Optimization-Based Dynamic Sensor Management for Distributed Multitarget Tracking

Ratnasingham Tharmarasa, Thiagalingam Kirubarajan, *Senior Member, IEEE*, Jiming Peng, *Member, IEEE*, and Thomas Lang

***Abstract*—In this paper, the general problem of dynamic assignment of sensors to local fusion centers (LFCs) in a distributed tracking framework is considered. With recent technological advances, a large number of sensors can be deployed for multitarget tracking purposes. However, due to physical limitations such as frequency, power, bandwidth, and fusion center capacity, only a limited number of them can be used by each LFC. The transmission power of future sensors is anticipated to be software controllable within certain lower and upper limits. Thus, the frequency reusability and the sensor reachability can be improved by controlling transmission powers. Then, the problem is to select the sensor subsets that should be used by each LFC and to find their transmission frequencies and powers in order to maximize the tracking accuracies and minimize the total power consumption. The frequency channel limitation and the advantage of variable transmitting power have not been discussed in the literature. In this paper, the optimal formulation for the aforementioned sensor management problem is provided based on the posterior Cramér–Rao lower bound. Finding the optimal solution to the aforementioned NP-hard multiobjective mixed-integer optimization problem in real time is difficult in large-scale scenarios. An algorithm is presented to find a suboptimal solution in real time by decomposing the original problem into subproblems, which are easier to solve, without using simplistic clustering algorithms that are typically used. Simulation results illustrating the performance of sensor array manager are also presented.**

***Index Terms*—Distributed tracking, multiobjective optimization, multisensor fusion, multitarget tracking, posterior Cramér–Rao lower bound (PCRLB), sensor resource management.**

I. INTRODUCTION

TECHNOLOGICAL advances in recent years have made sensor management a crucial aspect of tracking. Usage of a large number of sensors in tracking applications has become feasible because of the availability of inexpensive sensors. The two major issues in sensor management are optimal sensor placement and optimal sensor selection [31]. In the optimal sensor placement, positions of the sensors that are to be placed must be selected such that tracking performance is optimized [13]. In the optimal sensor selection, it has to be decided which of the already deployed sensors must be used at each measurement time step [7], [27], [28]. In this paper, the problem of optimal sensor selection in a distributed tracking system is considered.

In a centralized architecture, all deployed sensors are connected to a central fusion center (CFC). In order to get maximum information, it is necessary to use as many sensors as possible. However, physical limitations (e.g., limited frequency channels, limited capacity of processor) allow only a subset of sensors to be used at a time. Then, the problem is to select a subset of sensors that gives the optimal tracking performance. An algorithm to handle the aforementioned problem in a multitarget tracking scenario was proposed in [28]. In this paper, that work is extended to distributed architecture, which has few local fusion centers (LFCs) and one CFC [12]. Each LFC uses a certain number of sensors to collect information about the surveillance region. LFCs estimate their local tracks using the measurements received from their local sensors via wireless channel and send their estimates to the CFC. In this scenario, the problem is to decide which of the available sensors must be used by each LFC, and decide what frequency channel and transmission power (if controllable) should be used by each active sensor.

This paper is motivated by submarine tracking using predeployed large number of inexpensive sonobuoys in antisubmarine warfare (ASW) [13]. In ASW, sonobouys are deployed from aircraft over the region of interest and used/activated whenever needed. Since the lifetime of sonobuoys is limited to few hours, care must be taken for their efficient use. The sonobuoys' functions, such as when to be activated and what frequency and transmission power to be used to send the measurements to fusion centers, are controlled by the fusion centers via command signals. Due to frequency channel limitation, only a few of the available sonobuoys can be used at each time step. The receiver at the fusion center may also receive the measurements from a limited number of sensors at a time. Similar application is possible in ground target tracking also, where hundreds or even thousands of unattended ground sensors (UGSs) may be dropped over a large surveillance area to track the ground moving targets [22]. Since centralized architecture is possible only in small surveillance region, distributed architecture with more than one fusion center is necessary to handle the computational and communication requirement of large surveillance region coverage.

In the literature, several sensor management algorithms have been proposed for distributed/decentralized tracking scenarios

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[18], [26], [32]. However, in these works, only limited cases are considered. Area coverage problems are considered in [4], [11], and [14], where the objective is to cover each point in the surveillance region by certain number of sensors. Some other works have considered only a fixed and known number of targets [3], [23], where the objective is to cover each target by a certain number of sensors. In many papers, it is assumed that the LFCs are not fixed, i.e., the locations or the number of LFCs can be changed [15], [18]. This might be true if all the deployed sensors can act as an LFC and/or the LFCs are moving platforms. However, this is not always possible. In this paper, the scenario where the LFCs are different from the sensors is considered. After the deployment of all the sensors and the LFCs, locations and number are fixed.

In the literature, in order to reduce the computational load, sensors are clustered based on target or LFC locations, and each cluster is handled separately [6], [32]. However, target-based clustering is not always possible for two reasons: first, the number of targets may be different from the number of LFCs; second, targets might be closely spaced. It is assumed that a particular number of sensors are required to track each target and one sensor can detect only one target [3], [19], [23]. This, in practice, is not a valid assumption. If a good estimate is available for a target at the current time, then that target could be tracked even with one sensor at the next measurement time. In addition, if there are many targets in the coverage region of a sensor, then that sensor can detect all of them with corresponding detection probabilities. LFC-based clustering is also not optimal if many targets are in one LFC's field of view while no or very few targets are in the fields of view of other LFCs. Hence, in this paper, no clustering is used.

In general, sensors and fusion centers communicate through wireless frequency channels. Hence, the bandwidth limitation, which limits communication, is an important issue [30]. In centralized tracking, the cochannel interference need not be considered since all the sensors are connected to one fusion center, and each sensor uses a different frequency channel. An advantage of distributed tracking is the reusability of the frequency channels. However, there is a tradeoff between reusability and reachability. The transmission power of the sensors can be software controllable with minimum and maximum limits [8]. By varying the transmitting power, it is possible to save power as well as to increase the reachability of each sensor. However, in the literature, there has been no consideration of the variable transmission power and the frequency reusability issues.

The main goal of sensor management is to improve the tracking performance of the targets that are in the surveillance region. The tracking performance is measured by combining tracking accuracies of the existing targets and the detection probabilities of new incoming targets. In a typical tracking scenario, the detection probability of new incoming targets or the tracking accuracies of established tracks cannot be considered as the sole performance metric. However, in the literature, two problems mentioned before are considered separately. In this paper, these two problems are considered together, and multiobjective optimization is used to handle them jointly. The posterior Cramér–Rao lower bound (PCRLB) gives a measure of the achievable optimum performance, and importantly, this bound can be calculated predictively [13]. Furthermore, the PCRLB is independent of the filtering algorithm employed. Hence, PCRLB is used to measure the tracking accuracies of the existing targets in this paper.

In this paper, following scenario is considered: the sensors and the LFCs are already deployed and their positions are known; each LFC can use a certain maximum number of sensors because of physical limitation [5]; only a limited number of frequency channels are available; transmission power of each sensor is software controllable within certain lower and upper limits; in order to extract the signal, SNR at each LFC for each frequency must be greater than or equal to a known threshold level; LFCs communicate with the CFC at each measurement time step; active sensors are changed at every measurement step. In order to eliminate the redundancy, an additional constraint is forced: one sensor can be used by at most one LFC.

First, the PCRLB for the aforementioned architecture is derived. Then, the optimal formulation for the sensor management for the aforementioned scenario is given based on the PCRLB. This is an NP-hard multiobjective mixed-integer optimization problem, and the optimal solution is not easily found in real time. An algorithm is proposed to find a suboptimal solution in real time by decomposing the original problem into subproblems. Subproblems are easier to solve using algorithms like CPLEX solver [10].

The remainder of the paper is structured as follows. Section II describes the general sensor management for distributed tracking system, and then, gives the optimal formulation. In Section III, the solution methodology is presented. Section IV presents simulations results that demonstrate the effectiveness of the proposed algorithms. Conclusions are given in Section V.

II. Problem Description and Formulation

In this section, the description of the problem and a formulation based on the PCRLB, which gives a measure of the tracking accuracy, are presented.

A. Problem Description

A multitarget tracking problem is considered under a distributed tracking system that has a hierarchical level architecture with feedback. The architecture and a sample scenario are shown in Fig. 1. In the sample scenario, there are three targets, each of which enters the surveillance region at different times. The time steps at which they enter the surveillance region are shown next to the initial positions ($\star$).

In a hierarchical level architecture, sensors are connected to LFCs, and LFCs are, in turn, connected to the CFC. Each LFC updates its local tracks based on the measurements from the local sensors and sends its tracks to the CFC. Then, the CFC performs track-to-track fusion and sends back the updated tracks to all the LFCs, i.e., a distributed tracking system with full feedback is considered.

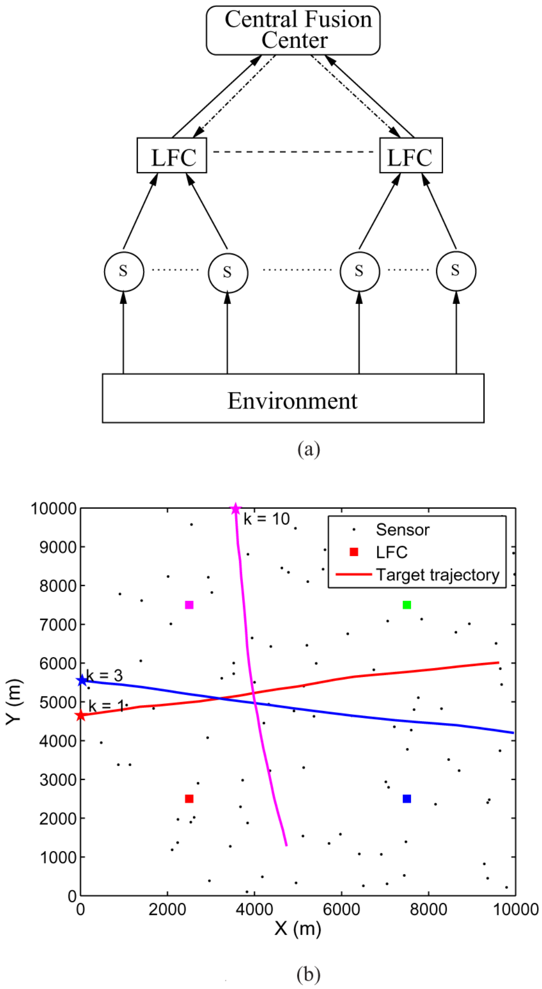


Fig. 1. Architecture and a sample scenario. (a) Architecture. (b) Sample scenario.

There are M LFCs and N sensors, and it is assumed that the number of LFCs and sensors along with their locations are fixed and known. Each LFC can handle a certain maximum number of sensors n_j because of physical limitations [5]. Sensors transmit their measurements to their LFCs through the allocated frequency channels. The available number of channels F is also limited. Thus, even though a large number of sensors are available, only a few sensors can be used at a time. Hence, sensors will be activated or deactivated by a control message whenever the active sensors are changed [33]. Any active sensor will be connected to one of the LFCs through a frequency channel. Note that one sensor can be connected to at most one LFC to avoid the redundancy and reduce the correlation between the tracks from each LFC. The transmission powers of the sensors are software controllable within certain lower and upper limits. In order for the LFCs to recover the signals sent by the sensors, the SNR at each LFC for each channel must be greater than or equal to a known threshold level.

The objective is to maximize the tracking performance of the system. The tracking performance is measured by the accuracies of the existing targets' estimates and the detection probabilities of new incoming targets. Then, the problem is to assign the sensor subset for each LFC and assign the transmitting frequency and the power to each sensor such that SNR is above the threshold level in order to maximize the tracking performance.

Since a hierarchical architecture with full feedback is considered, each LFC has the knowledge of the entire system. Therefore, even if sensor management is performed at every LFC, the result remains the same. In order to avoid the redundancy and reduce the workload of the LFCs, sensor management is performed at the CFC, and the results, i.e., which sensors should be used by each LFC and what frequency channel and how much transmission power should be assigned to each sensor, are broadcast to all the LFCs. However, if an LFC does not receive any message from the CFC due to communication problems, it will perform the sensor management based on its own knowledge.

B. *Problem Formulation*

First, the objectives that should be maximized or minimized need to be identified. In target tracking, one of the main objectives is to estimate the target states accurately. In this paper, the PCRLB is used as the performance measure of tracking accuracy.

1) Background on PCRLB: Let X_k be an unknown and random state vector that is estimated from the measurement data Z_k. Let $\hat{X}_k(Z_k)$ be an unbiased estimate of X_k and $C(k)$ be the error covariance matrix. The PCRLB, which is defined to be the inverse of the Fisher information matrix (FIM) $J(k)$ [29], then gives a lower bound of the error covariance matrix, i.e.,

$$C(k) \stackrel{\triangle}{=} \mathbb{E}\{[\hat{X}_k(Z_k) - X_k][\hat{X}_k(Z_k) - X_k]'\} \geq J(k)^{-1} \quad (1)$$

where $\mathbb{E}$ denotes expectation over (X_k, Z_k) and $[\cdot]'$ denotes the transpose. The inequality in (1) means that $C(k) - J(k)^{-1}$ is a positive semidefinite matrix. The (i, j)th term of $J(k)$ is given by

$$J_{ij}(k) = \mathbb{E}\left(\frac{-\partial^2 \ln(p(X_k, Z_k))}{\partial X_k(i)\partial X_k(j)}\right) \quad (2)$$

where $X_k(i)$ denotes the ith component of $X_k(i)$.

Consider the general tracking problem with the state and measurement equations given by

$$X_{k+1} = F_k X_k + \nu_k \quad (3)$$

$$Z_k(j,i) = \begin{cases} h_k^i(X_k^t) + \omega_k^i(j), & \text{if originated from target } t \\ \upsilon_k^i(j), & \text{if false alarm} \end{cases} \quad (4)$$

where $X_k = \left[X_k^1, X_k^2, \ldots, X_k^T\right]'$, X_k^t is the state vector of target t, T is the total number of targets in the surveillance region, F_k is a linear function, ν_k is an independent white noise with covariance Γ_k, $Z_k(j,i)$ is the jth measurement at the ith sensor, h_k^i (in general) is a nonlinear function, $\omega_k^i(j)$ is a zero-mean Gaussian random variable with covariance Σ_k, and $\upsilon_k^i(j)$ is uniformly distributed across the surveillance region A with hypervolume V.

Then, the FIM, the inverse of the PCRLB, for multitarget tracking at time k is given by [16], [28]

$$J(k) = J_X(k) + \sum_i^n J_{Z_i}(k) \tag{5}$$

where

$$J_X(k) = \left[\Gamma_k + F_k J(k-1)^{-1} F_k'\right]^{-1} \tag{6}$$

$$\left[J_{Z_i}(k)\right]_{t_1 t_2} = \mathbb{E}\left\{\left[H_k^i\right]_{t_1}' \left[Q_k^i\right]_{t_1 t_2} \Sigma_k^{-1} \left[H_k^i\right]_{t_2} \middle| X_k\right\} \tag{7}$$

with the (a,b)th element of matrix $\left[H_k^i\right]_t$ being given by

$$\left[H_k^i\right]_t(a,b) = \frac{\partial \left[h_k^i\right]_t(a)}{\partial X_k^t(b)} \tag{8}$$

where $\left[h_k^i\right]_t(a)$ is the ath component of the measurement vector and $X_k^t(b)$ is the bth component of the state vector of target t. Q_k^i is the information reduction matrix (IRM) for sensor i [34] and $\left[Q_k^i\right]_{t_1 t_2}$ is the (t_1, t_2)th block of the IRM. $\left[J_{Z_i}(k)\right]_{t_1 t_2}$ gives the (t_1, t_2)th block of $J_{Z_i}(k)$. The aforementioned equations have been derived for the centralized tracking. For more detailed information, see [28].

In order to obtain the PCRLB for the distributed tracking, consider the optimal distributed estimation algorithm.

2) Optimal Distributed Estimation Using Information Filter: If the estimate and the corresponding covariance of the jth LFC at time k is given by $\hat{X}^j(k/k)$ and $P^j(k/k)$, $j = 1, 2, \ldots, M$, respectively, the central estimate in terms of the local estimates is given by [1], [9]

$$\begin{aligned} P(k/k)^{-1}\hat{x}(k/k) &= P(k/k-1)^{-1}\hat{x}(k/k-1) \\ &\quad + \sum_{j=1}^{M} \left[P^j(k/k)^{-1}\hat{x}^j(k/k)\right. \\ &\quad \left. - P^j(k/k-1)^{-1}\hat{x}^j(k/k-1)\right] \end{aligned} \tag{9}$$

and the corresponding covariance is given by

$$P(k/k)^{-1} = P(k/k-1)^{-1} + \sum_{j=1}^{M} P^j(k/k)^{-1} - P^j(k/k-1)^{-1}. \tag{10}$$

Under the assumption that the LFCs have the feedback from the CFC at every measurement step, $P^j(k/k-1)^{-1} = P(k/k-1)$ for all j. Then, $P^j(k/k)^{-1} - P^j(k/k-1)^{-1}$ gives the information gained from the jth LFC's sensors.

Hence, the tracking accuracies of the distributed architecture with feedback at every measurement time step is equivalent to that of centralized architecture, assuming that the track-to-track associations are perfect. Then, the PCRLB equations for centralized tracking are true for the architecture considered in this paper. Note that the ensuing algorithm is not restricted to the architecture with feedback at every measurement step. The proposed algorithm can still be used by deriving and replacing the PCRLB equations for the scenario, in which feedback is not available at every measurement step.

3) Objectives: In this paper, two main objectives are considered. The first is to minimize the estimation uncertainties of existing targets. This is equivalent to minimizing the PCRLB of those targets. The trace of the PCRLB is used as the scalar performance measure. However, the ensuing algorithm is not dependent on using this measure. Even determinant or any other of the PCRLB can be used as the scalar performance.

Let S_{ijf} be the indicator function that takes the value 1 if sensor i is assigned to LFC j through the frequency channel f and 0 otherwise. Then, the first objective is given by

$$\min_{\{S_{ijf}\}} \quad \text{trace}\left\{\left[J_X(k) + \sum_{i=1}^{N}\sum_{j=1}^{M}\sum_{f=1}^{F} S_{ijf} J_{Z_i}(k)\right]^{-1}\right\}. \tag{11}$$

The second objective is to quickly detect the new incoming targets. It is equivalent to minimizing the missing probability of the new target. Then, the second object is given by

$$\min_{\{S_{ijf}\}} \quad \mathbb{E}\left(\prod_{i=1}^{N}\left(1 - \sum_{j=1}^{M}\sum_{f=1}^{F} S_{ijf} P_d(i, X_{\text{new}})\right)\right) \tag{12}$$

where X_{new} is the new target state, $P_d(i, X_{\text{new}})$ is the probability of detecting a target with state X_{new} by sensor i, and $\mathbb{E}$ is the expectation over possible new target states.

In most cases, $\mathbb{E}$ has to be found numerically. In this paper, it is assumed that the new targets appear only through the perimeter of the surveillance region. Then, m particles are distributed along the perimeter of the surveillance region to represent the possible states of the new target.[1] Note that these particles are not used in tracking algorithms. Then, the second objective can be rewritten as

$$\min_{\{S_{ijf}\}} \quad \frac{1}{m}\sum_{p=1}^{m}\prod_{i=1}^{N}\left(1 - \sum_{j=1}^{M}\sum_{f=1}^{F} S_{ijf} P_d(i,p)\right) \tag{13}$$

where $P_d(i,p)$ is the probability of detecting a new target, whose state is given by particle p, by sensor i.

The objectives are slightly modified in order to avoid wasting a lot of power for marginal improvement in the tracking performance. The modified objectives corresponding to (11) and (13) are

$$\min_{\{\alpha_i\}} \sum_{t=1}^{T} \max\left(V_L, \text{trace}\left\{\left[\left(J_X(k) + \sum_{i=1}^{N}\alpha_i J_{Z_i}(k)\right)^{-1}\right]_t\right\}\right) \tag{14}$$

and

$$\min_{\{\alpha_i\}} \quad \max\left(M_L, \frac{1}{m}\sum_{p=1}^{m}\prod_{i=1}^{N}\left(1 - \alpha_i P_d(i,p)\right)\right) \tag{15}$$

respectively. In the previous equation, $\alpha_i = \sum_{j=1}^{M}\sum_{f=1}^{F} S_{ijf}$, V_L is the tolerable variance in the estimation error of a target, M_L is the tolerable missing probability of a new target, and $[\cdot]_t$ is the t-th block diagonal matrix that corresponds to target t.

[1]If new targets can appear anywhere in the surveillance region, particles should be placed uniformly all over the surveillance region.

4) Constraints: In this section, the constraints for the aforementioned objective functions are derived. The first constraint is that S_{ijf}, which indicates whether sensor i is connected to LFC j through frequency f, can take only one or zero, i.e.,

$$S_{ijf} \in \{0,\ 1\} \qquad \forall\, i, j, \text{ and } f. \tag{16}$$

Since α_i is introduced in the objective for simplification, the relationship of α_i with the S_{ijf}'s must be added as a constraint. Then,

$$\sum_{j=1}^{M}\sum_{f=1}^{F} S_{ijf} = \alpha_i \qquad \forall\, i \tag{17}$$

From (16) and (17), the integer α_i takes zero if it is not used by any fusion center. If a sensor is used by more than one LFC, then unnecessary duplicate information will be sent to the CFC from these LFCs. In addition, the tracks from these LFCs will be correlated, and this must be considered while fusing tracks. Hence, a sensor can be assigned to at most one LFC, i.e.,

$$\alpha_i \le 1 \qquad \forall\, i. \tag{18}$$

As a result, α_i is a binary integer.

Due to physical limitations, an LFC can handle a maximum of certain number n_j of sensors, i.e.,

$$\sum_{i=1}^{N}\sum_{f=1}^{F} S_{ijf} \le n_j \qquad \forall\, j. \tag{19}$$

Note that there is no need to use two channels to connect a sensor to an LFC, and in the previous equations, it is assumed that a sensor will be connected to an LFC through at most one frequency channel.

Two sensors that are connected to the same LFC cannot use the same frequency since transmissions from them will interfere with each other. Hence, at most one sensor can be connected to one LFC through one frequency, i.e.,

$$\sum_{i=1}^{N} S_{ijf} \le 1 \qquad \forall\, j \text{ and } f. \tag{20}$$

It is assumed that transmitting power of the sensors is software controllable with minimum and maximum limits. Hence, if a sensor is not active, then the transmitting power should be zero. Otherwise its transmission power should be greater than the lower limit p_l and less than the upper limit p_u, i.e.,

$$P_t^i \le p_u\, \alpha_i \qquad \forall\, i \tag{21}$$

$$P_t^i \ge p_l\, \alpha_i \qquad \forall\, i \tag{22}$$

where P_t^i is the transmitting power of sensor i.

The last constraint is that, in order to extract the signal, the SNR at each LFC for each frequency must be greater than or equal to the threshold level $\sigma_{\min}$ [17], i.e.,

$$\frac{P_t^i S_{ijf} r_{ij}^{-\lambda}}{\sum_{\substack{x=1\\x\ne i}}^{N}\sum_{\substack{y=1\\y\ne j}}^{M} P_t^x S_{xyf} r_{xj}^{-\lambda} + N_0} \ge S_{ijf}\,\sigma_{\min} \qquad \forall\, i, j, \text{ and } f \tag{23}$$

where r_{ij} is the distance between sensor i and LFC j, λ is the decaying factor, and N_0 is the environmental noise.

Then, the overall multiobjective optimization problem that has to be solved is

$$\min_{\{\alpha_i\}} \quad \sum_{t=1}^{T} \max\left(V_L, \operatorname{trace}\left\{\left[\left(J_X(k) + \sum_{i=1}^{N}\alpha_i J_{Z_i}(k)\right)^{-1}\right]_t\right\}\right) \tag{24}$$

$$\min_{\{\alpha_i\}} \quad \max\left(M_L,\ \frac{1}{m}\sum_{p=1}^{m}\prod_{i=1}^{N}(1-\alpha_i P_d(i,p))\right) \tag{25}$$

subject to

$$S_{ijf} \in \{0,\ 1\} \qquad \forall\, i, j, \text{ and } f \tag{26}$$

$$\sum_{j=1}^{M}\sum_{f=1}^{F} S_{ijf} = \alpha_i \qquad \forall\, i \tag{27}$$

$$\alpha_i \le 1 \qquad \forall\, i \tag{28}$$

$$\sum_{i=1}^{N}\sum_{f=1}^{F} S_{ijf} \le n_j \qquad \forall\, j \tag{29}$$

$$\sum_{i=1}^{N} S_{ijf} \le 1 \qquad \forall\, j \text{ and } f \tag{30}$$

$$P_t^i \le p_u\, \alpha_i \qquad \forall\, i \tag{31}$$

$$P_t^i \ge p_l\, \alpha_i \qquad \forall\, i \tag{32}$$

$$\frac{P_t^i S_{ijf} r_{ij}^{-\lambda}}{\sum_{\substack{x=1\\x\ne i}}^{N}\sum_{\substack{y=1\\y\ne j}}^{M} P_t^x S_{xyf} r_{xj}^{-\lambda} + N_0} \ge S_{ijf}\,\sigma_{\min} \qquad \forall\, i, j, \text{ and } f. \tag{33}$$

The solution methodology to this problem is given in the next section.

III. Solution Technique

Finding the optimal solution for the multiobjective NP-hard combinatorial optimization problem [20], specified in (24)–(33) in real time is not feasible for large-scale problems. Hence, an algorithm is proposed to find a suboptimal solution in real time. The flowchart for the proposed algorithm is shown in Fig. 2.

In the algorithm, first $\min(\sum_{j=1}^{M} n_j, F)$ optimal or suboptimal sensors are selected from the available sensors by considering only the objective function. Note that even though the constraints are not considered in selecting the aforementioned sensor subset, this solution will always satisfy all the constraints. Then, the sensors are added one by one so that the objective value is minimized and all the constraints are satisfied. After adding a sensor to the already selected sensors, feasibility check is performed as follows.

1) Sensors are assigned to LFCs. Note that this assignment has to be performed from the beginning whenever a new sensor is added to the selected sensor subset.

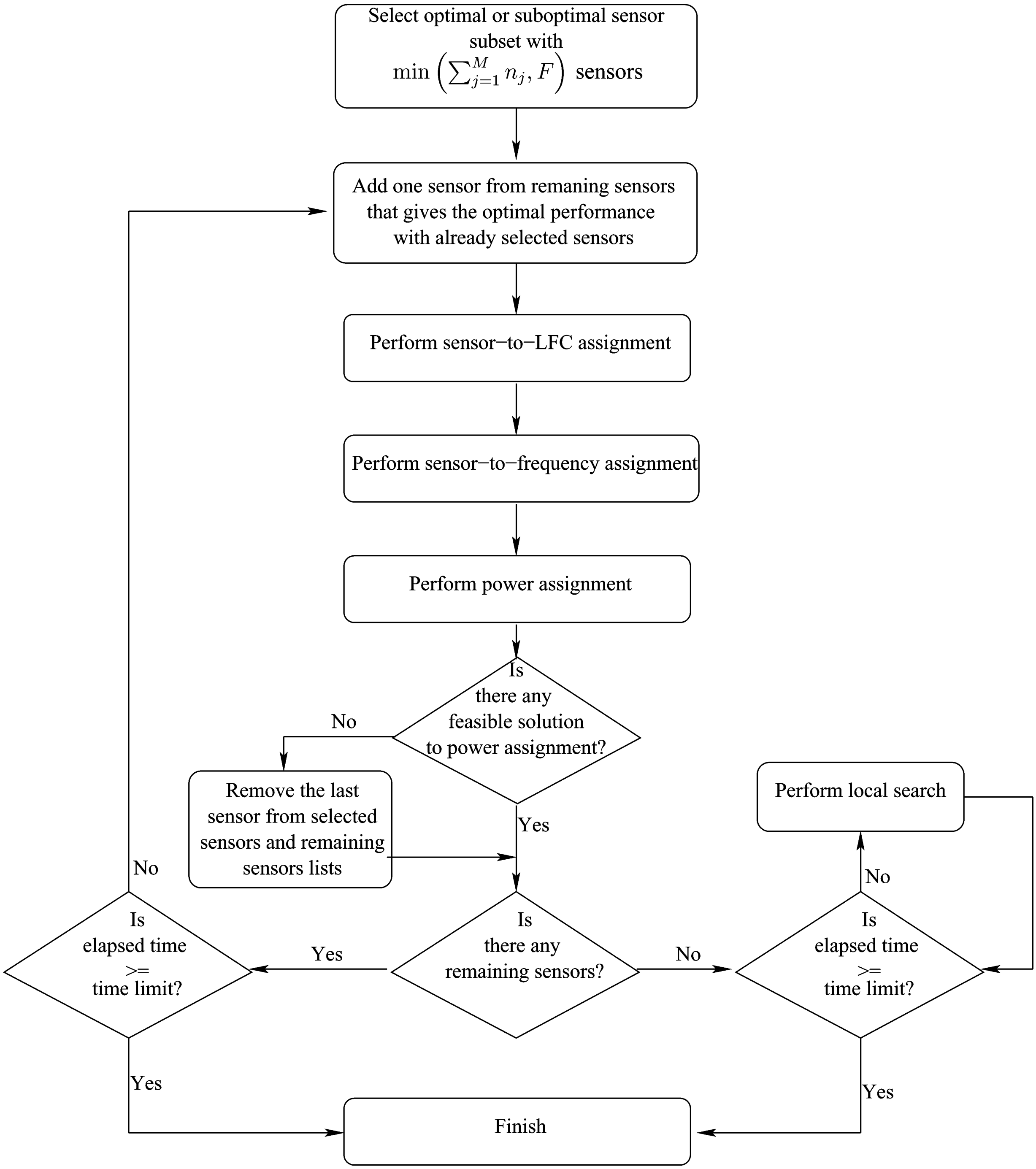


Fig. 2. Algorithm used to find a suboptimal solution.

2) After sensors are assigned to LFCs, the transmitting frequencies will be assigned to each sensor.
3) Finally, transmitting power is assigned to each sensor. However, if no feasible solution is found for power assignment, the selected sensor subset is not feasible and the sensor that was added last is removed from the selected sensors. Note that this removed sensor need not be checked for feasibility in the future after adding one or more sensors to the current sensor subset, since this is obviously infeasible.

After adding the maximum possible number of sensors, a local search is performed to find a better solution by swapping the sensors in and out until the stopping criterion is satisfied. While performing the local search, all the remaining sensors including sensors that were ended up with infeasible solutions should be considered.

The detailed explanation for the aforementioned steps is given next. Let $S_{ijf} = \alpha_i * \beta_{ij} * \gamma_{if}$, where α_i is 1 if that sensor is selected and 0 otherwise, β_{ij} is 1 if sensor i is assigned to LFC j and 0 otherwise, and γ_{if} is 1 if sensor i is assigned to frequency f and 0 otherwise.

The original problem is decomposed into four subproblems:

1) finding α_i (explained in Section III-A);
2) finding β_{ij} (explained in Section III-B);
3) finding γ_{if} (explained in Section III-C);
4) finding P_t^i (explained in Section III-D).

A. Active Sensor Selection

This section describes briefly the selection process of sensors that should be active. Since handling multiple objectives is difficult, both objectives are combined by giving suitable weights to each objective to form a single objective. The weights can be selected based on design requirements. The combined objective is

$$\min_{\{\alpha_i\}}\left\{\sum_{t=1}^{T}\max\left(V_L, \operatorname{trace}\left\{\left[\left(J_X(k)+\sum_{i=1}^{N}\alpha_i J_{Z_i}(k)\right)^{-1}\right]_t\right\}\right)\right.$$
$$\left.+\, W_d * \max\left(M_L, \frac{1}{m}\sum_{p=1}^{m}\prod_{i=1}^{N}(1-\alpha_i P_d(i,p))\right)\right\} \quad (34)$$

where W_d is the weight given to the detection objective function.

To find α_i, the number of sensors to be selected must be determined first. The maximum number of sensors that can be active at a time is $\sum_{j=1}^{M}\min(n_j, F)$. However, if $\sum_{j=1}^{M}\min(n_j, F)$ sensors are selected by considering only the objective function, it might not be able to find a feasible β_{ij}, γ_{if}, and P_t^i with selected sensors α_i. Hence, first $\min(\sum_{j=1}^{M} n_j,\ F)$ sensors, which definitely give a feasible solution to the original problem, are selected by finding a better initial solution followed by a local search. The solution consists of the following steps.

1) Select the best sensor that gives the minimum objective value when only one sensor is used.
2) Keep on adding sensors one by one until $\min(\sum_{j=1}^{M} n_j,$ $F)$ sensors are selected. If n sensors are already selected, then the $(n+1)$th sensor is the one that gives the minimum objective value when added with the already selected sensors.
3) Perform a local search by swapping sensors in and out such that the objective value is minimized (see [27]).

After finding a better solution with $\min(\sum_{j=1}^{M} n_j,\ F)$ sensors, add sensors one by one until no additional sensors can be (or need to be) added. The steps to select the $(n+1)$th sensor are as follows.

1) Rank the remaining sensors based on their performances when combined with the already selected sensors.
2) Select the best one as the $(n+1)$th sensor and solve for β_{ij}, γ_{if}, and P_t^i, as explained in Section III-B–D. If there is no feasible solution for P_t^i, select the next best sensor as the $(n+1)$th sensor and do the feasibility check again. Keep on changing the sensor in the rank order until a feasible solution is obtained.

After selecting the maximum possible number of sensors, a local search is performed by swapping the sensors in and out such that the objective value is minimized and a feasible solution is obtained for β_{ij}, γ_{if}, and P_t^i.

Note that the algorithm is interrupted at any stage if the time limit is reached.

B. Sensor-to-LFC Assignment

After the active sensors are selected, the LFCs that each of the selected active sensor will report have to be determined. In order to improve the SNR at each LFC for each frequency, the distances of the sensors from the assigned LFCs must be minimized while the distances from other LFCs are maximized.

Then, the sensor-to-LFC assignment β_{ij} can be formulated as

$$\max_{\{\beta_{ij}\}} \sum_{i=1}^{N}\sum_{j=1}^{M}\left(\frac{r_{ij}^{-\lambda}}{\sum_{\substack{y=1\\y\neq j}}^{M} r_{iy}^{-\lambda}}\right)\beta_{ij} \quad (35)$$

subject to

$$\sum_{i=1}^{N}\beta_{ij} \le n_j \qquad \forall\, j \quad (36)$$

$$\sum_{j=1}^{M}\beta_{ij} = \alpha_i \qquad \forall\, i \quad (37)$$

$$\beta_{ij} \in \{0,\ 1\} \qquad \forall\, i \text{ and } j. \quad (38)$$

The previous problem is a linear binary integer programming, and it can be solved using the CPLEX solver [10].

C. Sensor-to-Frequency Assignment

After finding the values of β_{ij} for the selected sensors α_i, the remaining problem is to assign the transmitting frequencies γ_{ij} and transmitting powers p_t^i to all the selected sensors. Since the sensor battery power is limited, the power consumption must be minimized to increase a sensor's lifetime. The remaining problem is

$$\min_{\{P_t^i\}} \sum_{i=1}^{N} P_t^i \quad (39)$$

subject to

$$\gamma_{if} \in \{0,\ 1\} \qquad \forall\, i \text{ and } f \quad (40)$$

$$\sum_{i=1}^{N}\alpha_i\ \beta_{ij}\gamma_{if} \le 1 \qquad \forall\, j \text{ and } f \quad (41)$$

$$P_t^i \le p_u\ \alpha_i \qquad \forall\, i \quad (42)$$

$$P_t^i \ge p_l\ \alpha_i \qquad \forall\, i \quad (43)$$

$$\sum_{i=1}^{N}\alpha_i\ \beta_{ij}\ \gamma_{if}\ P_t^i\ r_{ij}^{-\lambda} \ge \sigma_{\min}\left(\sum_{\substack{x=1\\x\neq i}}^{N} P_t^x \sum_{y=1}^{M}\gamma_{xf} r_{xj}^{-\lambda} + N_0\right) \qquad \forall\, j \text{ and } f. \quad (44)$$

This is also an NP-hard problem. If the transmission power is fixed, the previous problem can be solved easily. However, in order to incorporate the advantage of the variable transmission power, γ_{if} and P_t^i have to be considered together. The following approximation is used to solve the aforementioned problem.

1) All the LFCs are arranged in a particular order. Let the first LFC be the one at any one corner. The next LFC is the one closest to the previous LFC from the remaining LFCs.
2) Assign the frequencies to the first ($j = 1$) LFC's sensors. Since the number of sensors assigned to this LFC is less than or equal to F, simply assign any one frequency, but different, to one sensor.
3) Assign the frequencies to the jth LFC's sensors by solving the following optimization problem:

$$\min_{\{\overline{\gamma}_{if}\}} \quad \max_{\substack{i=1,\ldots,N_j \\ f=1,\ldots,F}} C_{if}\, \overline{\gamma}_{if} \tag{45}$$

subject to

$$\overline{\gamma}_{if} \in \{0,\ 1\} \qquad \forall\, i \text{ and } f \tag{46}$$

$$\sum_{f=1}^{F} \overline{\gamma}_{if} = 1 \qquad \forall\, i \tag{47}$$

$$\sum_{i=1}^{N_j} \overline{\gamma}_{if} \leq 1 \qquad \forall\, f \tag{48}$$

where N_j is the number of sensors assigned to the jth LFC and C_{if} is the cost of assigning frequency f to sensor i. Note that $\overline{\gamma}$ is used instead of γ since only the subset of sensors that are assigned to the jth LFC is considered. However, after finding the solution to $\overline{\gamma}$, γ will be updated. To find the value of C_{if}, the cost of assigning frequency f to sensor i, first the transmission powers corresponding to the sensors that use frequency f, including sensor i, are found by using the formulation given in the Section III-D, and then, C_{if} is calculated using

$$C_{if} = \max_{y \in \{i_f\}} \left(\frac{\sum_{\substack{x=1 \\ x \neq y}}^{N_f} P_t^x r_{xj_y}^{-\lambda} + N_0}{P_t^y r_{yj_y}^{-\lambda}} \right) \tag{49}$$

where i_f indicates the sensors that are using frequency f including sensor i, N_f is the number of sensors using frequency f, and j_y is the LFC to which sensor y is assigned.

Also, C_{if} gives the maximum of the noise-to-signal ratio for frequency f at any LFC when frequency f is assigned to sensor i. In order to improve the possibility of getting a feasible solution for P_t^i, the maximum value of the noise-to-signal ratio over all the frequencies is minimized in (45).

The previous problem can be reformulated as a linear integer problem as follows:

$$\min_{\{\overline{\gamma}_{if}\}} \quad T \tag{50}$$

subject to (46)–(48) and

$$C_{if}\, \overline{\gamma}_{if} \leq T \qquad \forall\, i, f. \tag{51}$$

This problem can also be solved using the CPLEX solver [10].

4) Continue this process until no more LFC remains.

D. Transmission Power Assignment

After finding α_i, β_{ij}, and γ_{if}, the remaining problem is to find the transmission power for each active sensor. In order to increase the lifetime of the sensors, transmitting powers must be minimized while satisfying the sensor usage constraints.

Transmitting power assignment P_t^i can be formulated as

$$\min_{\{P_t^i\}} \quad \sum_{i=1}^{N} P_t^i \tag{52}$$

subject to

$$P_t^i \leq \alpha_i\, p_u \qquad \forall\, i \tag{53}$$

$$P_t^i \geq \alpha_i\, p_l \qquad \forall\, i \tag{54}$$

$$\sum_{i=1}^{N} \alpha_i\, \beta_{ij}\, \gamma_{if}\, P_t^i\, r_{ij}^{-\lambda} \geq \sigma_{\min} \left(\sum_{\substack{x=1 \\ x \neq i}}^{N} P_t^x \sum_{y=1}^{M} \gamma_{xf} r_{xj}^{-\lambda} + N_0 \right) \qquad \forall\, j \text{ and } f. \tag{55}$$

The previous problem is a linear convex problem that can be solved using the CPLEX solver [10].

Note that for some α_i, β_{ij}, and γ_{if}, there will not be any feasible solution for power. In this case, α_i, β_{ij}, or γ_{if} has to be changed so that a feasible solution is found.

IV. Simulation Results

A. Scenario 1

In the first simulation scenario, the number of targets $T = 2$; the number of LFCs $M = 4$; the number of sensors $N = 100$; the maximum usable sensors by each LFC $n_j = 4$; the available number of channels $F = 5$; the measurement interval is 30 s; measurements are the bearings from the sensors to targets; the measurement standard deviation $\sqrt{\Sigma} = 0.05$ rad; the field of view of the sensor $V = 2\pi$ rad; the transmission power bounds $p_l = 0$ and $p_u = 1$ W; the threshold of SNR $\sigma_{\min} = 10$ dB; the probability of false alarm is 0.001.

Since the measurement model is nonlinear, an extended Kalman filter (EKF) based information filter is used to track the targets at each LFC [1], [2]. Due to the presence of multiple targets and false alarms, measurements must be associated to already established tracks, new tracks, or a dummy track that corresponds to tracks due to false alarms. First, the $(S+1)$-D (or multiframe) assignment algorithm, where S is the depth of the assignment, is used to associate the measurements with the already established tracks [24]. The remaining measurements, which are not associated with any of the already established tracks, are associated with new tracks or dummy track using the S-D algorithm [21]. New tracks are formed with the associated measurements using the iterated least squares (ILS) estimator [2].

Estimation at the CFC is performed using (9) and (10) that consider a single target. However, multiple targets can be tracked by each fusion center, and the estimate of each target has to be updated. Hence, the CFC will first group the estimates that belong to same target from all the LFCs. Since LFCs get feedback from the CFC, the track ID can be used to identify the target that corresponds to each estimate [25]. However, track ID will be the same only for the already established tracks. If new tracks are formed by LFCs, then the following technique is used to determine if they originated from the same target.

Let $\hat{x}^i(k)$ and $\hat{x}^j(k)$ be the estimates, and $P^i(k)$ and $P^j(k)$ be the covariances at LFCs i and j at time k, respectively. Then, the difference between the two estimates $\Delta^{ij}(k)$ is given by [1]

$$\Delta^{ij}(k) = \hat{x}^i(k) - \hat{x}^j(k) \tag{56}$$

with covariance

$$T^{ij}(k) = P^i(k) + P^j(k). \tag{57}$$

Two estimates are from the same target if and only if

$$D = \Delta^{ij}(k)^T [T^{ij}(k)]^{-1} \Delta^{ij}(k) \leq D_\alpha \tag{58}$$

where D_α is the threshold, and is selected such that

$$P(D > D_\alpha | \text{two states are the same}) = 0.01. \tag{59}$$

After updating the target states, the CFC will assign IDs to the new targets, and this information will be sent to LFCs with feedback.

The solution for the sensor management problem, i.e., the selected sensors, their LFC and frequency assignments, using the proposed algorithm is shown in Fig. 3, where "■" indicates the LFC and the corresponding capital letter (e.g., A, B, ...) near to it indicates its name. The "·" indicates the sensor, "●" indicates the selected sensor, and the corresponding small letter (e.g., a, b, ...) indicates that the sensor is assigned to the corresponding capital letter LFC (e.g., sensor "a" is assigned to LFC "A"). The number near the selected sensor indicates the frequency channel that is assigned to it. In addition, "$*$" indicates the target. When the decaying factor is high, the cochannel interference is less. Hence, it is possible to use more sensors with decaying factor 4 than decaying factor 2. However, even with decaying factor 2, the proposed algorithm assigns enough sensors to the already exiting targets and other sensors to cover the boundaries through which new targets can enter the surveillance region. Since no other method that can handle similar type of sensor selection problem could be found in the literature, the results of the proposed method could not be compared to that of any other.

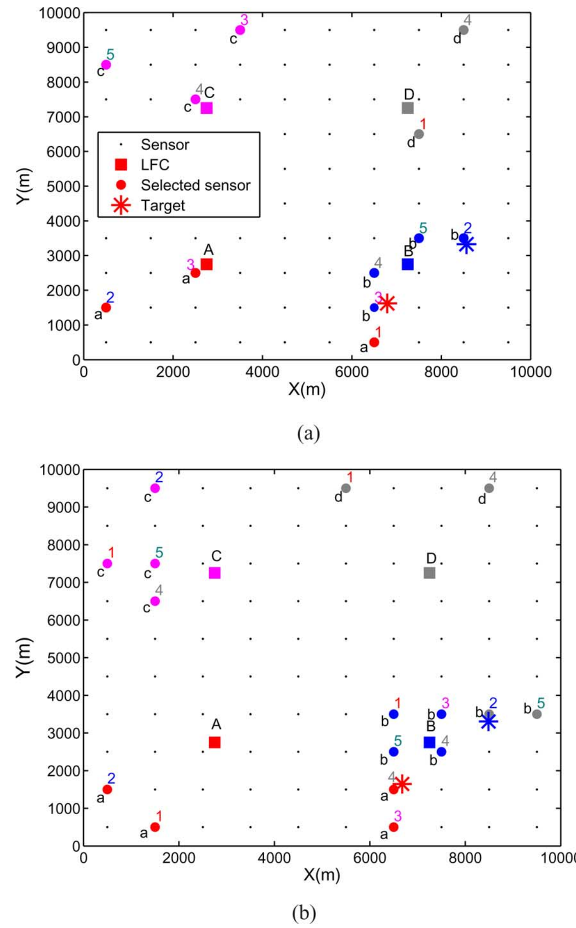


Fig. 3. Selected sensors and their LFC and frequency assignments for scenario 1. (a) Decaying factor $\lambda = 2$. (b) Decaying factor $\lambda = 4$.

B. Scenario 2

In order to compare the proposed method with other existing methods, a slightly different scenario is used. The differences are the sensors are randomly distributed in the surveillance region, the number of targets $T = 3$, and the available number of channels $F = 20$. Since the available number of channels (20) is greater than the maximum usable sensors by all the LFCs (4×4), the frequency assignment is not an issue and the solution can be found easily. However, no clustering is used in the proposed algorithm.

In the literature, sensors are clustered based on target or fusion center [32]. Target-based clustering cannot be applied to considered scenarios since number of targets is time varying and a sensor can get measurements from more than one target. Fusion-center-based clustering is applicable to the aforementioned scenario, and an algorithm using clustering is discussed next.

First, the sensors are clustered based on the LFCs, i.e., a sensor can be used only by the closest LFC. The clustered sensors are shown in Fig. 4. Clustering helps to perform the sensor-to-LFC assignment, and it is performed prior to selecting the active sensors. The remaining problem is to select the active sensors. In the literature [32], an LFC considers only its region

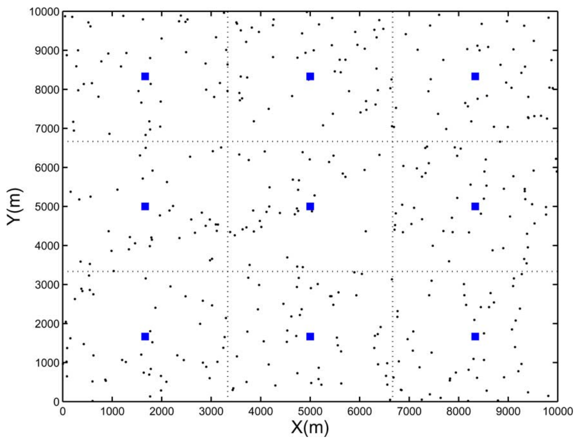
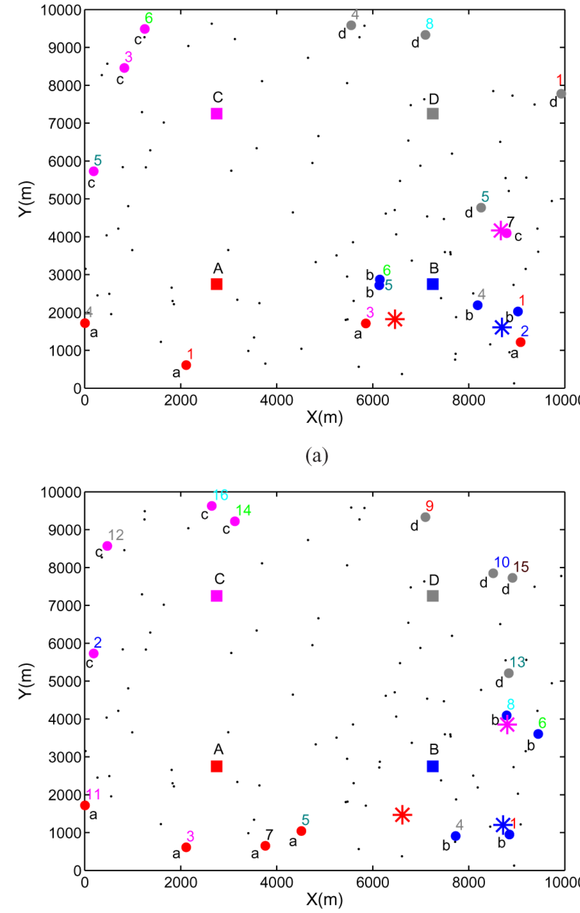


Fig. 4. Sample scenario with clustered sensors.



(a)

(b)

Fig. 5. Sensors selected with the proposed algorithm and an algorithm that used LFC-based clustering for scenario 2. (a) Proposed algorithm. (b) Algorithm using clustering.

to select its sensors. However, to reduce the difference between the proposed algorithm and the algorithm using clustering, it is assumed that the whole region is considered to select the active sensors. Also, tracking and coverage problems are widely considered separately [3], [4], [11], [14], [23], i.e., either the tracking accuracy of the existing target or the detection probability of existing and newly appearing targets is considered. However, again, to reduce the difference between the proposed algorithm and the algorithm using clustering, both already existing targets and the possible new targets are considered in sensor selection.

The comparisons of the proposed algorithm with the algorithm in [32] that used LFC-based clustering are shown in Figs. 5–7. Fig. 5 shows the selected sensors and their LFC and frequency assignments. The symbol notations in this figure are the same as in Fig. 3. There are three targets around LFC B. In the proposed algorithm, enough sensors are assigned to these targets, and other sensors are assigned to detect new targets. In the algorithm with clustering, only four sensors, which are not enough to track all three targets, are assigned to the existing targets. Figs. 6 and 7 show the comparison of the root-mean-square error (RMSE) and the PCRLB, respectively. The proposed algorithm improves the RMSE by more than 30% than the algorithm that used clustering.

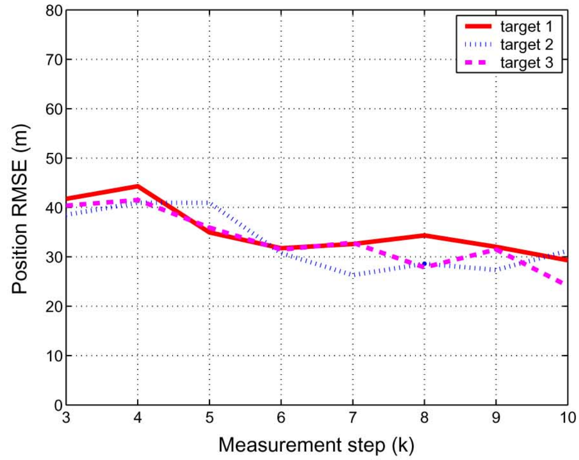
The average computation time of the proposed algorithm for the aforementioned scenario is 4.2 s. The corresponding time for LFC-based clustering algorithm is 3.1 s. Both algorithms are coded in MATLAB and run on a 2.4-GHz Pentium 4 processor. The proposed algorithm gives around 30% improvement in the performance than the algorithm that used clustering with around 35% more computation time. Computation time, however, does not matter as long as it is smaller than the allocated time, and it can be further reduced by coding the algorithms in *C*.

C. Scenario 3

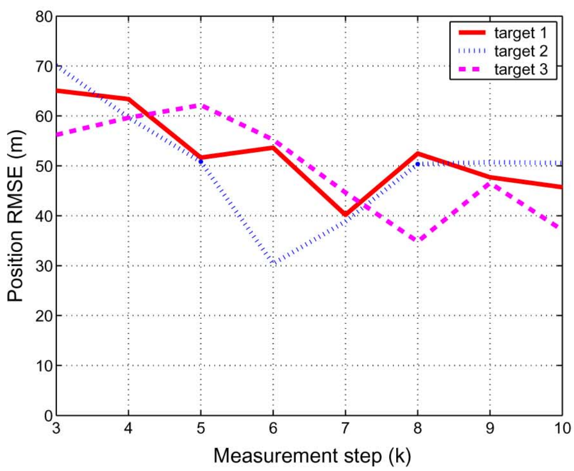
In the aforementioned scenario, all three targets were close to an LFC. In order to compare the performance of the algorithms in a scenario with more targets over longer period of time, the scenario shown in Fig. 8 is considered. In this scenario, there are six targets and each enter the surveillance region at different times. The numbers next to the entry point of each target show the entry time steps. The RMSE comparison for this scenario is shown in Fig. 9. From Fig. 9(a) and (b), it can be noted that there is a significant improvement in the RMSE when the targets are not evenly distributed over all the LFCs, and the improvement reduces when the distribution becomes even.

Even though the frequency and transmission power assignment with active sensor selection has not been considered in the literature so far, to see the effect of clustering on computation and on performance the following scenario is considered: the available number of channels $F = 6$, the maximum usable sensors by each LFC $n_j = 4$, and decaying factor $\lambda = 4$. In the algorithm with clustering, LFC-based clustering is used instead of sensor-to-LFC assignment, as in Section III-B. Algorithms are stopped if either allocated time is reached or a local optimum is found with one sensor swapping.

The best objective function values found by both algorithms in the allocated times are shown in Table I. When the allocated time is less than or equal to 15 s, the algorithm that used clustering gives the better solution. However, with more allocated



(a)



(b)

Fig. 6. RMSE comparison of the proposed algorithm with an algorithm that used clustering for scenario 2. (a) Proposed algorithm. (b) Algorithm using clustering.

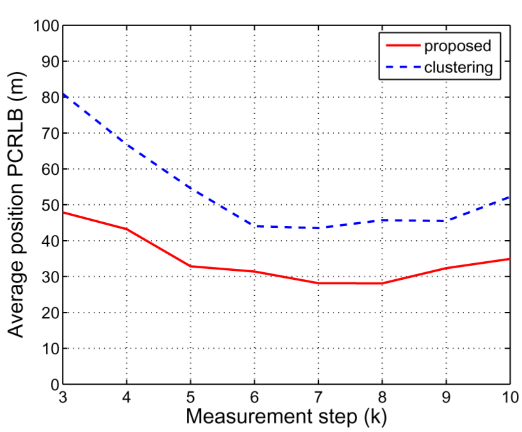


Fig. 7. PCRLB comparison of the proposed algorithm with an algorithm that used LFC-based clustering for scenario 2.

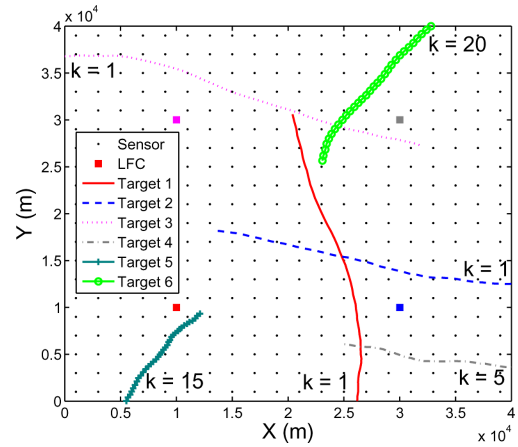
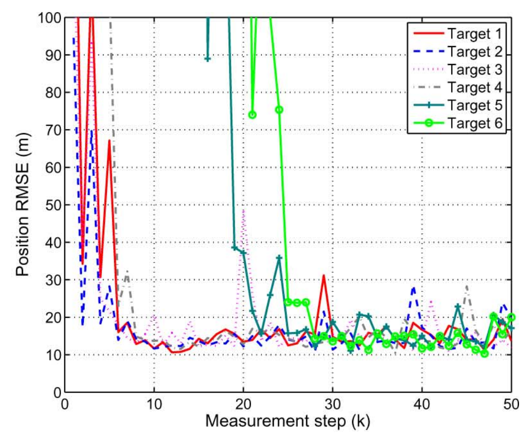
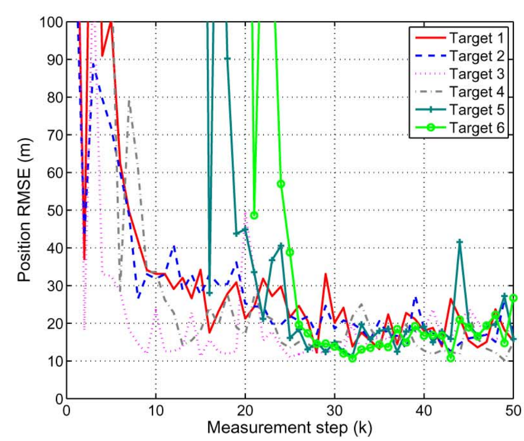


Fig. 8. Scenario 3: target trajectories, sensors, and LFCs.



(a)



(b)

Fig. 9. RMSE comparison of the proposed algorithm with an algorithm that used clustering for scenario 3. (a) Proposed algorithm. (b) Algorithm using clustering.

time, the proposed algorithm finds a solution that is better by 30%–50% over the one obtained by the algorithm with clustering. Note that the computation times can be reduced significantly by coding the algorithm in *C*, and in most cases, enough time will be available to reach a better solution using the proposed algorithm.

TABLE I
BEST OBJECTIVE FUNCTION VALUES FOUND USING CLUSTERING AND PROPOSED ALGORITHMS

Allocated time (seconds)	Scenario 1		Scenario 2		Scenario 3	
	Algorithm with clustering	Proposed algorithm	Algorithm with clustering	Proposed algorithm	Algorithm with clustering	Proposed algorithm
5	1222	5851	7214	10966	4637	12030
15	929	5831	6926	10964	3338	4637
25	929	715	6926	3285	3338	1978
35	929	668	6926	3285	3338	1978

V. CONCLUSION AND FUTURE WORK

In this paper, an optimization-based sensor management algorithm was considered for multitarget tracking under distributed architecture. The problem was to select subsets of sensors, assign them to LFCs, and assign the frequency and transmission power to each active sensor in order to maximize the tracking performance of multiple targets. The optimal formulation for the sensor management for the aforementioned problem was derived based on the PCRLB. Finding the optimal solution to the aforementioned problem in real time is a difficult task in large-scale scenarios. An algorithm was presented to find a suboptimal solution in real time by decomposing the original problem into four subproblems that were easier to solve without using the simplistic clustering algorithms that are commonly used in the literature.

For simplicity, only a hierarchical architecture is considered with feedback at every measurement step. Extensions to handle the architectures without feedback and/or without common CFC will be the subject of future research.

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