Proceedings of the 30th Chinese Control Conference
July 22-24, 2011, Yantai, China

Target Tracking with Guaranteed Coverage in Autonomous Mobile Sensor Networks

BAI Jing, CAO Xianghui, CHENG Peng, CHEN Jiming, SUN Youxian

State Key Lab of Industrial Control Technology, Zhejiang University, Hangzhou 310027, P. R. China
E-mail: jing.bai1987@gmail.com; {xhcao, pcheng, jmchen, yxsun}@iipc.zju.edu.cn

Abstract: The advancements in robotics and wireless communication provide a good opportunity to combine the mobility and wireless sensor networks so that different objectives can be satisfied simultaneously with less required resources. Specifically, mobility enables the sensors to dynamically adjust their positions for better sensing quality, and offers a higher probability for guaranteeing the coverage required at the same time. In this paper, we propose a novel coordinating scheme for autonomous mobile sensor networks so that the target sensing quality is optimized while the coverage requirement of the field of interest is also guaranteed. The whole problem is transformed into one finite horizon optimization problem, which is then solved efficiently. Extensive simulations demonstrate the effectiveness of the proposed method.

Key Words: Mobile Sensor Networks, Target Tracking, Coverage

1 Introduction

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

Target Tracking is a critical problem in the field of sensor networks [1]. Commonly, static sensors are deployed to detect the mobile target. Once the information captured by multiple sensors is available to a center node, which can be the head of activated sensors for tracking [2], information fusion strategies can be applied to abstract the desirable system state from the sensory measurements. However, for such kind of networks, in order to improve the tracking performance, we have to either enhance the capability of individual sensors or cost more energy.

Consider a mobile tracking system based on wireless sensor network. Due to limited capability of the sensors, within their sensing ranges, a target's presence can be known exactly, but it may not be identified or even captured in which high sensing quality is required. In applications where target identification and other higher services are demanded, tracking becomes not enough. Once the sensor network is deployed and keeps static, a target, if given enough intelligence, could find a best path that crosses the field of interest (FoI) and keeps the sensors' views obscure, unless the sensors are dense enough. In this case, mobile sensors are preferred, which are able to dynamically adjust their positions according to the target movements, making it uneasy to find a best cross path.

It is well recognized that sensors mobility provides great opportunity for the enhancement of performance of sensor networks [3]. At the same time, it also introduces different kinds of design challenges. One challenge is that the coverage state may also change along with the movement of sensors. For example, if sensors decide their moving strategies based on only sensing quality, as they do not consider the global area coverage, the results may force all the sensors gather together to the target vicinity, leaving a large part of the area uncovered. In addition, there are also cases that a subset of the mobile sensors have been enough to provide a desired sensing quality, and the other sensors will only provide very small improvement for sensing. 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 used in many tracking systems that based on wireless sensor networks, there exists a center node, either dynamically elected or statically assigned, that receives all sensors measurements and performs data fusion algorithms to obtain the target location. For example, a group leader is elected each time by activated sensors for target localizing. The leader's tracking information is handed over to another newly elected sensor [4]. In this paper, the center node is also assumed, which decides the moving strategies for the sensors in addition to localizing the target.

2 Related Works

Wireless sensor networks have many practical applications in target tracking. For example, underwater mobile vehicles equipped with reconfigurable sensor arrays are employed to monitor the ocean parameters [5]. 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 depends on the sensing graph and shape of formation [6]. The authors use a gradient based scheme to incorporate the formation geometry for improving the localization performance.

The authors in [7] investigates the 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.

Our previous work [4] has developed a target tracking and capturing system by using sensor networks and mobile wheeled robots. Specifically, the target states are estimated by static sensors and the communication network helps the wheeled robot to capture the evading target. Li *et al.* further consider an non-cooperative target by using ultrasonic modules [8] and [9]. The authors also propose an integrated strategy which allows the mobile sensors to move according to the sensing quality, communication quality and area coverage [10]. Note that, in [10], the three performance indexes are combined together with weighting factors and the problem is solved with a gradient-descent method. There are also some strict assumptions on the moving types of the target and the sensors.

In this paper, we aim to extend the idea of [10] 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 indexes 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 difficult of fast target and slow mobile sensors.

The contributions of this paper can be summarized as follows

1) We take both sensing quality and area coverage into consideration, and formulate the problem into one which optimizes the sensing quality while guaranteeing certain coverage requirement, which is different from the previous work [10]. The framework can be easily extended to adopt more performance indexes, e.g., connectivity among mobile sensors.
2) We utilize the predicted positions of target in a finite horizon to decide the moving strategy of the mobile sensors so that the 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) Our strategy allows multiple sensors to move at each time step, so that they can collaboratively decide their moving pattern, which further helps to improve the sensing quality while guaranteeing the area coverage constraint.

The paper is organized as follows. Section 3 presents the formulation of problem. Section 4 presents the finite horizon optimization algorithm, following which the algorithm's performances are deeply discussed. Section 6 describes the simulation results. Finally, Section 7 concludes the paper.

3 Problem Formulation

Totally M mobile sensors (indexed from 1 to M) are deployed in the field of interest (FoI) for cooperatively detecting the intruder and further estimating the state of the detected target. 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 itself and the target. For simplicity, we assume that the sensors are capable of detecting the boundaries of FoI and stay within automatically. Note that the target does not need to be cooperative.

Due to limited capability of each sensor, its measurement about the target is coarse. In this paper, we use the covariance matrices $\{R_i\}$ to model the sensory measurement uncertainties. It is well known that different forms of R_i can be derived depending on both the sensory models and the target maneuvering model for tracking. The radio signal strength (RSS) information is commonly used in sensor network based tracking system for approximating the distance between sensor nodes and the target, which, however, is just a highly coarse estimation and requires the target to be cooperative (i.e., the target can emit radio frequencies from time to time that can be received by the sensors). Providing that the target is non-cooperative, there are only a few sensing techniques available for the sensors. Typically, if without imposing strong assumptions on the target model such as constant velocity, a lightweight camera that can be carried by the sensor is preferred to provide the target bearing relative to it. However, such measurement is insufficient for estimating the distance between the sensor and the target. Alternatively, ultrasonic sensors are some accurate for estimating the relative distance but can only provide a rough estimate of the target bearing. Therefore, in this paper, we consider the mobile sensors 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.

Suppose the target moves according to the following dynamic process defined in 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 $\mathbf{W}[k]$ gives the model uncertainty. As a simple example, if the target moves with constant velocity, the state of the target can be its geographical position, i.e., $\mathbf{x}[k] = \begin{bmatrix} x_t[k] & y_t[k] \end{bmatrix}^T$. In this paper, supposing the target can change its velocity from time to time, we consider a more complicated second-order state, i.e., $\mathbf{x}[k] = \begin{bmatrix} x_t[k] & \dot{x}_t[k] & y_t[k] & \dot{y}_t[k] \end{bmatrix}^T$, where $\dot{x}_t$ and $\dot{y}_t$ are respectively the target's speed in horizontal and vertical directions[1]. And the observation model for the i-th sensor is given by

$$\begin{aligned} \mathbf{y}_i[k] &= \begin{bmatrix} d_i[k] & \theta_i[k] \end{bmatrix}^T + \mathbf{V}_i[k] \\ &\doteq H_i[k]\mathbf{x}[k] + \mathbf{V}_i[k] \end{aligned} \tag{2}$$

where $\mathbf{y}[k] \in \mathbb{R}^2$ is the observation vector, d_i and θ_i are respectively the distance and bearing of the target in view of the sensor. $H_i[k]$ is obtained by linearization according to [11]. In the above, $\mathbf{W}$ and $\mathbf{V}_i$, $i = 1, 2, \cdots, M$, are assumed zero-mean white noises which are independent from each other, with covariance matrices, $Q[k]$ and $R_i[k]$ accordingly. The covariance matrices for the i-th sensor is described by

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

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

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

It should be noticed that both $\mathbf{y}_i[k]$ and $\mathbf{V}_i[k]$ are defined in such a polar coordinate system with the i-th sensor's location $(x_i[k], y_i[k])$ as the origin. Therefore, all the sensory measurements cannot be directly combined. We need to first transfer them into a common coordinate system. Supposing that the sensors are aware of their geographical locations, we can define common horizontal and vertical axes which form a rectangular coordinate system. After simple manipulations, the measurement function can be transform from polar to rectangular coordinates, and particularly, the measurement noise covariance R_i can be transformed to

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

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 [12], particle filtering [13]. Here we assume that the measurements will first be processed locally at each sensor. With the above target model and sensor's measurement, each sensor can estimate and predict the target's state recursively by using the well-known Kalman filtering. The main results are shown as below.

$$\begin{aligned}
\hat{\mathbf{x}}_i[k|k-1] &= F\hat{\mathbf{x}}_i[k-1|k-1] \\
P_i[k|k-1] &= FP_i[k-1|k-1]F^T + Q[k] \\
K_i[k] &= P_i[k|k-1]H_i{}^T\left(H_iP_i[k|k-1]H_i{}^T + R_i\right)^{-1} \\
P_i[k|k] &= \left(I - K_i[k]H_i\right)P_i[k|k-1] \\
\hat{\mathbf{x}}_i[k|k] &= \hat{\mathbf{x}}_i[k|k-1] + K_i[k]\left(\mathbf{y}_i[k] - H_i\hat{\mathbf{x}}_i[k|k-1]\right)
\end{aligned}$$

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 by the sensor viewing in 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 $P_i[k|k-1]$ and $P_i[k|k]$, respectively.

Upon obtaining estimates and predictions of the target, the mobile sensors should share this information with other nodes (see Section 4) to achieve more accurate target state. The collective estimate and prediction are obtained by 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[2]. Note that such a strategy utilizes the computation and memory capacity of mobile sensors. With such information, we can estimate and predict the distances between the sensors and the target. Subsequently, the sensing noise covariances $\bar{R}_i$ and hence the following sensing quality [11] can be estimated and predicted.

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

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

Clearly, by directly optimizing J_{sense}, we may obtain a moving strategy which drives all the mobile sensors approaching the target[3]. As have been discussed above, we are going to jointly consider the sensing quality and coverage quality. One expression for measuring the area coverage can be defined 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 upon FoI is defined, while A_{cov} depends on the movements of the mobile sensors.

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

Problem 3.1 *Find the optimal Θ that solves*

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

where Φ is a given requirement for the area coverage.

Note that all the above functions are all time varying. It might be untrackable 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 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 senseless and practically infeasible. Therefore, we try to solve the problem in a finite horizon with the hope to find a balance between computation complexity and the performance.

4 Finite Horizon Optimization

Consider a fixed finite horizon window $L \geq 1$, we propose in the following an algorithm to solve the problem dynamically. At each step k, we calculate for all the sensors, in the consecutive time steps from $k+1$ to step $k+L$, the moving strategy $\Theta = \{\Theta_k, \Theta_{k+1}, \cdots, \Theta_{k+L-1}\}$, so that the average sensing quality from $k+1$ to $k+L$ is minimized while the average coverage constraint is satisfied at the same time. And then, we select the best subset of all the sensors to move actually.

[2] 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.

[3] 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

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 $L \geq 1$ case. 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 investigate one-step optimization, in which we aim to find out the best sensor at each time k that best solves the following optimization problem (a variant of Problem 3.1).

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

Chung *et al.* has proposed a gradient descent based method for purely optimize J_{sense} [14]. Considering in the polar coordinate system the range and bearing coordinates, d_i and θ_i for the i-th sensor, the gradient of J_{sense} can be expressed as

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

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 sensing range r_i of sensor i which located at (x_i, y_i), i.e.,

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

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

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

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

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

4.2 Multi-Step Optimization

By utilizing the multi-step predicted value of the targets, we can find out 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, which means

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

It is not difficult to extend the results of Section 4.1 to solve the problem above. 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., $\frac{1}{L} \sum_{i=1}^{L} J_{sense}^{k+i}$.

Remark 4.1 *Note that when the predicted positions of target can be 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 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.*

Remark 4.2 *It should be pointed out that the length of finite horizon need not to be too large. For example, if the speed of sensor is less than the target, then after a certain period, no matter how to move one sensor, it would be becoming far away from the target. Additionally, with the growing of L, the accuracy of estimation would also deteriorate due to the inaccurate model and measurement, which makes the information less useful or even misleading. In this case, there should be L_m, which has taken use of all the predicted information so that, no obvious improvement will be gained by further enlarging L.*

Remark 4.3 *Until now, we just consider that only one sensor can move at each step. Clearly, the solution can be extended to allow multiple sensors to move simultaneously. We just 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.*

5 Performance Discussion

The sensing and coverage performance would depend on the number of mobile sensors, the speed of the target as well as the sensors, the sensing range of the sensor, and the coverage requirement, which make an analytical evaluation very hard. In this section, we would like to discuss the performance of the proposed method in details.

Consider an extreme situation that the FoI can always be fully covered no matter how the mobile sensors moves. This is possible when the sensing range of the mobile sensor or the number of mobile sensors is large enough. In this case, the area coverage would be no problem. Even for this simplified case, it is still quite difficult to give an analytical expression of the sensing quality. 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 position without worrying the time cost as the target would almost remain the same place. Thus, there would be no need to further utilize the predicted position of the target, and it would be understandable that 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 all the 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 away 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 which locate near those positions in advance, which utilizes the communication to compensate the lack of speed and hence improve the average sensing performance as it is impossible to instantly reduce the current tracking error.

Remark 5.1 *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 position where they can obtain the best observation of 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.*

6 Simulations

We conduct extensive simulations to validate our design and evaluate the performances of the proposed methods. In a 50×50 2D FoI, totally 9 sensor nodes are deployed, each of which carries both a lightweight camera and an ultrasonic sensor. Their sensing ranges are all 9, i.e., $\forall 1 \leq i \leq 9, r_i = 9$. Initially, the sensors are uniformly distributed across the FoI with coverage 84%, which is also the best coverage 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. In the target movement model as shown in (1), the parameters are set as

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

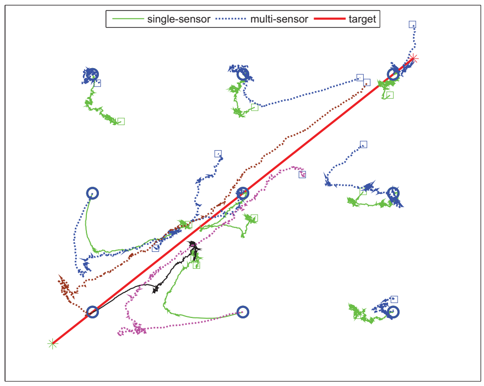
The sensors' measurement noises variances are assumed as:

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

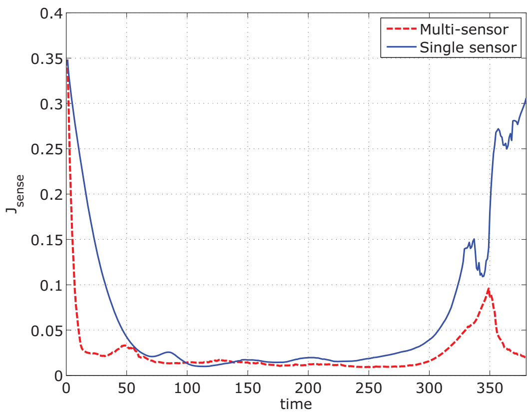
with $a_0 = 20, a_1 = 5, a_2 = 0.8$ and $\alpha = 0.01$. Obviously the optimal observation distance is 5.

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 $v_s = 0.1$. Under the single-sensor case, as can be seen from Fig. 1(a), the optimization often leads to the sensors moving close to the target. Because of both the coverage bound Φ and limited speed, the sensors can not keep close to the target, resulting a first decrease and then increase in J_{sense} as shown in Fig. 1(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. 1(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 taking the advantaged of the mobile sensors.

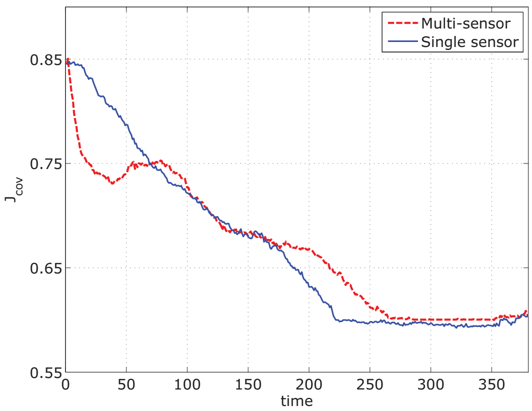
We conduct independently another group of simulations where 2 sensors are chosen each time. Clearly shown by Fig. 1, the sensors' moving range under multi-sensor case is larger than that under single-sensor case. The benefit of using multiple sensors is obvious that the sensing quality is improved almost all the time with guaranteed coverage.



(a) Traces of sensors and target



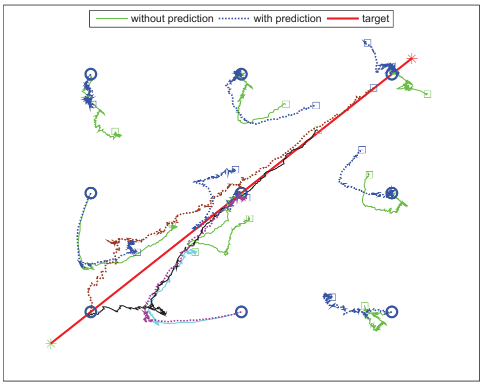
(b) Evolution of J_{sense}



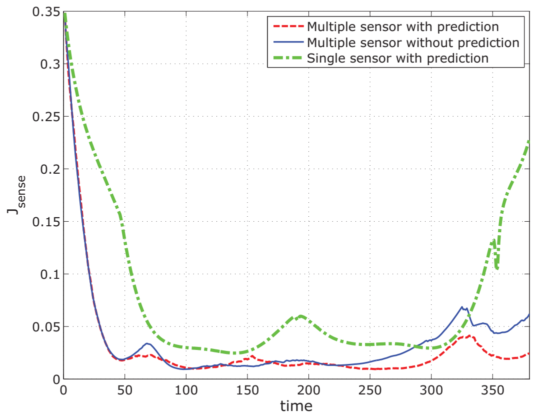
(c) Evolution of J_{cov}

Fig. 1: Performances between single-sensor and multi-sensor cases without prediction, where $v_s = 0.1, v_t = 0.1$.

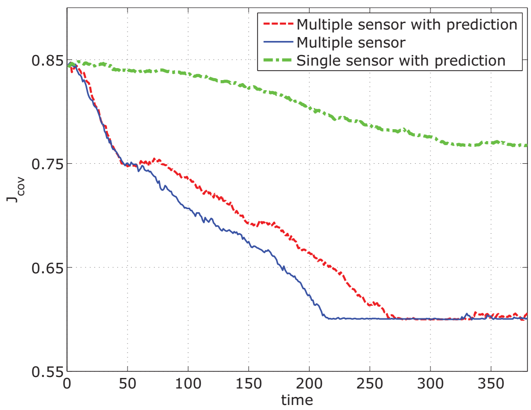
When the target moves faster than the sensors themselves, then if they still use the target state estimates to guide their movements, they will likely loss the target. By applying our multi-step optimization method, the simulation results under single- and multiple- sensor case are shown in Fig. 2, where the target and sensors speeds are respectively $v_s = 0.02$ and $v_t = 0.1$. We choose $L = 3$ for the multi-step method. Since the The power of predictions is more clearly shown under the multi-sensor case as in Fig. 2. We can also observe that the performance improvement caused by selecting more sensors is larger than that by applying the multi-step optimization method.



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



(b) Evolution of J_{sense}



(c) Evolution of J_{cov}

Fig. 2: Performances comparison between single-sensor and multi-sensor cases with and without prediction, where $v_s = 0.02, v_t = 0.1$.

7 Conclusion

In this paper, for target tracking with mobile sensors, we propose a gradient-based decentralized motion control strategy 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 the sensors' speed is not comparable to the target's.

References

[1] L. Song and D. Hatzinakos. A cross-layer architecture of wireless sensor networks for target tracking. *IEEE/ACM Transactions on Networking (TON)*, 15(1):145–158, 2007.

[2] J. Chen, K. Cao, Y. Sun, and X. Shen. Adaptive sensor activation for target tracking in wireless sensor networks. In *IEEE International Conference on Communications, ICC'09*, pages 1–5, 2009.

[3] G. Xing, J. Wang, Z. Yuan, R. Tan, L. Sun, Q. Huang, X. Jia, and H.C. So. Mobility-assisted spatiotemporal detection in wireless sensor networks. *IEEE Transactions on Parallel and Distributed Systems*, 2010.

[4] X. Shen, H. Li, J. Zhao, J. Chen, and Z. Wang. NemoTrack: A RF-Based Robot Tracking System in Wireless Sensor Networks (DEMO). In *Proc. the European Conference on Wireless Sensor Networks, Zurich, Swiss*, 2006.

[5] P. Ogren, E. Fiorelli, and N.E. Leonard. Cooperative Control of Mobile Sensor Networks: Adaptive Gradient Climbing in a Distributed Environment. *IEEE Transactions on Automatic Control*, 49(8):1292–1302, 2004.

[6] F. Zhang, B. Grochosky, V. Kumar, and M. Mintz. Cooperative Control for Localization of Mobile Sensor Networks. *Optimization-Based Control of Multi-Vehicle Systems(Springer-Verlag, LNCIS 309)*, pages 241–255, 2005.

[7] F. Zhang, B. Grochosky, V. Kumar, and M. Mintz. Optimization-Based Control of Multi-Vehicle Systems. *Optimization-Based Control of Multi-Vehicle Systems (Springer-Verlag, LNCIS 309)*, pages 63–78, 2005.

[8] H. Li. Networked Ultrasonic Sensors for Target Tracking: An Experimental Study. In *Proc. the European Conference on Wireless Sensor Networks, Zurich, Swiss*, 2006.

[9] H. Li, D. Miao, J. Chen, X. Shen, and Y. Sun. Networked Ultrasonic Sensors for Target Tracking: An Experimental Study. In *Proc. IEEE Global Communication Conference, Honolulu, HI, USA*, 2009.

[10] H. Li, D. Miao, J. Chen, X. Shen, and Y. Sun. Dynamic Target Tracking with Integration of Communication and Coverage using Mobile Sensors. In *Proc. Annual Conference of the IEEE Industrial Electronics Society, Porto, Portugal*, 2009.

[11] T. H. Chung. *Intelligent Information Gathering: Using Control For Sensing And Decision Making*. PhD thesis, California Institute of Technology, Pasadena, CA, USA, 2007.

[12] J. Lin, L. Xie, and W. Xiao. Target tracking in wireless sensor networks using compressed Kalman filter. *International Journal of Sensor Networks*, 6(3):251–262, 2009.

[13] L.L. Ong, T. Bailey, H. Durrant-Whyte, and B. Upcroft. Decentralised particle filtering for multiple target tracking in wireless sensor networks. In *2008 11th International Conference on Information Fusion*, pages 1–8. IEEE, 2008.

[14] T.H. Chung, J.W. Burdick, and R.M. Murray. A Decentralized Motion Coordination Strategy for Dynamic Target Tracking. In *Proc. IEEE International Conference on Robotics and Automation*, 2006.