Computer Communications 35 (2012) 1107–1114

Contents lists available at SciVerse ScienceDirect

Computer Communications

journal homepage: www.elsevier.com/locate/comcom

On optimizing sensing quality with guaranteed coverage in autonomous mobile sensor networks ☆

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ARTICLE INFO

Article history:
Available online 12 November 2011

Keywords:
Mobile sensor networks
Sensing quality
Tracking
Coverage

ABSTRACT

The advancements in robotics and wireless communications provide us with the opportunity to combine the mobility and wireless sensor networks so that various objectives can be achieved simultaneously with less required resources. Specifically, mobility enables sensors to dynamically adjust their positions for better sensing quality, and offers a higher probability for guaranteeing the required coverage at the same time. In this paper, we propose a novel coordinating scheme for autonomous mobile sensor networks to optimize the target sensing quality while guaranteeing the required coverage of the field of interest. The whole problem is transformed into a finite horizon optimization problem, to which several solving algorithms are designed. Extensive simulations demonstrate the effectiveness of the proposed method.

1. Introduction

In the past decades, wireless sensor networks have been becoming an effective and promising technology for long-term, unattended field monitoring. For a number of applications, sensors are not only required to provide direct measurements, but also to properly actuate so that certain performances can be improved while the system flexibility and robustness can be guaranteed.

Target tracking is a critical problem in the field of sensor networks [1–3]. Commonly, static sensors are deployed to detect mobile objects. After receiving the information captured by the sensors, some fusion strategies can be applied to abstract the desirable target state (e.g., location and velocity, etc.) in a center node, which can be the head of activated sensors for tracking [4]. However, for such kind of networks, in order to improve the tracking performance, we have to either enhance the capability of individual sensors or densely deploy more static sensors at the cost of more energy.

Usually, a target can be categorized into two classes, i.e., cooperative target and non-cooperative target. The former one can emit cooperative signals (e.g., radio frequencies, vibrations, and sound, etc.) from time to time, which can be interpreted by the sensors. On the other hand, in a lot of applications, many intelligent target would not emit such kind of signals, and the sensors have to actively detect the target by frequently broadcasting certain signals, such as infrared or ultrasonic waves. In this paper, we mainly focus on tracking the non-cooperative target.

It is well recognized that target tracking performances largely depend on both the sensing models and the target maneuvering model. The radio signal strength (RSS) information is widely used in sensor network based tracking system for approximating the distance between sensor nodes and the target. However, the RSS can only provide a highly coarse estimation of distance and requires cooperative targets.

Providing that the target is non-cooperative, there are only a few sensing techniques available for the sensors. Typically, if there is no strong assumptions imposed on the target model such as a constant velocity, a lightweight camera is preferred to provide the target bearing relative to the sensor itself. Note that such a measurement is incapable of estimating the distance between the sensor and the target. Alternatively, ultrasonic sensors are accurate for estimating the relative distance but can only provide a poor estimate of the target bearing. Therefore, in this paper, we consider the mobile sensors equipped with both camera and ultrasonic sensing modules, which means they can sense both the distance and the bearings of the target at the same time.

Consider a wireless sensor network based tracking system as illustrated in Fig. 1. Due to limited capability of the sensors, though a target's presence can be known exactly, it may not be identified or even captured as high sensing quality is required. However, once the sensor network is deployed and keeps static, a target, if given enough intelligence, could be easier to find a path across the field of interest (FoI) and keeps the sensors' views obscure, unless the sensors are dense enough. In this case, the mobile sensors are preferred, which are able to dynamically adjust their positions according to the target movements. Furthermore, the mobility of sensors can also help them to improve their sensing quality at the same time.

☆ This work is partially supported by Natural Science Foundation of China under Grants 61004060, 60974122 and U0735003.

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doi:10.1016/j.comcom.2011.11.004

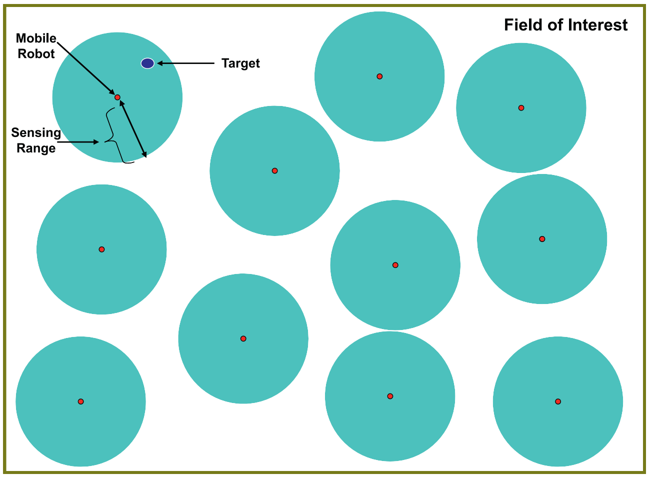


Fig. 1. An illustration of the mobile tracking system based on wireless sensor network.

It is well known that the mobility of sensors provides great opportunity for the enhancement of performance of sensor networks [5–9]. At the same time, it also introduces different kinds of design challenges. Specifically, for mobile sensor networks, it is of great importance to design a dynamic, distributed moving strategy based on the current state-of-the-art fusion technologies so that the sensing quality can be improved. One challenge is that the coverage state may change along with the movement of sensors. For example, if sensors decide their moving strategies just for improving the sensing quality, then all the sensors may gather together to the target vicinity as they do not consider the global area coverage, leaving a large part of the area uncovered. Extremely, if one target shows up at the boundary of the FoI, and moves along one side of the boundary randomly, in the purpose of only achieving optimal sensing quality, all the sensors will probably move towards the target without considering other parts of FoI. At this time, other intruders from the other side of the boundary will keep blind to the sensors, which indicates the failure of the whole monitoring and tracking system. In addition, there are also cases that a subset of the mobile sensors can provide a desired sensing quality, while the other sensors, which will only provide marginal improvement to the sensing quality, can serve to ensure coverage of the FoI. Therefore, with the help of mobility, it is possible and necessary to develop a strategy that jointly considers both sensing and coverage performances simultaneously.

As widely used in many tracking systems with wireless sensor networks, a center node, either dynamically elected or statically assigned, can receive all sensors' measurements and perform data fusion algorithms to obtain the target location. For example, a group leader is elected each time by activating sensors for the target localization. The leader's tracking information is handed over to another newly elected sensor [10]. In this paper, we also assume the existence of the center node, which can decide the moving strategies for the sensors in addition to localizing the target.

The remainder of this paper is organized as follows. A brief literature review is presented in Section 2. Section 3 presents the problem formulation. Section 4 gives a detailed description of the finite horizon optimization algorithm, following which the performance is discussed. The simulation results are shown in Section 6. Finally, Section 7 concludes this paper.

2. Related works

There have been many practical applications of target tracking with wireless sensor networks. For example, underwater mobile vehicles equipped with reconfigurable sensor arrays can be employed to monitor the ocean environment [11]. By introducing virtual bodies and artificial potentials, an adaptive gradient climbing method is proposed for seeking the local maxima or minima in the field of interest.

Considering the problem of cooperatively coordinating a group of mobile robots for localization in 1D and 2D space, Zhang et al. propose a framework for active perception. The performance is measured by the estimate quality of team localization, which relies on the sensing graph and shape of formation [12]. The authors incorporate the formation geometry by using a gradient based scheme in order to improve the localization performance. The authors in [13] investigate two typical multi-robot coordination problems. Specifically, the robot game is modeled as a hybrid system and the control inputs are calculated by solving a mixed integer linear program. Meanwhile the leader–follower formation control problem is dealt with by utilizing the model predictive control.

The multi-agent rendezvous problem is summarized in [14], which aims to design local control laws for each agent so that all the agents eventually rendezvous at a single unspecified location. Note that in their setting, each agent cannot actively communicate with each other but just continuously track the positions of all other agents within its sensing region. The authors propose two kinds of strategies, i.e., one depends on a common clock while the other can be implemented without referring to a synchronized clock.

Our previous work [10] has developed a target tracking and capturing system by using a sensor network and mobile wheeled robots. Specifically, the target state is estimated by static sensors, and the wheeled robot is coordinated to capture the evading target with the help of the communication network. Li et al. further consider an non-cooperative target by using ultrasonic modules [15]. The authors also propose an integrated strategy which allows the mobile sensors to move according to the sensing quality, communication quality and area coverage [16]. Note that, in [16], these three performance metrics are combined together with weighting factors and the problem is solved with a gradient–descent method. There are also some strict assumptions on the motion of the target and the sensors.

The mobility of wireless sensors have also been explored in the literature. Wang et al. survey the recent sensor motion strategies in order to enhance the quality of observation of the field of interest [17]. A virtual force algorithm is designed to improve area coverage by moving sensors [18]. In [19], in the purpose of prolonging the network lifetime, the authors propose an approach to optimize sensor locations in mobile sensor networks. However, it is still an open issue on the sensor movement strategies in the scenario of target tracking with ensured coverage.

In this paper, we aim to extend the idea of [16] in two aspects. First, we intend to design the coordinative moving strategy which minimizes the sensing quality while guaranteeing specified coverage quality, which is more applicable and easier to understood. It should be noted that more performance metrics can also be adopted as constraints, but for clarification, here we just take the sensing quality and coverage quality into account. Second, we will consider the moving strategy over more than one step so that the mobility of the whole network can be fully utilized. We will show that how such a framework can tackle the difficulty of fast target tracking and slow mobile sensors.

The major contributions of this paper can be summarized as follows:

1. Different from [16], we take both sensing quality and area coverage into consideration. We formulate the problem into one which aims to optimize the sensing quality while guaranteeing

certain coverage requirement. The framework can be easily extended to adopt more performance metrics, e.g., connectivity among mobile sensors
2. We take the advantage of sensors' mobility in solving the optimization problem. We utilize the predicted positions of target in a finite horizon to decide the moving strategy of the mobile sensors so that long-term sensing quality can be improved, especially for the case when the speed of the target is comparable or even faster than the mobile sensors.
3. The performances of the proposed method in various aspects are discussed. We also give some guidelines about how to solve the whole problem in a decentralized way.

3. Problem formulation

We assume that M mobile sensors[1] are deployed in the field of interest (FoI) for cooperatively monitoring and estimating the state of the detected targets. Suppose that each sensor has a detection range within which the presence of the target is known exactly. However, the sensing quality of each individual sensor, which will be defined in the following, is tightly related to the distance between the sensor itself and the target. For simplicity, we assume that the sensors are capable of detecting the boundaries of FoI and staying within it automatically. Note that the target does not need to be cooperative.

Suppose the target moves according to the following dynamic process defined in the discrete-time domain

$$\mathbf{x}[k+1] = F\mathbf{x}[k] + \mathbf{W}[k] \tag{1}$$

where $\mathbf{x}[k] \in \mathbb{R}^n$ is the process state in step k, $F \in \mathbb{R}^{n\times n}$ is the linearized process model matrix, and $\mathbf{W}[k]$ represents the model uncertainty. As a simple example, if the target moves with a constant velocity, the state of the target can be its geographical position, i.e., $\mathbf{x}[k] = [\,x_t[k] \quad y_t[k]\,]^T$. In this paper, supposing the target can change its velocity from time to time, we consider a more complicated second-order state, i.e., $\mathbf{x}[k] = [\,x_t[k] \quad \dot{x}_t[k] \quad y_t[k] \quad \dot{y}_t[k]\,]^T$, where $\dot{x}_t$ and $\dot{y}_t$ are the speed in horizontal and vertical directions[2] respectively.

Due to the limited capability of each sensor, its measurement of the target is coarse, which is given by

$$\mathbf{y}_i[k] = [\,d_i[k] \quad \theta_i[k]\,]^T + \mathbf{V}_i[k] \doteq H_i[k]\mathbf{x}[k] + \mathbf{V}_i[k] \tag{2}$$

where $\mathbf{y}_i[k] \in \mathbb{R}^2$ is the observation vector for sensor i, d_i and θ_i are the distance and bearing of the target accordingly in view of the sensor. $H_i[k]$ is obtained by linearizing the equation according to [20]. In the above, $\mathbf{W}$ and $\mathbf{V}_i$, $i = 1,2,\ldots,M$, are assumed to be zero-mean white noises which are independent from each other, with covariance matrices, $Q[k]$ and $R_i[k]$ accordingly. In this paper, the sensory measurement uncertainty, $\{R_i\}$, is modeled as follows

$$R_i = \mathbb{E}\{\mathbf{V}_i[k]\mathbf{V}_i'[k]\} = \begin{bmatrix} \left(\sigma^i_{range}\right)^2 & 0 \\ 0 & \left(\sigma^i_{bearing}\right)^2 \end{bmatrix} \tag{3}$$

where $\left(\sigma^i_{range}\right)^2$ stands for the variance of the range measurement noise, and $\left(\sigma^i_{bearing}\right)^2$ denotes the variance of the bearing measurement noise. Specifically, $\left(\sigma^i_{range}\right)^2$ and $\left(\sigma^i_{bearing}\right)^2$ can be modeled by two functions $f_r(d_i)$ and $f_b(d_i)$, respectively, where d_i is the distance between the target and the ith sensor. As for commonly used lightweight camera, there exists an optimal observing distance from the target, such that either farther or closer to the target will cause the observation obscure.

It should be noted that both $\mathbf{y}_i[k]$ and $\mathbf{V}_i[k]$ are defined in a polar coordinate system with the ith sensor's location $(x_i[k], y_i[k])$ as the origin. Therefore, all the sensory measurements cannot be directly fused. We need to first transfer them into a uniform coordinate system. Supposing that the sensors are aware of their geographical locations, we can define the uniform horizontal and vertical axes without difficulties. After some simple manipulations, the measurement function can be transformed from the polar coordinates to the rectangular ones. Particularly, the measurement noise covariance R_i can be obtained as

$$\overline{R}_i[k] = T_i R_i[k] T_i^T \tag{4}$$

where

$$T_i = \begin{bmatrix} \cos(\theta_i) & -\sin(\theta_i) \\ \sin(\theta_i) & \cos(\theta_i) \end{bmatrix} \tag{5}$$

There are different ways to integrate the sensory information, such as Kalman filtering [21,22], particle filtering [23], etc. Here we assume that the measurements will first be processed locally at each sensor. With the above target model and measurement, each sensor can estimate and predict the target's state recursively by using the well-known Kalman filtering. The main results can be presented as below.

$$\hat{\mathbf{x}}_i[k|k-1] = F\hat{\mathbf{x}}_i[k-1|k-1]$$

$$P_i[k|k-1] = FP_i[k-1|k-1]F^T + Q[k]$$

$$K_i[k] = P_i[k|k-1]H_i^T(H_iP_i[k|k-1]H_i^T + R_i)^{-1}$$

$$P_i[k|k] = (I - K_i[k]H_i)P_i[k|k-1]$$

$$\hat{\mathbf{x}}_i[k|k] = \hat{\mathbf{x}}_i[k|k-1] + K_i[k](\mathbf{y}_i[k] - H_i\hat{\mathbf{x}}_i[k|k-1])$$

where $\hat{\mathbf{x}}_i[k|k-1] := \mathbb{E}\{\mathbf{x}_i[k]|\mathbf{y}_i[0],\ldots,\mathbf{y}_i[k-1]\}$ is the predicted target state form the sensor view at step $k-1$, while $\hat{\mathbf{x}}_i[k|k] := \mathbb{E}\{\mathbf{x}_i[k]|\mathbf{y}_i[0],\ldots,\mathbf{y}_i[k]\}$ is the estimated state. The corresponding prediction and estimation error covariances are denoted by $P_i[k|k-1]$ and $P_i[k|k]$, respectively.

Once the estimates and predictions of the target have been obtained, each mobile sensors need to share its own information with other nodes (see Section 4) to derive more accurate target state. Typically, the collective estimate and prediction can be obtained by using the following fusion algorithm.

$$P^{-1} = \sum_{i=1}^{M} P_i^{-1} \tag{6}$$

$$\hat{\mathbf{x}} = P\sum_{i=1}^{M} P_i^{-1}\hat{\mathbf{x}}_i \tag{7}$$

where $\hat{\mathbf{x}}$ and P are the fused state estimate and the error covariance accordingly[3]. Note that such a strategy utilizes the computation and memory capacity of mobile sensors, and hence we can estimate and predict the distances between the sensors and the target. Subsequently, the sensing noise covariances $\overline{R}_i$ and whereafter the following sensing quality [20] can be obtained.

$$J_{sense} := \det\left[\left(\sum_{i=1}^{M}\overline{R}_i^{-1}\right)^{-1}\right], \tag{8}$$

where $\det[\cdot]$ means the determinate of a matrix.

[1] Indexed from 1 to M.

[2] Possibly, one can consider higher order of the state of the target which could move with time-varying accelerations.

[3] If the right side terms are estimates of the sensors, then $\hat{\mathbf{x}}$ and P correspond to fused estimate. Otherwise, they correspond to fused prediction.

Clearly, by directly optimizing J_{sense}, we may obtain a moving strategy which drives all the mobile sensors to approach the target as close as possible at the next step[4].

As discussed above, we are going to jointly consider the sensing quality and coverage quality. The area coverage can be evaluated as follows

$$J_{cov} = \frac{A_{cov}}{A_{tot}} \tag{9}$$

where A_{cov} is defined as the area covered by at least one sensor and A_{tot} means the total area of the FoI. Undoubtedly, A_{tot} is determined initially once FoI is defined, while A_{cov} depends on the locations of the mobile sensors.

Denote the moving strategy of all the mobile sensors by Θ, which can contain their velocities and accelerations. We are interested in the following problem.

Problem 3.1. Find the optimal Θ that solves

$$\begin{cases} \min & J_{sense} \\ s.t. & J_{cov} \geqslant \Phi \end{cases} \tag{10}$$

where Φ is a given requirement for the area coverage.

Note that all the above functions are all time varying. Usually, it is untractable to completely solve Problem 3.1 in an infinite horizon sense. Moreover, due to possibly high maneuverability of the target and the model noise $\mathbf{W}[k]$ in (1), the error of the model based prediction of the target's location augments along the time. In this case, deciding moving strategy for a sensor accounting for infinitely long time is unnecessary and practically infeasible. Therefore, we try to solve the problem in a finite horizon with the hope of finding a balance between computation complexity and the performance.

4. Finite horizon optimization

Considering a fixed finite horizon window $L \geqslant 1$, we solve Problem 3.1 dynamically. At each step k, we calculate the moving strategy $\Theta = \{\Theta_k, \Theta_{k+1}, \ldots, \Theta_{k+L-1}\}$ for all the sensors in the consecutive time steps from $k+1$ to step $k+L$ so that the average sensing quality from $k+1$ to $k+L$ is minimized while the average coverage constraint is satisfied. And then, we select the best subset of all the sensors to move eventually.

In this section, we first investigate the case when $L = 1$ and only one sensor can move at each step, following which we consider the general case in which $L \geqslant 1$. Finally, we extend the results to allowing more sensors to move at each step, and prove how much improvement can be provided.

4.1. One-step optimization

First of all, we focus on the one-step optimization, which aims to find out the best sensor at each time k that solves the following optimization problem (a variant of Problem 3.1).

$$\begin{cases} \min\limits_{\Theta_k} & J_{sense}^{k+1} \\ s.t. & J_{cov}^{k+1} \geqslant \Phi \end{cases} \tag{11}$$

Chung et al. has proposed a gradient descent based method for purely optimizing J_{sense} [24]. Considering the range and bearing coordinates in the polar coordinate system, i.e., d_i and θ_i for the ith sensor, the gradient of J_{sense} can be expressed as

[4] In fact, because of the measurement noise, they are not necessary to approach the target as close as possible, but maintain certain distances governed by the measurement noise

$$\nabla_{r_i,\theta_i} J_{sense}(r_i, \theta_1, \ldots, r_M, \theta_M) = \frac{\partial J_{sense}}{\partial r_i} e_{r_i} + \frac{1}{r_i}\frac{\partial J_{sense}}{\partial \theta_i} e_{\theta_i} \tag{12}$$

Then the local motion of sensor i can be obtained by

$$u_{sens,i}(r_i, \theta_i) = \left[\left(\frac{\partial J_{sense}}{\partial r_i}\right), \frac{1}{r_i}\left(\frac{\partial J_{sense}}{\partial \theta_i}\right)\right] \tag{13}$$

where

$$u_{sens,i}(x_i, y_i) = T_i^T u_{sens,i}(r_i, \theta_i) \tag{14}$$

In order to account for the area coverage, we first introduce the function $\Omega_i(x_t, y_t) = \Omega(x_t, y_t, x_i, y_i, r_i)$ to represent if the target location (x_t, y_t) is within the detection range r_i of sensor i which located at (x_i, y_i), i.e.,

$$\Omega_i(x_t, y_t) = \begin{cases} 1, & \|(x_t, y_t) - (x_i, y_i)\| \leqslant r_i \\ 0, & \text{otherwise} \end{cases} \tag{15}$$

where $\|\cdot\|$ represents the Euclidean distance between two points in the FoI.

For evaluating the coverage quality, J_{cov} can be calculated according to (9)

$$\begin{aligned} J_{cov} &= \frac{1}{A}\oint_A \left[1 - \prod_{k=1}^{M}(1 - \Omega_k(x, y))\right] dxdy \\ &= 1 - \frac{1}{A}\oint_A \prod_{k=1}^{M}(1 - \Omega_k(x, y)) dxdy, \end{aligned} \tag{16}$$

where M is the number of sensors in the area A. Note that $1 - \Omega_i = 0$ when the point (x_t, y_t) is within the detection range of sensor i.

At this point, we are ready to present the one-step optimization algorithm, whose main procedures are summarized in Algorithm 1. Note that the lower bound for coverage, i.e., Φ, should not be too large in order to avoid that the condition may always be violated. Meanwhile, we may also dynamically tune the parameter Φ to balance the sensing quality and area coverage without any difficulty.

Algorithm 1. One-Step Optimization

```
Require Coverage Constraint Φ
calculate the gradients of J_sense;
sort the sensors according to the gradients;
for i = 1 : M do
    check whether the coverage constraint Φ is satisfied;
    if true then;
     select output sensor i;
  end
end
```

4.2. Multi-step optimization

We can further improve the performance by utilizing the multi-step predicted values of the targets. Specifically, we hope to find the best sensor at time k, so that the average sensing quality in the consecutive L steps is minimized while the average coverage requirement is still satisfied. The optimization problem is as follows.

$$\begin{cases} \min\limits_{\Theta_k} & \frac{1}{L}\sum\limits_{i=1}^{L} J_{sense}^{k+i} \\ s.t. & \frac{1}{L}\sum\limits_{i=1}^{L} J_{Cov}^{k+i} \geqslant \Phi \end{cases} \tag{17}$$

It is not difficult to extend the results of Section 4.1 to solve the above problem. It is interesting that $J_{cov}^{k+i} = J_{cov}^{k+1},\ i = 2, 3, \ldots, L$. Thus we only have to deal with the average sensing quality, i.e., $\frac{1}{L}\sum_{i=1}^{L} J_{sense}^{k+i}$.

Note that when the predicted positions of the target are taken into account, it is possible to evaluate how the current motion would affect the sensing quality not only at the next step but also at the consecutive finite steps. Hence it is expected that the long-term average sensing quality can be improved. It should be emphasized that in (17), J_{sense}^{k+i} is the value calculated from the time k without considering the possible movement of other sensors in the consecutive later time steps.

It should be pointed out that we may not need to consider a large length of finite horizon. For example, if the speed of sensor is less than the target, then after a certain period, no matter how to move the sensor, it would be becoming far away from the target. In this case, there might be a threshold L_m, which has taken use of all the predicted information so that, no obvious improvement will be gained by further enlarging L.

4.3. Multiple sensors

Until now, we just consider the case that only one sensor can move at each step. The method can be adapted to allow multiple sensors to move simultaneously. To this end, we need to calculate the gradients of J_{sense} according to different subset of mobile sensors, and choose the best subset which minimizes the gradient while maintaining the coverage requirement. Then one normal question is how to decide the required number of sensors which are allowed to move at each time step.

In general, the performance of both tracking and coverage would get improved by allowing more sensors to move at each time step, while the computational complexity will also increase dramatically at the same time. On the other hand, the improvement of performance will not be obvious once the number of sensors, which are allowed to move collaboratively, is larger than a threshold. For given speed value of target and sensors, by simulation, we can find a suggesting number of sensors which are able to guarantee required tracking and coverage performance. Moreover, in practice, we can further increase/decrease the allowable number of sensors according to the on-line performance. We will show in Section 6 how the number of sensors selected at each time affect the overall performance.

5. Performance discussions

There are some key factors which affect the whole system performances, such as the number of mobile sensors, the speed of the target as well as that of the sensors, the detection range of the sensors, and the coverage requirement, which in all makes an analytical performance evaluation very hard. In this part, we aim to discuss how those factors would affect the performance and shed light on the energy consumption, computation complexity, scalability, etc.

5.1. Tracking and coverage performance

Consider the extreme case that the FoI can always be fully covered no matter how the sensors move, i.e., the area coverage is ensured. Even for this simple case, it is still quite difficult to give an analytical expression of the achievable sensing quality. Therefore, consider two typical cases as follows.

1. The speed of target is neglectable compared with that of the sensors. In this case, the sensors can move into their aimed positions without worrying about the time cost, as if the target almost remained at the same place. Thus, there would be no need to further utilize the predicted position of the target, and it would be understandable that the one-step optimization would be enough to obtain the optimal solution. Furthermore, in this situation, once the target has been detected, the sensing quality, i.e., J_{sens}, would almost be the optimal one at all time. Moreover, such a strategy also guarantees that the average sensing quality is very close to the optimal one.
2. The speed of target is not neglectable compared with that of the sensors. In this case, the target would move a considerable distance when the sensors are adjusting their positions. Hence, the decision of mobile sensors should not ignore the moving pattern of the target. Suppose the predicted positions of the target are accurate enough in the next consecutive time steps, then by solving (17), the algorithm can move those who are located near those predicted positions in advance. This can be implemented by utilizing the communication to compensate the shortcoming of sensors speed and hence improve the average sensing performance as it is impossible to instantly reduce the current tracking error.

If the coverage constraint is taken into account, the situation would become much more complicated. Generally speaking, in order to improve the sensing quality, the sensors would like to approach the target, hence reduce the coverage performance. From this aspect of view, it is expected that the proposed algorithm would gradually reduce the coverage performance which can be shown in the simulation part.

5.2. Energy consumption

Consider the energy cost for mobility. It would be desirable to move as less sensors as possible so that the energy expenditure for moving, communication and computation can be saved and hence the network lifetime can be prolonged. In order to save both moving and computation energy, the number of sensors, which are allowed to move at each time step, should be reduced as long as the performance requirement can be satisfied. Hence once the required sensing quality has been met, we may reduce the number of sensors allowed to move at each time so that the energy cost can be reduced. Practically, a dynamic scheme can be used so that the number of sensors can be changed at each time step according to the performance achieved. In the simulation part, we will show how the number of moving sensors at each time affects the sensing quality as well as the area coverage.

The communication energy is mainly consumed for information collection and motion coordination. The mobile sensors are required to report its information to the sink node periodically at each time step, while the sink node will coordinate the corresponding nodes to move after information fusion and on-line optimization. Therefore, in order to save the communication energy, it is always better to reduce the sampling rate once the required tracking performance can be satisfied.

5.3. Computation complexity

The complexity of the algorithm depends on two aspects: (1) The computation complexity of J_{cov} grows with the total number of sensors in the area. However, once the area can always be covered, there would be no need to calculate J_{cov} any more. It should be emphasized that by revising the definition of Ω_i accordingly, (16) can still be used for different kinds of sensing shape. (2) The computation complexity of the gradients grows with the number of sensors in the area, the number of sensors which are allowed to move at each step, and the time horizon L.

Normally, for monitoring with mobile sensors, the number of sensors in the FoI can be considered the same all the time. On the other hand, the number of sensors allowed to move at each step and the time horizon L also contribute on the sensing and area coverage performance, thus it is interesting and meaningful to balance the performance and computation complexity by properly choosing these two parameters.

Currently, it is still too difficult to give an analytical expression for the two parameters in advance. Basically, when the speed of target is too small compared with that of the sensors, L can be set to *1* without loss of generality. On the other extreme when the speed of target is too large, we may use a moderate L as the motion of a currently nearby sensor cannot affect the sensing performance after a long time because the target has been out of its detection range.

5.4. Scalability

Note that the proposed algorithms in these paper are centralized solutions. There are two constraints for centralized algorithms, i.e., the access to global information, and the computational burden. In this paper, we mainly focus on the case when the communication and computation is much faster than the motion of target and sensors so that the problem can be solved in a centralized way. However, for large-scale wireless sensor networks, a centralized computation and coordination would become impractical. In this case, since the movement of target would be not so fast to cover the whole area of all sensors, we may be able to dynamically select a cluster according to the position of target so that the task can be realized within the cluster while the task itself can be relayed between two clusters.

5.5. On relaxing the assumptions

As the communication is fast and the communication range is large compared with the motion of target and sensors, the assumption of a fully connected communication graph is not so conservative, and thus the full information can be utilized to achieve the optimal solution at each time step. However, if the assumption is removed, the sensors have to made their decisions based on their local information.

In this case, we can extend the results above in a simple way. For example, for one-step optimization, we can simply rewrite the constraint of coverage to be $A_{cov}^{k+1} \geqslant f\left(M_l, A_{cov}^k\right)$, where A_{cov}^{k+1} represents the area covered by the local subset of sensors containing M_l sensors). This new constraint means the local subset of sensors must guarantee certain covered area at the next time step which relates to the number of local sensors and previous covered area. Meanwhile, the objective function can be modified for the local subset of sensors.

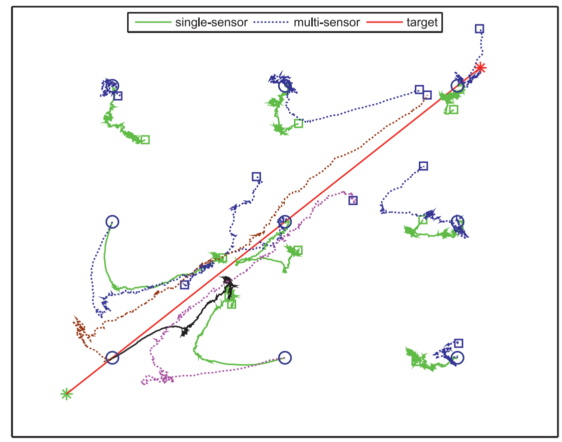
6. Simulations

We conduct extensive simulations to validate our design and evaluate the performances of the proposed algorithms. In a 50×50 2D FoI, totally 9 sensor nodes are deployed, each of which carries both a lightweight camera and an ultrasonic sensor. All their detection ranges are 9, i.e., $\forall 1 \leqslant i \leqslant 9, r_i = 9$. Initially, the sensors are uniformly distributed within the FoI with coverage 84%, which is also the best coverage that the sensors are able to achieve. The coverage threshold of the FoI is 70% of the best coverage, i.e., $\Phi = 58.8\%$. The target moves simply from the bottom left corner to the top right corner with a constant velocity. For the target movement model as shown in (1), the parameters are set as

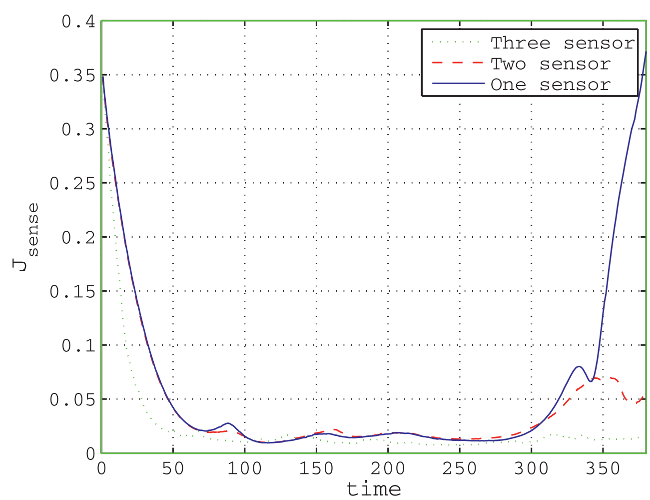
$$F = \begin{bmatrix} 1 & 1 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 1 \\ 0 & 0 & 0 & 1 \end{bmatrix}, \quad Q = \begin{bmatrix} 1 & 1.5 & 0 & 0 \\ 1.5 & 3 & 0 & 0 \\ 0 & 0 & 1.5 & 1.5 \\ 0 & 0 & 1.5 & 3 \end{bmatrix}.$$

The sensors' measurement noises variances are

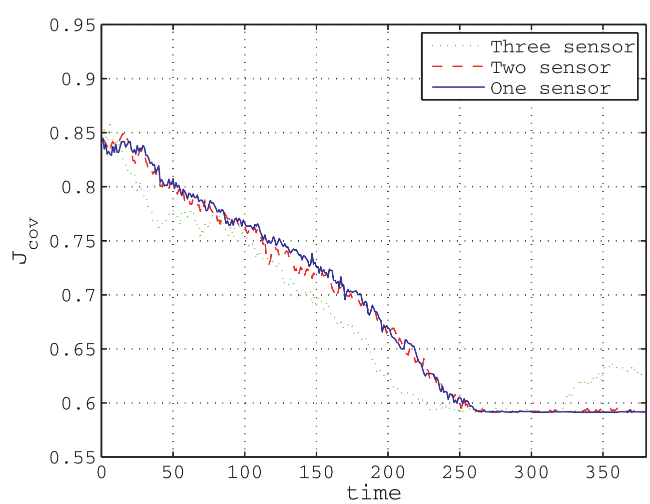
$$f_r(d_i) = a_2|d_i - a_1| + a_0,$$
$$f_b(d_i) = \alpha f_r(d_i),$$



(a) Traces of sensors and target



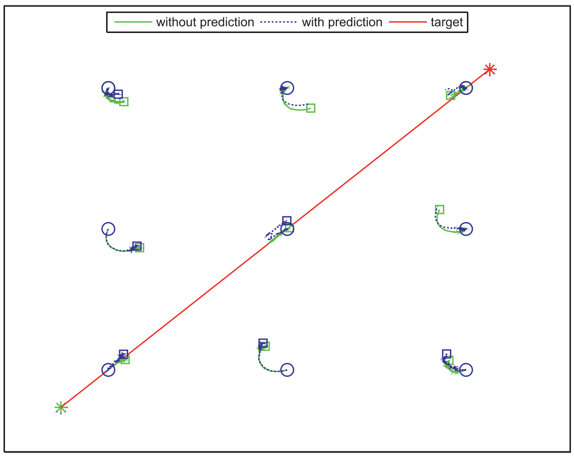
(b) Evolution of J_{sense}



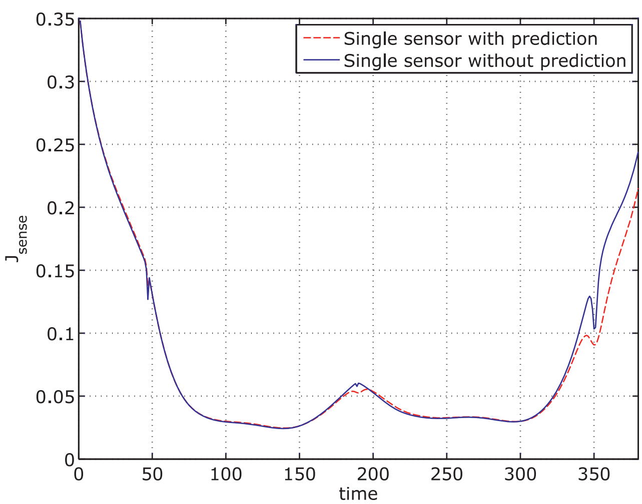
(c) Evolution of J_{cov}

Fig. 2. Performances between single-sensor and multi-sensor cases without prediction, where $v_s = 0.1$, $v_t = 0.1$.

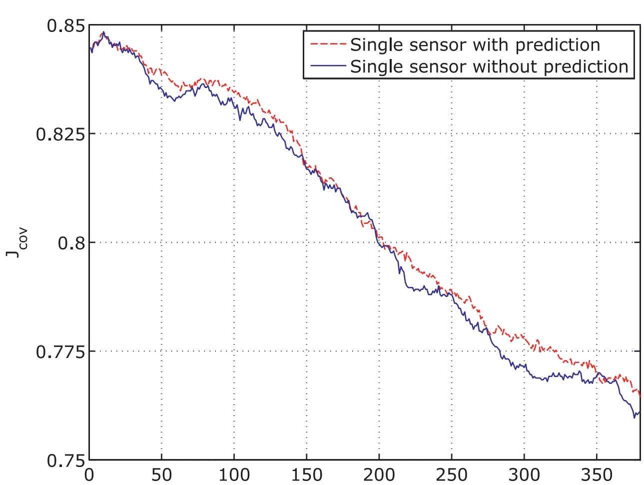
with $a_0 = 20$, $a_1 = 5$, $a_2 = 0.8$ and $\alpha = 0.01$. Obviously the optimal observation distance is 5.



(a) Traces of sensors and target



(b) Evolution of J_{sense}

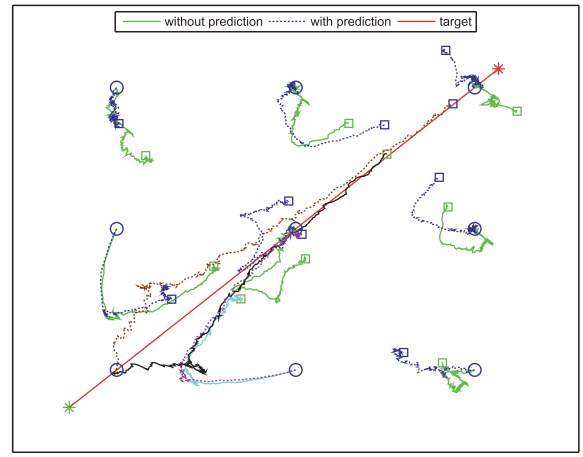


(c) Evolution of J_{cov}

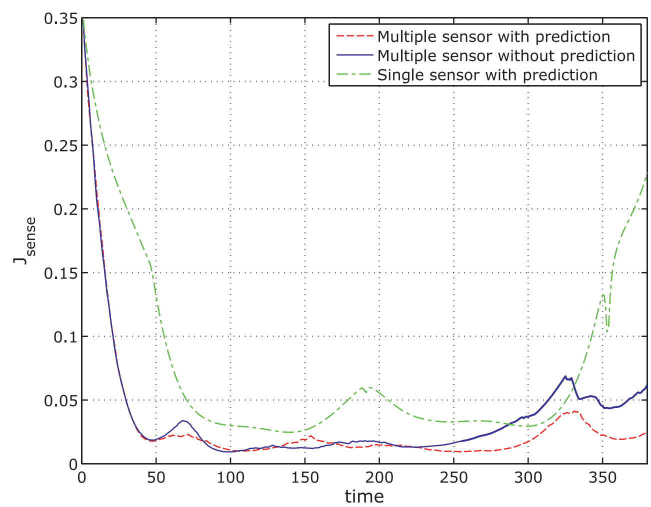
Fig. 3. Performances with and without prediction under single-sensor case, where $v_s = 0.02$, $v_t = 0.1$.

6.1. Performances of Algorithm 1

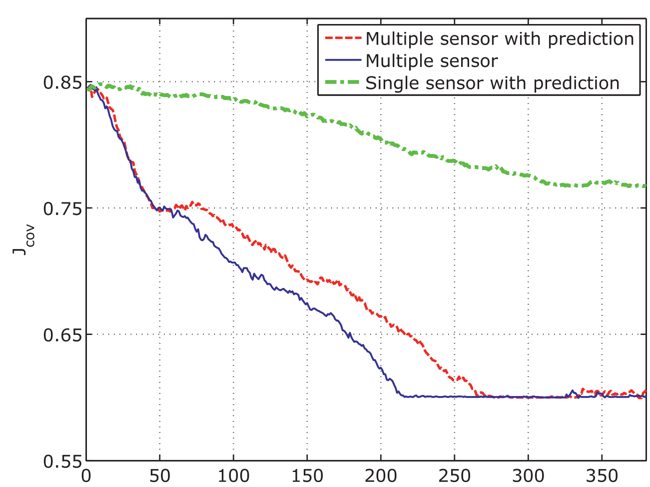
We first consider the case that the target moves at most as fast as the sensor. Let the target's speed $v_t = 0.1$ and the sensors' speed



(a) Traces of sensors and target in multi-sensor case



(b) Evolution of J_{sense}



(c) Evolution of J_{cov}

Fig. 4. Performances comparison between single-sensor and multi-sensor cases with and without prediction, where $v_s = 0.02$, $v_t = 0.1$.

$v_s = 0.1$. Algorithm 1 is applied for the single-sensor case, i.e., only one sensor is allowed to move at each step. As can be observed from Fig. 2(a), the optimization force the sensors to move close to the target to improve sensing quality. Because of both the bounded coverage and limited speed, the sensors cannot get any closer to the target at each moment, resulting that the sensing quality first decreases and then increases, as shown in Fig. 2(b). Apparently, when the target moves to the center of the FoI, its average distance from the sensors is the smallest, and thus the sensing quality is roughly the best. From Fig. 2(c), we can conclude that the sensing quality is improved at the cost of degrading the coverage quality. Fortunately, as a lower coverage bound is guaranteed, the whole system is actually dynamically optimized by taking the advantage of the mobility of sensors.

6.2. The effect of multiple sensors

When the speed of target is considerable, selecting only one sensor in each step may not be enough. In this case, we move multiple sensors at each time by exploring the cooperation among the mobile sensors. We independently conduct three more groups of simulations in which 1, 2 and 3 sensors can move at each time, respectively. From Fig. 2, it is clear that the benefit of using multiple sensors is obvious since the sensing quality is improved almost all the time with guaranteed coverage bound. Moreover, we can see that the more sensors move at each time, the better sensing quality can be achieved. However, such improvement becomes trivial when more than 3 sensors move at each time.

6.3. The effect of multi-step prediction

When the target moves faster than the sensors themselves, the current state estimate would not be enough to guide the movement of sensors, and is likely to lose the target. This may be tackled by further utilizing the predicted positions of the target. By applying our multi-step optimization method, the sensing quality can be improved. The simulation results for single-sensor case are shown in Fig. 3, where the target and sensors speeds are set to be $v_s = 0.02$ and $v_t = 0.1$ respectively. For the multi-step method, L is set to be 3. Since the sensors move much slower compared with the target, moving only one sensor at each time is far from enough for the requirement of tracking performance. And that is why the sensor traces are very similar with and without predicting the target's location in the multi-step method. However, even for this case, we can still observe that the sensing quality is improved by employing the predictions from Fig. 3(b). The effectiveness of using the predictions is more clearly shown under the multi-sensor case, as in Fig. 4. Intuitively, we can say that comparing with the multi-step optimization, single-step optimization falls short-sighted.

From Fig. 4, it can be observed that even for the case when the speed of sensors is much less than the target, cooperatively moving strategy does provide much better performance. What's more, by taking the predictions of target state into account, the tracking performance can be further improved.

7. Conclusion

In this paper, we propose a gradient-based motion control strategy, for target tracking with mobile sensors, which also takes the area coverage into consideration. The mobility of sensors is explored to improve the sensing quality while guaranteeing the coverage requirement. We investigate how the finite optimizing horizon affects the sensing quality as well as the area coverage. Moreover, we examine how to collaboratively move multiple sensors so that the sensing quality can be improved even if the sensors' speed is not comparable to the target's.

Our future work includes relaxing some assumptions, e.g., using more realistic, possibly more complex, models for the target and sensors, designing decentralized algorithms, and conducting experimental validations.

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