy for an agent is essentially a function that specifies what the agent has to do after every possible history. Concretely speaking, the strategy prescribes what to offer when it is the turn of the agent to make an offer, and whether to accept or reject an offer in periods when the agent's turn is to respond to a proposal made by an opponent. A strategy profile is a collection of strategies for all involved agents. We would like to find strategies leading to an outcome that is profitable for all participants and nobody can benefit from using another strategy.

A fundamental concept for analyzing behaviors of rational agents is the Nash equilibrium.[16] A strategy profile of a game of alternating offers is a Nash equilibrium if no agent can profit by deviation given that all other agents use the strategies specified for them in the profile. Unfortunately, a simple Nash equilibrium does not seem sufficient in extensive games in the sense that it ensures the equilibrium of its strategies only from the beginning of the negotiation, but it may be unstable if starting from certain intermediate stages.

A stronger notion for extensive games is that of subgame perfect equilibrium (SPE),[12] which requires that the strategy profile included in every subgame is a Nash equilibrium of that subgame. This is a comprehensive concept implying that agents are rational at any stage of the negotiation process: no one can be better off by using another strategy regardless of what happened in the history. This article adopts the notion of SPE to develop negotiation strategies for target division among sensors. Later we will show that if all agents honor SPE strategies, there is an offer made in the first period that is preferred by all parties over all possible future outcomes.

We begin from strategies at step K, the last period in the R-interval for negotiation. Our point is that an agreement will be reached at the last period because disagreement is the worst case for anyone and agents will do their best to prevent this from happening. It is formally stated in the following.

LEMMA 1. *If it is agent i's turn to make an offer in period K, then following the SPE strategy agent i will propose the offer $D \in A$ that maximizes $U_i(D, K)$, and all other agents will accept this offer.*

Here we can see rational behaviors from all participants. Agent i chooses the offer that is best for its own payoff, and the other agents accept this offer because it is better than disagreement for them.

Then we discuss strategies at periods before K. The intention is that the agent whose turn it is to make an offer considers the agreement that will be reached at the next stage and proposes something that is better for all parties than what they will attain in the future. Suppose $a(t+1)$ represents the agreement that will be reached at stage $t+1$; we claim the set of offers acceptable for all parties at stage t is

$$Super(t) = \{D \in A | \forall i \; U_i(D, t) \geq U_i(a(t+1), t+1)\} \tag{15}$$

The above definition is obvious, for a rational agent will accept any offer that gives it a better payoff than what it will gain in the upcoming stage.

Further, it is important to note that the set $Super(t)$ is nonempty for any period before K. This is induced from the characteristic that all agents lose over time as indicated in C3. Particularly, the agreement $a(t+1)$ is included in $Super(t)$ because we have $U_i(a(t+1), t) > U_i(a(t+1), t+1)$ for any agent i.

The set, $Super(t)$, of acceptable offers is very useful to establish SPE strategies at periods before K. The nonemptiness of this set ensures that the agent whose turn it is to make an offer has enough choices to make its proposal acceptable to opponents. In other words, agreement can be achieved at any stage of the negotiation process. The formal SPE strategy for period t ($t < K$) is given in Lemma 2.

LEMMA 2. *If it is agent i's turn to make an offer in period $t < K$, then, following the SPE strategy, agent i will propose the offer $D \in Super(t)$ that maximizes $U_i(D, t)$, and all other agents will accept this offer.*

Apart from rationality according to the SPE strategies (stated in Lemmas 1 and 2), agents are also expected to possess some awareness of social welfare.[17] This is concerned with selecting the best offer when multiple optimums exist according to the utility of the agent having the turn to make an offer. A supplementary rule is thus required to guide the proposing agent to the right choice in light of social responsibility. We prescribe herein that if an agent encounters multiple maximums when making a proposal, it chooses the one of them which maximizes the sum of utilities of other agents. The interpretation is that an agent, though self-interested, will give the best opportunity for the social welfare provided that its own profit is not sacrificed.

Now we formulate agreement $a(t)$ according to the SPE strategies in combination with the supplementary rule. By $Compet(i, t)$ we denote the set of best offers for agent i, which has the turn to make an offer at period t; so we have

$$Compet(i, K) = \left\{ D \in A \,|\, U_i(D, K) = \max_{D \in A} U_i(D, K) \right\} \tag{16}$$

$$Compet(i, t) = \left\{ D \in Super(t) \,|\, U_i(D, t) = \max_{D \in Super(t)} U_i(D, t) \right\}, \quad t < K \tag{17}$$

Formulas (16) and (17) define the set of agreements that comply with the SPE strategies. Then the supplementary rule is employed to select a solution desirable for other agents as a whole. This is given by

$$a(t) = \arg \max_{D \in Compet(i, t)} [U_1(D, t) + \cdots + U_{i-1}(D, T) + U_{i+1}(D, t) + \cdots + U_n(D, t)] \tag{18}$$

The derivation of $a(t)$ in terms of (18) brings about a useful thread for the backward analysis of the SPE strategy profile. First, we calculate the offer $a(K)$ for the agent that has the turn to make an offer at time K. This offer is then used as the basis for computing the set of acceptable offers in the proceeding period, from which a new offer $a(K - 1)$ is figured out for another agent having the turn (to make a proposal) at $K - 1$ and similarly for other previous periods.

Apparently all agents prefer $a(t)$ in period t to $a(t + 1)$ in period $(t + 1)$. In other words, $a(t)$ is better for all parties than what can be achieved in the future. The fact of $U_i(a(t), t) > U_i(a(t + 1), t + 1)$ for any agent causes the game to be ended in the first period with agreement $a(0)$. This is stated in the following lemma.

LEMMA 3. *If all the agents use the SPE strategies for negotiation and the supplementary rule for accounting for social welfare, then in the first period the agent who has the turn to make an offer will propose $a(0)$, and all other agents will accept this offer.*

Additionally it is worth noting that the final outcome of our negotiation game is Pareto efficient, and so is any other offer emerging in the backward analysis. This is obviously warranted by the nature of formula (18). The connotation is that our bargaining process is actually performed upon Pareto (optimal) solutions for multiple agents. This means that negotiation space can be restricted to a degraded subset using the concept of Pareto efficiency, although for a generic game formulation we have in Section 4.2 referred to the set of offers, A, as containing all possible divisions of targets. An algorithm to construct a set of Pareto nondominated solutions in multiobjective environments can be found in Ref. 18.

5. SIMULATION TESTS AND RESULTS

To examine the effectiveness of our negotiation model in target distribution, simulation tests were made for scenarios in which the sensor network consisted of sensors 1, 2, and 3. We assume, for simplicity, that the covariance of measurement noises only depends on the distance between sensor and target. All sensors exhibit the same quality in accuracy and their measurement covariance is given by

$$Cov(dist) = \begin{bmatrix} 0.8 & 0 \\ 0 & 0.8 \end{bmatrix} + dist \cdot \begin{bmatrix} 0.00005 & 0 \\ 0 & 0.00005 \end{bmatrix} \tag{19}$$

where *dist* denotes the corresponding distance. Further we supposed that four targets were present in the area and were collectively monitored by the three sensors stated above. The sensors had to divide the targets among themselves to decide which sensors should track which targets. Next we present the results of simulations in two scenarios. In the first case all four targets moved along certain trajectories, and in the second setting the locations of targets were stochastically generated in order to obtain a wide coverage of geographical distributions of targets.

5.1. Test with Targets Moving on Trajectories

In this test we assumed that the sensors were located at (−100 km, 0), (0, 0), and (100 km, 0), respectively, and targets made their movements as depicted in Table I. The sampling period for tracking was fixed to be 0.1 s for every target. As the targets were moving in the environment, decisions on target division among sensors had to be made frequently to adapt to recent status of sensor–target relative positions for improving system performance. Here we specified the length of

Table I. Descriptions of movements of targets.

	Initial position	Velocity in x direction	Velocity in y direction
Target 1	(−110 km, 10 km)	50 m/s	0
Target 2	(−120 km, 5 km)	50 m/s	0
Target 3	(120 km, −5 km)	−60 m/s	0
Target 4	(110 km, −10 km)	−60 m/s	0

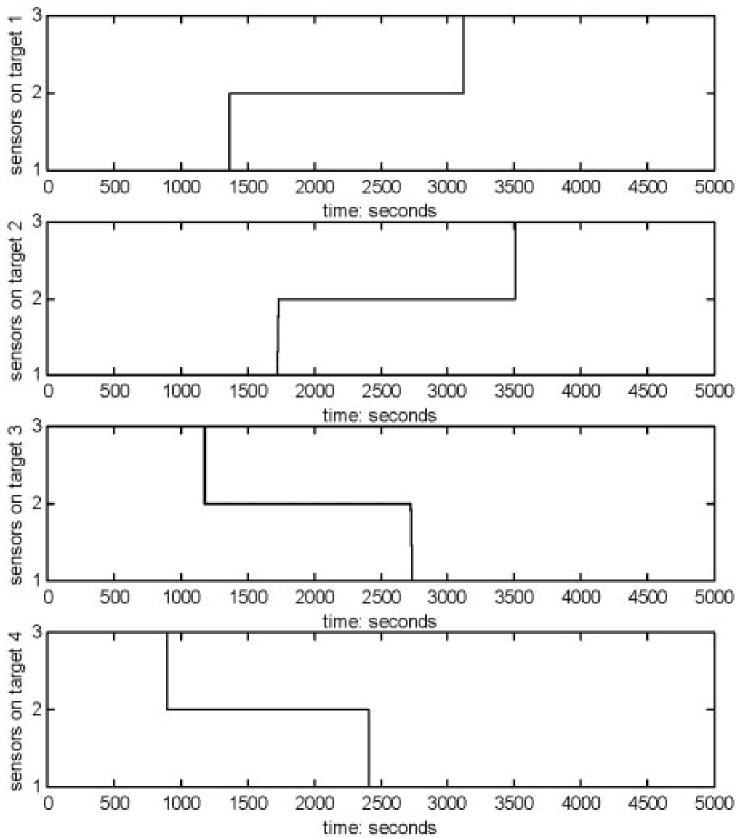

Figure 3. Targets handing off from one sensor to another.

the R-interval to be 6 s, meaning that the negotiations happened every 60 sampling periods for target distribution across sensors. All three sensors were involved in the negotiations, which caused the targets to occasionally be handed off from one sensor to another as shown in Figure 3, where targets 1 and 2 were initially tracked by sensor 1, intermediately by sensor 2 and finally by sensor 3, and the opposite sequence occurred to targets 3 and 4. These switches among sensors and targets were smooth and reasonable, according to our intuition, at least.

For an in-depth analysis of the results presented above, we intend to make an assessment in terms of two criteria: the sum of sensor information gains in the global picture and the degree of targets concentrated to particular sensors. The concentration degree for a distribution profile D is defined as

$$cd(D) = \frac{\sum_{i \neq j} |num(D_i) - num(D_j)|}{(n-1)m} \tag{20}$$

where $num(D_i)$ denotes the number of targets in the allocation D_i to sensor i. Additionally, dynamic target distribution was also realized by maximizing the global sensor information gains for every second. The performance of both negotiation and optimization is depicted in Figure 4 in terms of the criteria of the sum of sensor information gains and the concentration degree. The solid lines in the figure correspond to the performance of negotiation and the dashed lines correspond to that of optimization. We see clearly here that, by negotiation, the degree of concentration is reduced significantly at the cost of a slight loss in the sum of information gains.

The average values of performance over 4800 s are illustrated in Table II for both negotiation and optimization. This table convincingly indicates that it is worthwhile to accept a trivially reduced tracking accuracy in return for a more robust task division to enhance system survivability.

Undoubtedly what we see now is a very simplified example assuming sensors aligned in line and targets moving in parallel to that line. Our purpose for doing so is only to create an illustrative scenario from which readers can see some easily understandable results without detailed calculation. Indeed the proposed negotiation model is unaffected by where sensors are arranged and how targets are moving because merely instantaneous positions of sensors and targets are needed for negotiation.

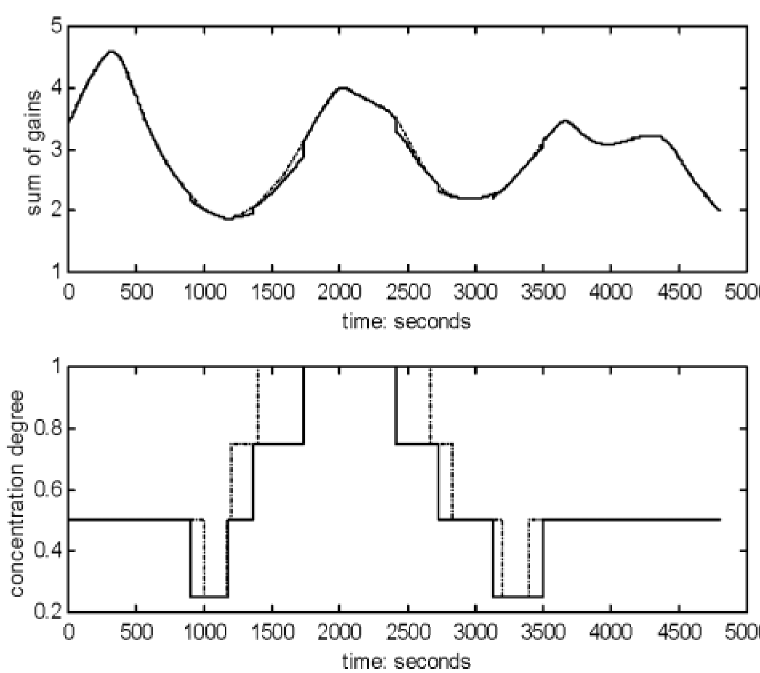

Figure 4. Comparison of results by negotiation and optimization.

Table II. Comparison of average performance along trajectories.

	Sum of sensor information gains	Concentration degree
Negotiation	2.9710	0.5722
Optimization	2.9873	0.6319

5.2. Tests with Randomly Located Targets

To investigate the performance of the proposed negotiation model in a wide spectrum of various target locations, further experiments were made by just "dropping" four targets randomly within the range of (-100 km, 100 km) in both x and y coordinates. Sensors were positioned at ($-50\sqrt{3}$ km, -50 km), (0, 100 km), and ($50\sqrt{3}$ km, -50 km), respectively. A total of 16 experiments were made, with each experiment consisting of 200 randomly generated combinations of target positions. For each generated combination of targets, we divided them among sensors using the mechanisms of negotiation and global optimization, respectively. Table III gives a comparison of the average performance in these tests in terms of the sum of sensor (information) gains and the concentration degree. Again we see from this table that in all the tests, negotiation produced obviously superior performance in concentration degrees and very similar results in sensor (information) gains in comparison to the outcomes from global optimization.

Table III. Comparison of average performance with randomly generated targets.

Number of tests	Optimization: Sum of sensor gains	Optimization: Concentration degree	Negotiation: Sum of sensor gains	Negotiation: Concentration degree
1	1.7129	0.4838	1.6976	0.3762
2	1.7229	0.4575	1.7079	0.3650
3	1.7338	0.4875	1.7125	0.3675
4	1.7740	0.4750	1.7608	0.3713
5	1.7132	0.4688	1.6950	0.3675
6	1.7279	0.4700	1.7134	0.3825
7	1.7304	0.4950	1.7129	0.3875
8	1.7804	0.4950	1.7683	0.3912
9	1.7502	0.4850	1.7367	0.3937
10	1.7168	0.4750	1.7007	0.3625
11	1.7359	0.4850	1.7203	0.3812
12	1.7647	0.5100	1.7471	0.3950
13	1.8047	0.4763	1.7884	0.3738
14	1.7155	0.4838	1.7042	0.4013
15	1.7938	0.4938	1.7745	0.3750
16	1.7944	0.4800	1.7795	0.3800

6. CONCLUSION AND DISCUSSION

This article proposes a negotiation model to deal with target distribution among geographically dispersed sensors in multitarget tracking. Every sensor is assumed to be an autonomous agent that interacts with its opponents to receive more jobs and to get better payoffs. A SPE strategy profile is established for agents to bargain over the division of targets and to find agreement without delay. Such immediate arrival at consensus maintains required communications at a minimal amount.

A significant advantage of using negotiation in task distribution is that a solution taking into account interests of all parties can be expected. This can lead to, on one side, distribution of targets to possibly more sensors to enhance system survivability under potential threat of adversaries and, on the other side, still near-optimal measuring performance in the global picture.

Another nice merit of our work is its adaptation to various scenarios, that is, with varied sensor and target numbers. We do not have to reconfigure the protocol of the game nor change the structure of sensor utility functions in face of a new scenario. All decisions are made through negotiations of sensors in terms of situations, leading to adaptive and cooperative behavior of the whole sensor network without the requirement of defining an overall goal function in advance. In fact, designing a comprehensive, explicit objective for sensor management is often difficult in complex and perplexing scenarios. Under other circumstances, a goal function devised beforehand might become inappropriate during an unfolding situation. Negotiation is valuable in relieving us from such difficulties.

The method proposed in this article is applicable to both decentralized and centralized data fusion systems. It fits directly into a decentralized sensor network where sensor stations need to bargain over what to observe in order to achieve coordinated sensing behaviors. Moreover, the negotiation model is also useful in a centralized fusion system in the sense that the central node wants to work out a robust sensing plan across sensors.

Further investigations can be conducted to study the negotiation model in more complicated scenarios and under many practical constraints. Among suggested points for future studies are the following:

- experiments under variable terrain conditions
- adaptive organization of simultaneous local negotiations (in case of a large number of sensors in the network)
- negotiation with limited computation
- negotiation under uncertain and approximate information.

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APPENDIX: WHY IS BALANCED TARGET DISTRIBUTION BENEFICIAL?

Here we provides useful supplementary material by analyzing why a balanced distribution (of targets across sensors) can enhance the robustness in target monitoring. We intend to explain this in terms of the probability of the sensor network being detected and the expected number of losses of tracks under threats of enemy attacks.

We are in the position that a sensor is subject to some risk of betraying its location as long as it sends signals for measurements, and the sensor's probability of being detected is proportional to the number of targets it measures in a sampling period. By p we denote here the value of the detection probability when a sensor is allocated to only one target; then the probability of the sensor being discovered turns to $k \cdot p$ when it is associated with k targets. We discuss in the following the properties of the network using detection probabilities of individual sensors.

We begin from the simplest case of two-sensor and two-target tracking where one can either make an equal distribution by allocating every sensor to a respective target or assign both targets to a single sensor. It is obvious that an equal distribution will yield a smaller overall detection probability $P(1,1)$ of the network than the probability $P(2,0)$ when one sensor measures two targets and the other remains quiescent, due to the fact $P(1,1) = p + p - p^2$ whereas $P(2,0) = 2p$. Further we assume that enemy attack will occur to a sensor if it has been detected. The expected number of losses of tracks when assigning two targets to a single sensor is double of that with an equal distribution, because $EN(2,0) = 2 \cdot 2p = 4p$ whereas $EN(1,1) = p + p = 2p$.

Next we move to a general case with n sensors, with m_i standing for the number of targets assigned to sensor i. The analysis is performed, without loss of generality, upon the change of assignments to a pair of sensors, say sensor 1 and sensor 2. Suppose sensor 1 is allocated to more sensors than sensor 2, that is, $m_1 > m_2$; we now make a redistribution by assigning $m_1 - \delta$ targets to sensor 1 and $m_2 + \delta$ targets to sensor 2 with $\delta < m_1 - m_2$. The conclusion that is shown in the following is that this reduction of the difference of the numbers of targets between both sensors will lead to improvement of the robustness for the whole sensor network.

From the initial distribution we have the overall probability of being detected for the whole network as

$$P(m_1, m_2, \ldots, m_n) = P(m_1, m_2) + P(m_3, \ldots, m_n) - P(m_1, m_2)P(m_3, \ldots, m_n)$$

where

$$P(m_1, m_2) = m_1 p + m_2 p - m_1 m_2 p^2$$

After the redistribution toward balance, the overall detection probability of the network becomes

$$\begin{aligned} &P(m_1 - \delta, m_2 + \delta, \ldots, m_n) \\ &\quad = P(m_1 - \delta, m_2 + \delta) + P(m_3, \ldots, m_n) - P(m_1 - \delta, m_2 + \delta)P(m_3, \ldots, m_n) \end{aligned}$$

where

$$P(m_1 - \delta, m_2 + \delta) = (m_1 + m_2)p - (m_1 - \delta)(m_2 + \delta)p^2$$

By subtraction of the overall detection probabilities before and after redistribution, we obtain

$$\begin{aligned} &P(m_1, m_2, \ldots, m_n) - P(m_1 - \delta, m_2 + \delta, \ldots, m_n) \\ &\quad = \delta(m_1 - m_2 - \delta)p^2[1 - P(m_3, \ldots, m_n)] > 0 \end{aligned}$$

This clearly demonstrates the decrement of the overall detection probability by a more balanced distribution of targets.

Likewise we examine the change in the expected number of losses of tracks caused by the redistribution. Previously we have the expected number of losses of tracks as

$$EN(m_1, m_2, \ldots, m_n) = m_1^2 p + m_2^2 p + \sum_{i=3}^{n} m_i^2 p$$

Reducing the difference of workloads between two sensors pushes this measure to a new value given by

$$EN(m_1 - \delta, m_2 + \delta, \ldots, m_n) = (m_1 - \delta)^2 p + (m_2 + \delta)^2 p + \sum_{i=3}^{n} m_i^2 p$$

Clearly the expected number of losses of tracks decreases owing to this redistribution, as is seen from

$$EN(m_1, m_2, \ldots, m_n) - EN(m_1 - \delta, m_2 + \delta, \ldots, m_n) = 2\delta(m_1 - m_2 - \delta)p > 0$$