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REACTIVE TUNING OF TARGET ESTIMATE ACCURACY IN MULTISENSOR DATA FUSION

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Dealing with conflicting and target-specific requirements is an important issue in multisensor and multitarget tracking. This paper aims to allocate sensing resources among various targets in reaction to individual information requests. The proposed approach is to introduce agents for every relevant target responsible for its tracking. Such agents are expected to bargain with each other for a division of resources. A bilateral negotiation model is established for resource allocation in two-target tracking. The applications of agent negotiation to target covariance tuning are illustrated together with simulation results presented. Moreover, we suggest a way of organizing simultaneous one-to-one negotiations, making our negotiation model still applicable in scenarios of tracking more than two targets.

INTRODUCTION

Sensor management aims to control the data acquisition process in a multisensor system to enhance the performance of data fusion. It plays the role of process refinement in the JDL data fusion model with the goal of best

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utilizing available sensing resources in reaction to identified intelligence requirements. In sophisticated data fusion applications, the sensor manager has to cope with a disparate set of information requests and conflicts in order to engender directed sensing events (Denton et al. 1994).

Modern tracking systems present an active practical field motivating sensor management and demonstrating its significance (Blackman and Popoli 1999). Simultaneous tracking of multiple targets entails decisions about what sensors to assign to which objects at every instant for achieving the best possible accurate state estimates of the environment. So far, allocating sensors across targets has been mainly treated as an optimization problem in choosing sensor-to-target associations based on an objective function constructed beforehand in terms of entropy-based information metrics (Schmaedeke 1993; Schmaedeke and Kastella 1998; Dodin et al. 2000) or the expected overall utility (Greenway and Deaves 1994; Dodin and Nimier 2001) of a sensing plan. The sensor manager, driven by one such objective function, would proceed to maximize the overall information gain acquired on all targets in the global picture. However, it is difficult to deal with target-specific requirements, like maintaining the specified covariance of state estimates on particular targets, given an optimization framework.

It is important here to stress that the ultimate goal of sensor management is to guide sensors to satisfy information requests which can be situation- and target-dependent. Dynamic response to information requests is crucial for adaptive allocation of resources in accordance with demands imposed during mission completion. The scheme of covariance control was developed (Kalandros and Pao 1998; Kalandros et al. 1999) to assign sensor combinations to each target for meeting a desired covariance level. By doing this, the sensor allocation problem is decomposed into independent sub-problems for individual targets, each dealing with a target-specific covariance goal. Nevertheless, separate covariance controllers on individual targets can occasionally induce conflicting commands on sensors and thereby result in delay or even loss of certain planned measurements.

This paper proposes an agent negotiation model for allocation of sensing resources in reaction to identified information requests. We associate an agent with every relevant target responsible for its tracking. All such agents are supposed to be rational and self-interested; they want access to as many sensor resources as possible for optimizing their own performance. However, as available resources are constrained, agents have to bargain over the division of resources in order to reach a solution that cares for everybody's interest and is commonly acceptable. The use of a negotiation mechanism is motivated by the recognition that the task of multitarget tracking elicits inherently conflicting goals for data fusion, i.e., the improvement of tracking accuracy on one target implies degradation of performance on another. We believe that the proposed negotiation model can help to determine a good trade-off of tracking performance among various targets.

For a different approach to managing a distributed data fusion network, see Nicholson and Leung (2004). A recent survey of negotiation-based approaches to multisensor management is given in Johansson (2006).

The paper is organized as follows. The following section presents a general perspective of our approach, outlining the basic concepts and framework. A bilateral negotiation model for resource distribution in two-target tracking is proposed in Section 3 and its applications to target covariance tuning are illustrated. Then, in Section 4, we discuss a way of employing the proposed negotiation model for tracking scenarios with more than two targets. Finally, the paper is concluded in Section 5.

RESOURCE ALLOCATION IN REACTION TO REQUESTS: A NEW PERSPECTIVE

Our paper aims to update sensor-to-targets assignments to comply with the demands on local tracking performance, i.e., reducing estimate covariance on particular targets. In this section, we will first introduce an objective function to be manipulated when attempting to tune the estimate accuracy on a target and then highlight a negotiation-based framework to redistribute resources across targets in reaction to imposed information requests.

A Key to Target Estimate Accuracy

We consider a target observed by a set of sensors and study the role of the sensors in reducing the uncertainty of its estimate. The target and sensor observations are modeled by the standard state based equations:

$$x(k) = Fx(k-1) + w(k-1) \tag{1}$$

$$y_i(k) = H_i x(k) + v_i(k) \tag{2}$$

In the above, $x(k)$ is the current state of the target and $y_i(k)$ denotes the measurements of the target from sensor i in the sensor combination. The elements $w(k)$ and $v_i(k)$ represent the system noise and measurement noise, respectively, both of which are assumed to have zero-mean, white, Gaussian probability distributions. Such assumptions justify the usage of the sequential Kalman filter to fuse data from multiple sensors in the update stage. This can be a sequential procedure performing a separate filtering for each sensor in the combination and then propagating its estimate to the next filter.

A mathematically identical alternative to the conventional Kalman filter was introduced in (Durrant-Whyte and Stevens 2001) and termed therein as the information filter. It offers a simpler but equivalent form for estimation updating in multisensor situations by

$$P^{-1}(k|k)\hat{x}(k|k) = P^{-1}(k|k-1)\hat{x}(k|k-1) + \sum_{i\in S} H_i^T R_i^{-1} y_i(k) \tag{3}$$

$$P(k|k)^{-1} = P(k|k-1)^{-1} + \sum_{i\in S} H_i^T R_i^{-1} H_i \tag{4}$$

where S denotes the sensor combination applied to the target at time k; P is the covariance of state estimate, and R_i stands for the noise covariance of sensor i.

From Eq. (4), we see that $\sum_{i\in S} H_i^{\mathrm{T}} R_i^{-1} H_i$ is an important matrix for discerning the difference of covariance of state estimates before and after measurements. The bigger this matrix, the smaller the updated covariance will be. In view of this, we define *sensor information gain*, $g(k)$, for the target at time k as

$$g(k) = \left\| \sum_{i\in S} H_i^{\mathrm{T}} R_i^{-1} H_i \right\| \tag{5}$$

which can be considered as a total contribution of the applied sensors to information attainment or uncertainty reduction. Clearly, $g(k)$ is increased by including more and/or better sensors in the combination S.

Sensor information gain provides a convenient objective function that can be utilized as a basis for control of the sensor allocation strategy and as such it can be used as the basis for negotiation.

Request-Triggered Negotiation

As was stated previously, sensor information gain is a key factor affecting the covariance of state estimates. A higher tracking accuracy can be achieved by applying more and/or better sensors to the target. However, the total resources are limited and there are interactions between the performance on different targets. The sensor manager has to, on the one hand, update sensor assignments to tune the state covariance of certain targets in the requested direction, and on the other hand, care for the effect of such events on other targets and try to engender a graceful degradation of performance on them. Obviously, there may be a lot of alternatives when making such a decision. Here we intend to use the mechanism of negotiation for finding a good trade-off between conflicting benefits with respect to tracking of various targets.

The framework to redistribute resources in reaction to information requests is depicted in Figure 1, where new sensor-to-target assignments are generated through bargaining of agents responsible for tracking of respective targets. Negotiations are trigged by information requests produced by the block *mission planning*. This block is outside the scope of the paper but located at level four of the top-down procedure for sensor management (Xiong and Svensson 2002). It concerns meta-reasoning about system-level tasks and requests for tracking different targets. Our work is contingent upon the availability of relevant guidelines from mission planning and hereby efforts are dedicated to agent negotiations to comply with requests of accuracy on individual targets.

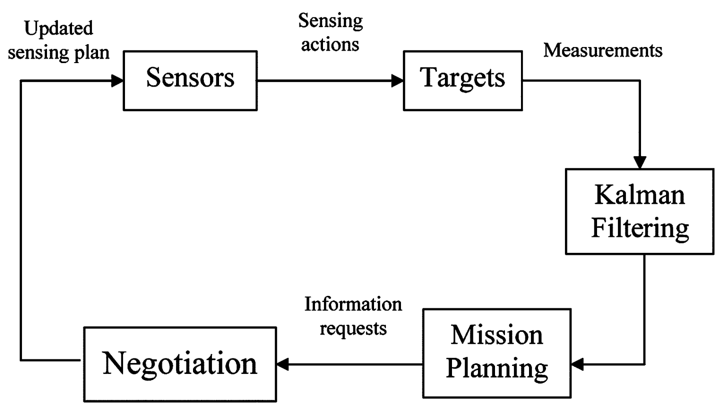

Figure 1. Redistributing resources in terms of information requests.

A distinguishing merit of agent negotiation is that it can scale well to goal uncertainty (lack of a clear general goal) prevalent in real applications. Sometimes the mission planning might merely give a simple guideline of possibly reducing the covariance of a certain target, but it is vague in the sense of how far or to which degree this should be achieved. Another important aspect is the one in which we have exact desired covariance levels for each target but the lack of sufficient sensors makes it impossible to meet all these desired standards. Consequently, ambiguity arises about how to treat those target-specific requirements in constructing a global allocation decision. Negotiation provides a powerful means to deal with interactions between local interests and facilitate a mechanism to arrive at a good balance between them.

Another important attribute of our work is that it is requirement-oriented to improve local tracking performance rather than a global figure. This does make sense in complex tracking scenarios where the diversity of targets and situations leads to distinct and time-varying demands (of tracking performance) across various targets. Request-triggered negotiation offers a flexible way of updating sensor assignments to tune local performance wherever necessary.

BILATERAL NEGOTIATION IN TWO-TARGET TRACKING

Here we consider a scenario with two targets originally measured with sensor subsets O_1 and O_2, respectively. Now with the unfolding situation, there is a need to increase the tracking accuracy on one of the targets, say target 2. However, owing to the limitation of resources, the improvement of performance on one target leads to the loss of precision on another. This section proposes a game-theoretic negotiation model to cope with such interactions and reach a rational trade-off between conflicting interests.

Agents and Their Preferences

We arrange for an agent for every target responsible for its tracking. Both agents need to use sensors for tracking their respective targets, they bargain over the division of resources in reaction to information requests. The following behaviors are supposed of such agent(s) in the tracking process:

- Rationality. Both agents are self-interested and rational; they try to maximize their own benefits in negotiations.
- Requisition versus reaction. Since the accuracy of target 2 is to be increased, it is agent 2 that wants to achieve a higher sensor

information gain and hence launches the negotiation. Contrarily, agent 1 is passively involved in the negotiation and has to react to the requisition of the opponent by giving up some benefits.

- Unilateral existing. Agent 2, anxious to be better off, would like an agreement as soon as possible. It may choose to opt out as a threat to enforce the other agent to be a bit generous. In case of opting out, agent 2 will interrupt the usage of sensors by its opponent for several time steps and agent 1 would have to start another negotiation to re-attain resources. Therefore, for its own interest, agent 1 will try to prevent agent 2 from opting out by giving offers beneficial to the opponent.
- Initial conservation. After negotiation begins, the old division profile is retained until an agreement is reached or agent 2 opts out, i.e., both agents keep available resources in tracking their respective targets during the negotiation.

There are three kinds of outcomes as long as a negotiation is initiated. One case is disagreement, i.e., the negotiation continues forever without any agreement and without opting out of any agents. Otherwise, the negotiation will end with an agreement reached at some time $t \in T$ or opting out by agent 2. Every agent is assumed to have its own preference over all possible outcomes: $\{(A \cup opt) \times T\} \cup \{Disagreement\}$, where A is the set of agreements (divisions) and T refers to the time interval within which the negotiation is finished. Establishment of utility functions for all agents is a prerequisite for developing efficient negotiation strategies.

As agent 1 loses benefit once the negotiation is finished while agent 2 gets better off from the consequence, they have opposite attitudes toward disagreement, as stated in C1 (the first characteristic of agent preferences).

C1: Best/worst case with disagreement. Disagreement is the best case for agent 1 whereas the worst outcome for agent 2. For any outcome $x \in \{(A \cup opt) \times T\}$, we have utilities as $U_1(Disagreement) > U_1(x)$ and $U_2(Disagreement) < U_2(x)$.

For outcomes in $\{A \times T\}$, we consider sensor information gains during the negotiation as an important basis to yield their utility values. We denote by (S_1, S_2) the agreement which assigns sensor subsets S_1, and S_2 to agents 1 and 2, respectively, with the properties as

$$S_1 \cup S_2 = O_1 \cup O_2 \tag{6}$$

$$\left\| \sum_{i \in S_1} H_i^{\mathrm{T}} R_i^{-1} H_i \right\| < \left\| \sum_{i \in O_1} H_i^{\mathrm{T}} R_i^{-1} H_i \right\| \tag{7}$$

$$\left\| \sum_{i \in S_2} H_i^{\mathrm{T}} R_i^{-1} H_i \right\| > \left\| \sum_{i \in O_2} H_i^{\mathrm{T}} R_i^{-1} H_i \right\| \tag{8}$$

The utilities of reaching such an agreement at time t is defined as the average of sensor information gains in the period from the beginning of the negotiation until its completion. So we write:

$$U_1(S_1, t) = \frac{t \cdot \left\| \sum_{i \in O_1} H_i^{\mathrm{T}} R_i^{-1} H_i \right\| + \left\| \sum\limits_{i \in S_1} H_i^{\mathrm{T}} R_i^{-1} H_i \right\|}{t + 1} \tag{9}$$

$$U_2(S_2, t) = \frac{t \cdot \left\| \sum_{i \in O_2} H_i^{\mathrm{T}} R_i^{-1} H_i \right\| + \left\| \sum\limits_{i \in S_2} H_i^{\mathrm{T}} R_i^{-1} H_i \right\|}{t + 1} \tag{10}$$

The above defined utilities of outcomes with agreements manifest the other two important characteristics of agent preferences in the negotiation:

C2: Sensor information gain valuable. For all $t \in T, j \in$ Agents and sensor combinations P_j and S_j allocated to agent j:

$$U_j(S_j, t) < U_j(P_j, t) \Leftrightarrow \left\| \sum_{i \in S_j} H_i^{\mathrm{T}} R_i^{-1} H_i \right\| < \left\| \sum_{i \in P_j} H_i^{\mathrm{T}} R_i^{-1} H_i \right\|$$

For agreements reached at the same time step, each agent prefers to get a larger sensor information gain.

C3: Gain/Losses over time. For any $t_1, t_2 \in T$ and agreement $S = (S_1, S_2)$, if $t_1 < t_2$ then we have $U_1(S_1, t_1) < U_1(S_1, t_2)$ and $U_2(S_2, t_1) > U_2(S_2, t_2)$.

Opting out is artificially incorporated into the process to provide driving a force toward quick agreements. Our presumption is that if agent 2 opts out of the negotiation, it will prevent the opponent from using resources from time t to $t + k - 1$, and then at time $t + k$ all sensors turn to be occupied by agent 2. The utilities from opting out for both agents are hence expressed as:

$$U_1(opt, t) = \frac{t \cdot \left\| \sum_{i \in O_1} H_i^{\mathrm{T}} R_i^{-1} H_i \right\|}{t + k + 1} \tag{11}$$

$$U_2(opt, t) = \frac{(t + k) \cdot \left\| \sum_{i \in O_2} H_i^{\mathrm{T}} R_i^{-1} H_i \right\| + \left\| \sum_{I \in O_1 \cup O_2} H_i^{\mathrm{T}} R_i^{-1} H_i \right\|}{t + k + 1} \tag{12}$$

Evident from the above formulae is the fourth characteristic of preferences of agents:

C4: Cost/benefit of opting out over time. For any $t \in T$, $U_1(opt, t) < U_1(opt, t + 1)$ and $U_2(opt, t) > U_2(opt, t + 1)$. Agent 2 prefers opting out early while later opting out is more beneficial for agent 1.

Extensive Game of Alternating Offers

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

- Agents = {Agent 1 for tracking target 1, Agent 2 for tracking target 2};
- A is the set of possible divisions of sensors upon $O_1 \cup O_2$;
- H is the set of sequences of offers and responses by agents;
- $P(h)$ determines which agent has the turn to make an offer after a non-terminal history h;
- U_i: utility functions of agents on the set of outcomes $\{(A \cup opt) \times T\} \cup \{Disagreement\}$.

In this game the agents alternate offers. In case an offer is rejected, the negotiation moves to the next round where the agent rejecting in the preceding period has to make a proposal. The first action in the game occurs in period 0 when agent 2 makes the first offer and agent 1 must accept or reject it. Acceptance by agent 1 ends the game with agreement while rejection causes the game to continue into period 1, in which it is the turn of agent 1 to propose something and agent 2 decides whether to accept or reject it or to opt out. Acceptance or opting out by agent 2 in period 1 stops the game, otherwise the game proceeds to period 2 in which agent 2 will make an offer again. The game continues in this manner as long as no agreement is reached and no agent chooses to opt out. If the negotiation continues forever without agreements and without opting out by an agent, then disagreement is the outcome of this bargaining game.

Rational Negotiation Strategies

Negotiation strategies, as a key element in our negotiation game, are utilized by both agents to maximize the expected values of their respective utilities. A strategy for an agent is essentially a function that specifies what the agent has to do after every possible history, i.e., what to propose in the turn to make an offer as well as how to respond facing a proposal from the other agent. A strategy profile is a collection of strategies for both agents. We aim to develop rational bargaining strategies leading to an outcome that is profitable for both parties and where nobody can get better off by using another strategy.

A fundamental concept in game theory is the Nash Equilibrium (Nash 1953) referring to a steady state in which every player holds a correct expectation of the opponent's behavior/strategies and acts rationally. A stronger requirement for bargaining games is that agents are rational at any stage of the process, not only from the beginning of the negotiation. This leads to the concept of subgame perfect equilibrium (SPE) (Osborne and Rubinstein 1994) meaning that the strategy profile included in every subgame is a Nash equilibrium of that subgame. Our paper follows the notion of SPE to develop negotiation strategies for resource allocation in two-target tracking. Later, we will show that if both agents honor SPE strategies, negotiation will be finished with agreement within two time steps.

Before discussing the negotiation strategies, the following three notions are introduced to help making later formulations easy and concise.

1. $Poss(t)$: the set of offers better than opting out for agent 2 at time t

$$Poss(t) = \{S = (S_1, S_2) | U_2(S_2, t) > U_2(opt, t)\} \tag{13}$$

2. $S_b(t)$: the best offer for agent 1 in $Poss(t)$ at time t

$$U_1(S_b(t), t) = \max_{S \in Poss(t)} U_1(S, t) \text{ and } S_b(t) \in Poss(t) \tag{14}$$

3. *Compet*(t): the set of offers in *Poss*(t) which yield better utilities for agent 1 at time t than what it can achieve in the next time step

$$Compet(t) = \{S \in Poss(t) | U_1(S, t) \geq U_1(S_b(t+1), t+1)\} \tag{15}$$

In the following we consider a subgame starting from stage t in which agent 2 has the turn to make an offer. Owing to the generality of this subgame, its Nash equilibrium offers the SPE strategies for the whole bargaining game. We begin from SPE strategies at time $t+1$ then move backwards to time t.

At time $t+1$, agent 1 has to propose something that maximizes its own utility but prevents agent 2 from opting out. Hence, agent 1 will propose $S_b(t+1)$ which is its best offer from $Poss(t+1)$. Further, since maximizing the utility of agent 1 equals minimizing that of agent 2, the utility $U_2(S_b(t+1), t+1)$ of agent 2 will be very similar to its utility from opting out $U_2(opt, t+1)$. If agent 2 rejected $S_b(t+1)$, it would follow that agent 2 will do the same later in responding to proposals by agent 1 due to $U_2(S_b(t+1), t+1) \geq U_2(S_b(t+3), t+3)$. As countermeasures, agent 1 will also reject offers by agent 2 afterwards to push the game into the outcome of disagreement, which is best for agent 1 but worst for agent 2. In view of this, agent 2 has the only option to accept the offer $S_b(t+1)$ at $t+1$. The above statements are summarized in Lemma 1.

Lemma 1. For the subgame starting from stage t, then following the SPE strategies agent 1 will propose the offer $S_b(t+1)$ at $t+1$ and agent 2 will accept it.

Now we move to the proceeding stage t when agent 2 makes an offer and agent 1 responds to it. As agent 1 is rational, it cares whether a proposal received at time t gives it a higher payoff than what it can obtain in the next period such that only offers from the set *Compet*(t) will be accepted. On the other side, reaching agreement at time t is in line with the interest of agent 2, as it can not benefit from moving to the next stage and getting a utility very similar to $U_2(opt, t+1)$. For the sake of agreement, agent 2 will choose an offer best for it from the set *Compet*(t) if this set is nonempty, otherwise any proposals by agent 2 at time t will be rejected. These points are briefed in Lemma 2 as the SPE strategies at stage t.

Lemma 2. For the subgame starting from stage t, then following the SPE strategies agent 2 will propose the offer $S^* \in Compet(t)$ such that

$$U_2(S^*, t) = \max_{S \in Compet(t)} U_2(S, t) \tag{16}$$

and agent 1 will accept it, provided that *Compet*(t) is nonempty. Otherwise, if there is no offer in the set *Compet*(t), agent 1 will choose rejection as the response.

Finally, by applying the developed SPE strategies from the beginning of the negotiation game, we get to the following theorem.

Theorem. If both agents honor SPE strategies for negotiation of resources in two-target tracking, then an agreement will be found within one or two time steps depending on the set *Compet*(0):

- If *Compet*(0) is empty, any offer of agent 2 at time 0 will be rejected. At time 1, agent 1 proposes a counteroffer $S_b(1)$ which will be accepted by agent 2.
- If *Compet*(0) is nonempty, agent 2 will give an offer $S' \in Compet(0)$ such that $U_2(S', 0) = \max_{S \in Compet(0)} U_2(S, 0)$ and agent 1 will accept this offer immediately.

Applications of Bilateral Negotiations for Target Covariance Tuning

This part is dedicated to demonstrate the usage of our negotiation model to tune target covariance in terms of information requests. Here we will not dwell on how such requests are generated but assume that they are available from the *mission planning* block in Figure 1. The applications of the negotiation model for meeting two common requirements in target tracking are illustrated in Subsections 3.4.1 and 3.4.2, respectively.

Improving the Worst Accuracy. One common requirement in target covariance control is to improve the worst accuracy. In this case, the agent with the lowest tracking accuracy launches the negotiation to receive higher sensor information gain, and the other agent is passively involved in the game and has to accept a reduced performance. We performed simulation tests to study this process with the initial condition of target 1 being tracked by all the resources while target 2 tracked by none of the resources. Figure 2 shows the simulation results when the k parameter in (11) and (12) was set to 5. We can see in the figure that at first the covariance on target 2 was always bigger than that on target 1, therefore it was agent 2 that launched negotiations in early stages. But

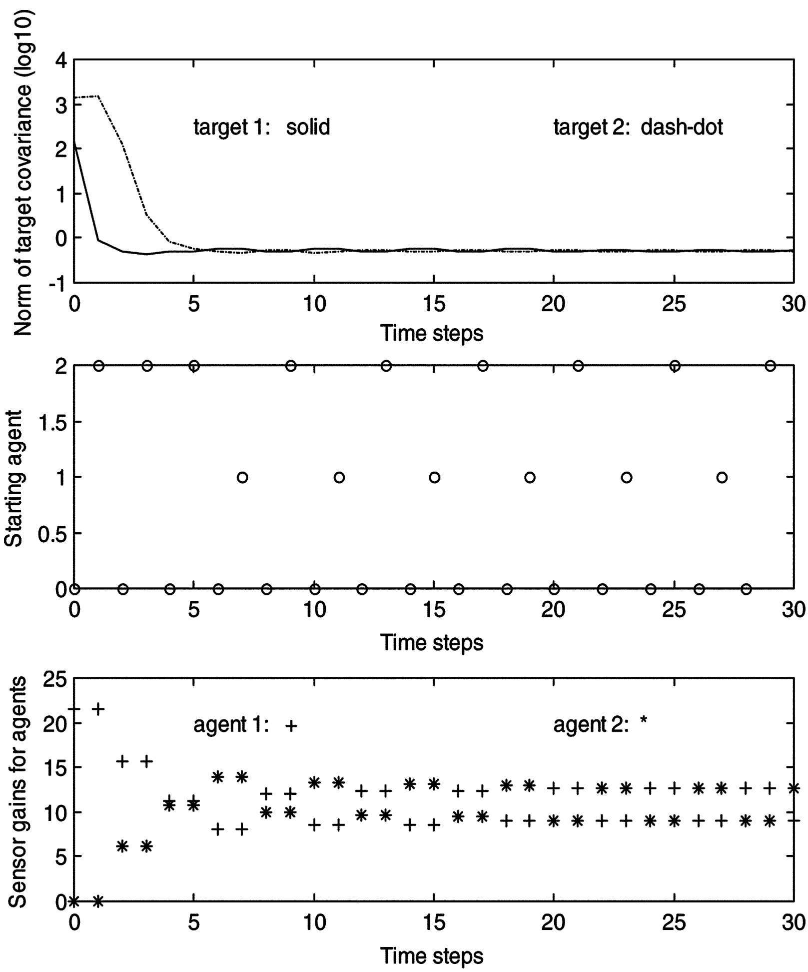

Figure 2. Improving the worst tracking accuracy when $k = 5$.

after entering the steady state, both agents started negotiations alternatively to increase the lowest tracking accuracy on whatever target.

Interestingly, parameter k can be considered as reflecting the emotion of the requesting agent in the negotiations. A small value of k implies that this agent is very anxious or greedy to be better off and vice versa. The influence of variations of k on the covariance tuning processes is illustrated in Figures 3 and 4 that depict the cases with k as 15 and 24, respectively. Comparison of the processes with different k values

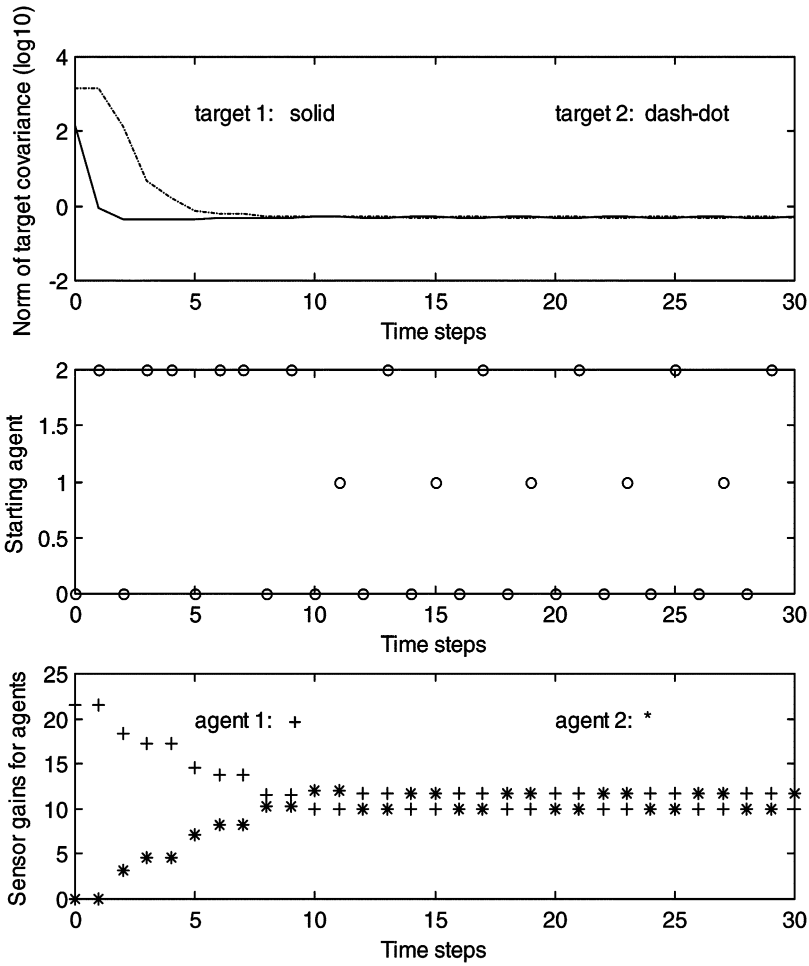

Figure 3. Improving the worst tracking accuracy when $k = 12$.

indicates that a smaller value of the k parameter can enable quicker convergence at the beginning but larger oscillations later in the steady state.

Another alternative is to adapt the k parameter according to the difference in target covariance by

$$k = \frac{K_{\min}}{1 - e^{-\nabla}}$$

where $K_{\min}$ is the minimum value of this parameter and ∇ stands for the absolute value of the difference in target covariance norms. The

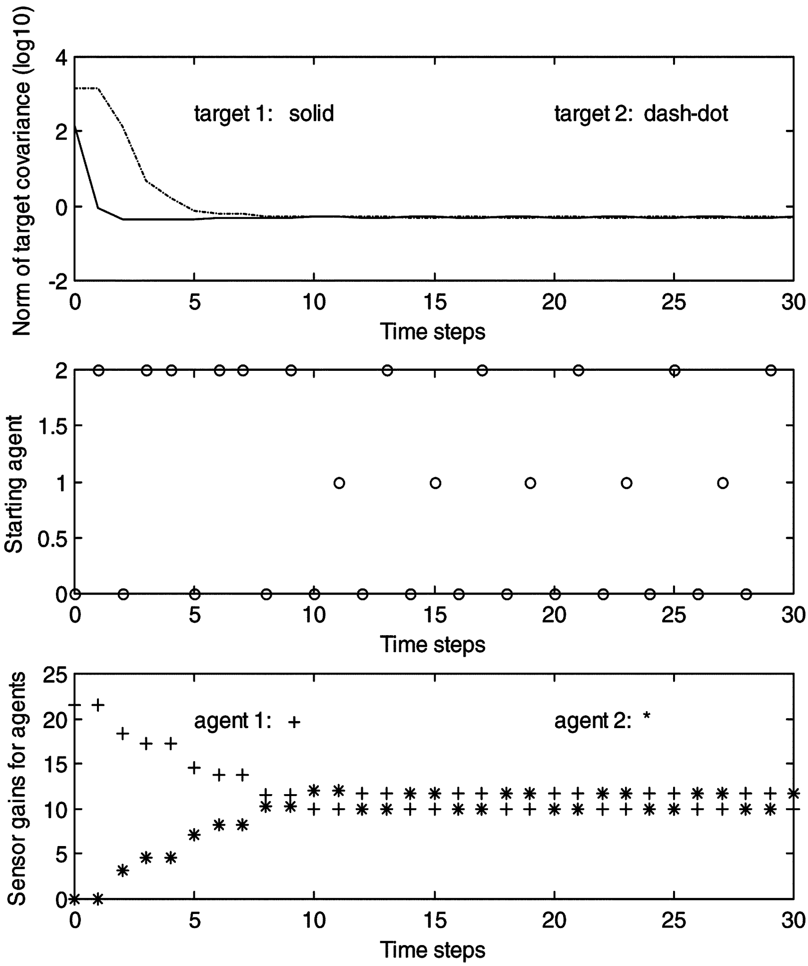

Figure 4. Improving the worst tracking accuracy when $k = 24$.

covariance tuning process using this adaptive strategy of k parameter is shown in Figure 5 which exhibits not only quicker covergence in the beginning but also smaller oscillations in the steady state.

Dealing with Desired Covariance Levels. In many other applications we may have different desired covariance levels for different targets. Negotiation is needed as long as the accuracy on one of the targets does not meet its desired objective. When the covariance on both targets is

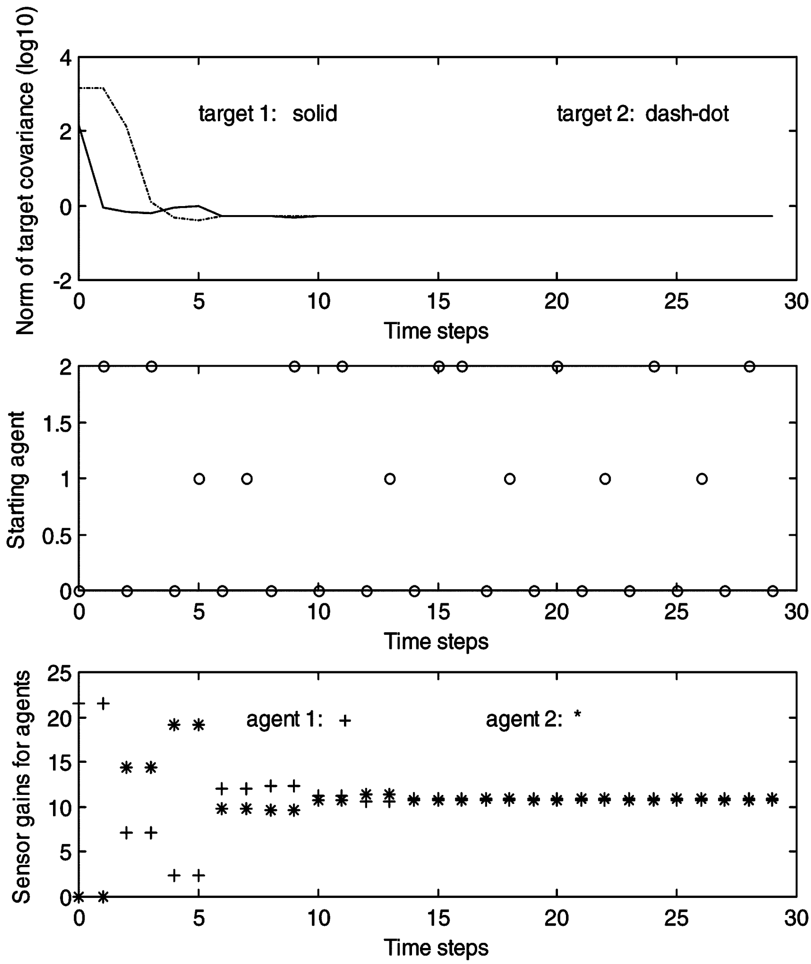

Figure 5. Improving the worst tracking accuracy with adaptation of *k*.

above their respective levels, the agent with the biggest difference with respect to its desired level is allowed to launch a negotiation for getting better/more resources. Again, we conducted simulation tests to examine the negotiation-based processes of target covariance tuning in face of desired levels. We also supposed that initially target 1 got attention from all sensors whereas target 2 did not get observations.

Figure 6 showed the process when the desired covariance levels were set as 0.43 for target 1 and 0.71 for target 2 in the first half period, and

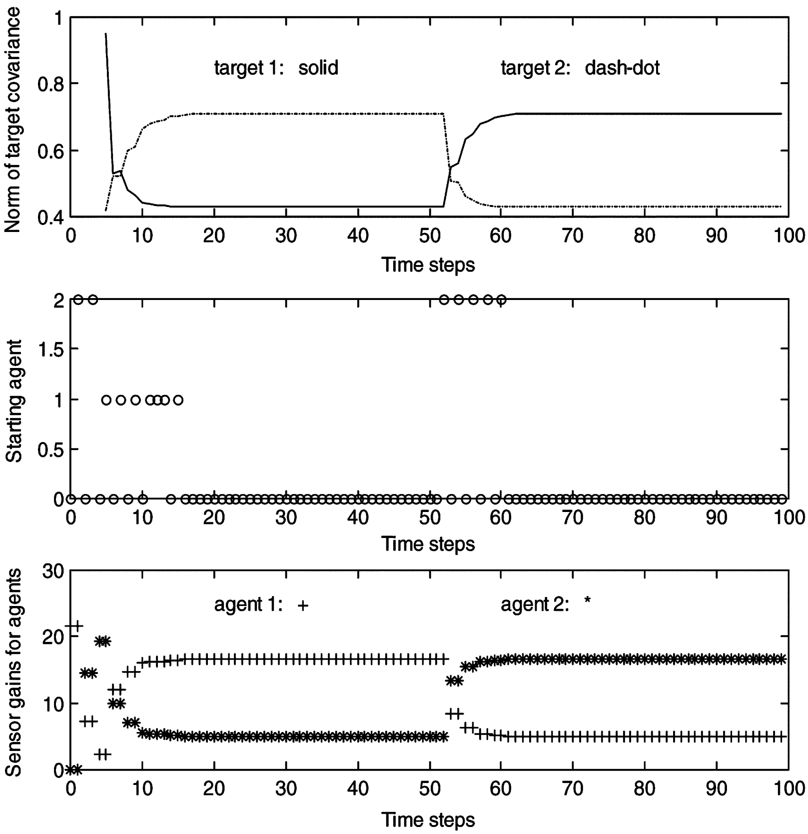

Figure 6. Satisfying the desired covariance levels on both targets.

then in the second half period both targets exchanged their desired levels. Negotiations helped to tune the covariance of both targets below their respective levels very quickly such that the process was most of the time stationary with no negotiations launched by any agent.

Then we changed the desired covariance levels to 0.42 and 0.70. The first was set for target 1 and the second for target 2, and then in the second half period the two targets exchanged their desired covariance levels. Figure 7 illustrated the covariance tuning process in reaction to such desired levels. The limitation of resources made it impossible to satisfy the requirements on the two targets at the same time. Therefore, both agents were constantly interacting with each other by means of negotiation.

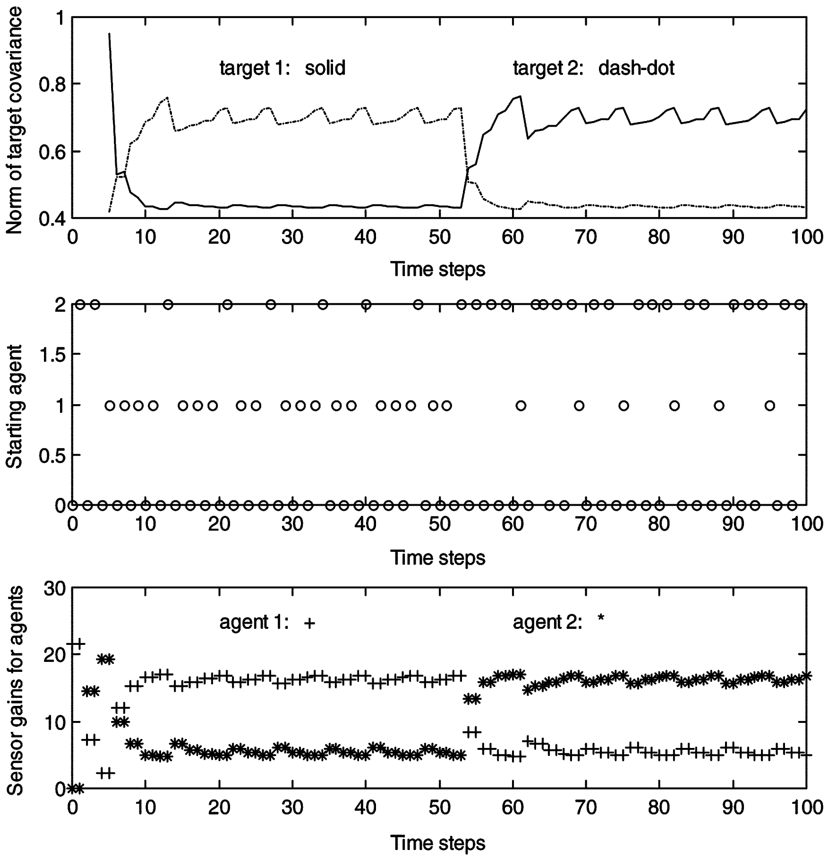

Figure 7. Covariance tuning when desired levels are not achievable simultaneously.

EXTENSION TO MULTIPLE TARGET CASES

This section discusses one possibility of using the bilateral negotiation model to deal with resource allocation in tracking more than two targets. We still arrange for an agent for every target responsible for its tracking and then organize simultaneous one-to-one negotiations in target covariance tuning. For doing this we need evaluations of tracking performance on all targets with respect to information requirements. We presume that such evaluations can be provided by *mission planning* in the form of satisfactory degrees, with *satis_degree*(i) standing for the degree value for target *i*. Further, a negative satisfactory degree means that improvement of tracking performance on the underlying target is being requested, and vice versa. We attempt to organize multiple bilateral negotiations through a mating process, i.e., associating the best performance agent with the worst performance agent, the second best with the second worst and so on, until no targets with negative satisfactory degrees are left. Given in the following is a procedure for organizing multiple bilateral negotiations, which is to be executed at every time step of a multitarget tracking process.

Procedure for Organizing Multiple Bilateral Negotiations

```
New_starting = Ø;
Worst = min_{i∈Unengaged} satis_degree(i);
Stage 1:
While ((||Unengaged|| ≥ 2) and (Worst < 0))
   Begin
      p = arg max_{i∈Unengaged} satis_degree(i);
      q = arg min_{i∈Unengaged} satis_degree(i);
      add pair (p,q) to New_starting;
      remove p, q from Unengaged;
      Worst = min_{i∈Unengaged} satis_degree(i);
   End;

Stage 2:
For every pair (p,q) in Previous_started
   Begin
      update allocation with results from negtia(A_p, A_q);
      add p, q to Unengaged;
      remove pair (p,q) from Previous_started;
   End;

Stage 3:
For every pair (p,q) in New_starting
   Begin
      Launch the negotiation negtia(A_p,A_q) by agent A_q;
      If agreement is reached by negtia(A_p,A_q) within the time step
         Then Begin
            update allocation with results from negtia(A_p, A_q);
```

```
            add p, q to Unengaged;
            End
        Otherwise
          add pair (p,q) to Previous_started;
      End;
```

The above procedure consists of three stages. Stage 1 serves the matching purpose to find agent pairs from the list *Unengaged* containing all agents that are so far not involved (in negotiations). Since the matched pairs of agents are to launch negotiations right now, they are put into the list *New_starting*. Stage 2 is tasked to continue the negotiations for agent pairs (in the list *Previous_started*) that initialized bargaining in the preceding period. As negotiations need maximally two time steps, all pairs of agents that began previously must finish now with their agreements taken into effect in the current period. Finally, at stage 3, we launch negotiations for every agent pair in the list *New-_starting*. If a pair of newly started agents can reach their consensus within the time step, their agreement is honored at once. Otherwise, this pair of agents is added into the list *Previous_started* for continuation in the upcoming period.

CONCLUSION

This paper advocates using agent negotiation in resource allocation to cope with trade-offs of tracking performance between various targets. A bilateral negotiation model for two-target tracking is thoroughly investigated with the development of the SPE negotiation strategies that ensures reaching of agreements within two time steps. The applications of our negotiation model for target covariance tuning are illustrated with given results from simulation.

Further the proposed bilateral negotiation model can also be used in multitarget tracking cases with more than two targets. The way suggested to achieve this is to organize multiple one-to-one negotiations simultaneously. We hesitate to introduce negotiations with many agents altogether in this context, since doing this would greatly increase the number of time steps required to reach agreements. Comparatively, bilateral negotiations are simpler and quicker, making them attractive in real-time applications. We believe that local interactions between agents can be a good means to approach global goals in complex scenarios.

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