Target Tracking and Mobile Sensor Navigation in Wireless Sensor Networks

Enyang Xu, Zhi Ding, *Fellow*, *IEEE*, and Soura Dasgupta, *Fellow*, *IEEE*

Abstract—This work studies the problem of tracking signal-emitting mobile targets using navigated mobile sensors based on signal reception. Since the mobile target's maneuver is unknown, the mobile sensor controller utilizes the measurement collected by a wireless sensor network in terms of the mobile target signal's time of arrival (TOA). The mobile sensor controller acquires the TOA measurement information from both the mobile target and the mobile sensor for estimating their locations before directing the mobile sensor's movement to follow the target. We propose a min-max approximation approach to estimate the location for tracking which can be efficiently solved via semidefinite programming (SDP) relaxation, and apply a cubic function for mobile sensor navigation. We estimate the location of the mobile sensor and target jointly to improve the tracking accuracy. To further improve the system performance, we propose a weighted tracking algorithm by using the measurement information more efficiently. Our results demonstrate that the proposed algorithm provides good tracking performance and can quickly direct the mobile sensor to follow the mobile target.

Index Terms—Mobile sensor navigation, weighted tracking, TOA

1 Introduction

In recent years, wireless sensor networks have found rapidly growing applications in areas such as automated data collection, surveillance, and environmental monitoring. One important use of sensor networks is the tracking of a mobile target (point source) by the network [1]. Mobile target tracking has a number of practical applications, including robotic navigation, search-rescue, wildlife monitoring, and autonomous surveillance. Typically, target tracking involves two steps. First, it needs to estimate or predict target positions from noisy sensor data measurements. Second, it needs to control mobile sensor tracker to follow or capture the moving target. In this paper, we study the problem of mobile target positioning in a sensor network that consists of stationary sensors and a mobile sensor. The goal is to estimate the target position and to control the mobile sensor for tracking the moving target.

1.1 Brief Literature Review

The challenge of target tracking and mobile sensor navigation arises when a mobile target does not follow a predictable path. Successful solutions require a real-time location estimation algorithm and an effective navigation control method. Target tracking can be viewed as a sequential location estimation problem. Typically, the target is a signal emitter whose transmissions are received by a number of distributed sensors for location estimation. There exist a number target localization approaches-based various measurement models such as received signal strength (RSS), time of arrival (TOA), time difference of arrival (TDOA), signal angle of arrival (AOA), and their combinations [2], [3]. For target tracking, Kalman filter was proposed in [4], where a geometric-assisted predictive location tracking algorithm can be effective even without sufficient signal sources. Li et al. [5] investigated the use of extended Kalman filter in TOA measurement model for target tracking. Particle filtering has also been applied with RSS measurement model under correlated noise to achieve high accuracy [6].

In addition to the use of stationary sensors, several other works focused on mobility management and control of sensors for better target tracking and location estimation. Zou and Chakrabarty [7] studied a distributed mobility management scheme for target tracking, where sensor node movement decisions were made by considering the tradeoff among target tracking quality improvement, energy consumption, loss of connectivity, and coverage. Rao and Kesidis [8] further considered the cost of node communications and movement as part of the performance tradeoff.

To enable target tracking by a mobile sensor with a prior knowledge on target motion, [9], [10] presented a proportional navigation strategy and several variants. In [11], a continuous nonlinear periodically time-varying algorithm was proposed for adaptively estimating target positions and for navigating the mobile sensor in a trajectory that encircles the target. Belkhouchet et al. [12] modeled the robot and the target kinematics equations in polar coordinates, and proposed a navigation strategy that attempts to position the robot in between a reference point and the target so as to successfully follow the target. Using the similar set of nonlinear kinematics equations, Vargas et al. [13] proposed a cubic navigation function, which is both

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Manuscript received 8 Aug. 2011; revised 4 Nov. 2011; accepted 18 Nov. 2011; published online 8 Dec. 2011.
For information on obtaining reprints of this article, please send e-mail to: tmc@computer.org, and reference IEEECS Log Number TMC-2011-08-0444.
Digital Object Identifier no. 10.1109/TMC.2011.262.

simple and effective. In our work, we adopt this simple navigation function.

1.2 New Contributions

In this work, we consider the joint problem of mobile sensor navigation and mobile target tracking based on a TOA measurement model. Our chief contributions include a more general TOA measurement model that accounts for the measurement noise due to multipath propagation and sensing error. Based on the model, we propose a min-max approximation approach to estimate the location for tracking that can be efficiently and effectively solved by means of semidefinite programming (SDP) relaxation. We apply the cubic function for navigating the movements of mobile sensors. In addition, we also investigate the simultaneous localization of the mobile sensor and the target to improve the tracking accuracy. We present a weighted tracking algorithm in order to exploit the measurement information more efficiently. The numerical result shows that the proposed tracking approach works well.

There are several important reasons for us to utilize the TOA measurement model. First, TOA measurements are easy to acquire, as each sensor only needs to identify a special signal feature such as a known signal preamble to record its arrival time. Second, our particular use of TOA is a more practical model because we do not need the sensors to know the transmission start time of the signal a priori. As a result, our TOA model enables us to directly estimate the source location by processing the TOA measurement data. Furthermore, Xu et al. [14] have shown that direct TOA localization offers some performance gain over TDOA localization. Since the mobile sensor navigation control depends on the estimated location results, more accurate localization algorithm from TOA measurements leads to better navigation control.

The rest of the paper is organized as follows. In Section 2, we describe the tracking and navigation problem that involves the localization of a mobile target and the control of a mobile sensor. In Section 3, we discuss the cubic navigation law for tracking of the target. We present the weighted tracking approach in Section 4 and analyze the posterior Cramer-Rao bound in Section 5. Our numerical results are shown in Section 6 before concluding in Section 7.

2 Problem Statement

We consider a sensor network of N anchored nodes at the positions denoted by a set of m-dimensional vectors $\mathbf{x}_1, \ldots, \mathbf{x}_N$ (with $\mathrm{m} = 2$ or 3 for 2D or 3D space, respectively). A moving target travels nearby, whose maneuver is not known in advance. However, the moving target is a signal emitter whose signal transmission is measured by the N anchor sensor nodes. A mobile sensor also emits signals to allow sensors to collect information necessary to determine its location. The mobile sensor, at the same time, can also measure signal from the target. In the data fusion center, a mobile sensor controller directs the mobile sensor to reach and follow the target based on multiple sensor measurements.

To track a moving target with a mobile sensor, the data fusion center must estimate the locations of both the target

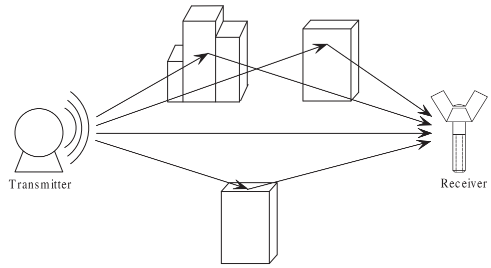

Fig. 1. Illustration of the signal transmission path from the transmitter to the receiver.

(located at $\mathbf{y}_j$) and the mobile sensor (located at $\mathbf{z}_j$) at time instant T_j. This paper considers the scenario that each anchor sensor node records and sends, to the data fusion sensor, its TOA measurement of target signal and mobile sensor signal. In other words, the mobile sensor controller receives the TOA measurements regularly from the anchor sensors to estimate the target and mobile sensor locations and to direct the movement of the mobile sensor for target tracking.

In wireless environment, signals from transmitters to their receivers may undergo both line-of-sight (LOS) and nonline-of-sight (NLOS) propagations. We illustrate a typical scenario that involves multipath channels consisting of both LOS and NLOS propagations in Fig. 1. There are two kinds of measurement noises, noise due to multipath signal propagation and noise due to limited sensing precision of each sensor [3]. Because of the generally complex multipath effects, noise from multipath propagation in the estimated signal time of arrival is approximately proportional to the actual signal propagation time, and the observed signal propagation time should be no less than the LOS propagation. In other words, the multipath propagation noise is typically nonnegative. This is consistent with the noise model of the distance measurement in [15]. As a result, the TOA measurement at the sensor closer to the target will suffer less from the multipath propagation noise. In addition, noise from sensing error is not related to the distance between the target and the sensor, and is i.i.d. among all the sensors. Moreover, it can be many times weaker than the noise from multipath propagation according to [3].

Therefore, we model the time of arrival measurements at the anchor node $\mathbf{x}_i$ at time instant T_j for the signal from the target and the mobile sensor, respectively, as

$$t_{ji} = \frac{1}{c}\|\mathbf{x}_i - \mathbf{y}_j\| + t_{j0} + \frac{1}{c}\|\mathbf{x}_i - \mathbf{y}_j\| n_{ji} + \delta_j, \tag{1}$$

$$\tau_{ji} = \frac{1}{c}\|\mathbf{x}_i - \mathbf{z}_j\| + \tau_{j0} + \frac{1}{c}\|\mathbf{x}_i - \mathbf{z}_j\| \eta_{ji} + \rho_j. \tag{2}$$

Here, c is the signal traveling speed, t_{j0}, τ_{j0} are, respectively, the time instants that the target and the mobile sensor transmitted their signals. Furthermore, note that $\frac{1}{c}\|\mathbf{x}_i - \mathbf{y}_j\| n_{ji}$, $\frac{1}{c}\|\mathbf{x}_i - \mathbf{z}_j\| \eta_{ji}$ with $n_{ji} \geq 0$, $\eta_{ji} \geq 0$ are multipath propagation noise, whereas δ_j and ρ_j are noise from sensing error.

Moreover, we have the time of arrival measurement at the mobile sensor at time instant T_j for the signal from the target as

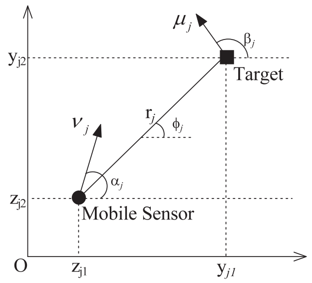

Fig. 2. Illustration of the navigation problem.

$$\varphi_j = \frac{1}{c}\|\mathbf{y}_j - \mathbf{z}_j\| + t_{j0} + \frac{1}{c}\|\mathbf{y}_j - \mathbf{z}_j\|\zeta_j + \kappa_j, \tag{3}$$

where $\frac{1}{c}\|\mathbf{y}_j - \mathbf{z}_j\|\zeta_j$ with $\zeta_j \geq 0$ represents the multipath propagation noise, and κ_j is the noise due to sensing error.

After the data fusion center receives the measurement data, it estimates the target location $\mathbf{y}_j$ and the mobile sensor location $\mathbf{z}_j$. Based on estimated locations, the controller directs the mobile sensor to approach and follow the target by applying its navigation law. At each time instant, the mobile sensor can adjust its moving speed and direction according to the control signal from the controller.

In short, the mobile sensor navigation and tracking process consists of two steps: mobile sensor movement control and tracking. Thus, we will discuss these two steps in the next two sections.

3 Mobile Sensor Navigation Strategy

A navigator in this case aims to control the mobile sensor to get close to the moving target from any initial position. Since the target maneuvers are not known a priori to the controller, solving the problem requires a real-time strategy.

In Fig. 2, we illustrate the geometric model of the navigation problem in a 2D space. At time instant T_j, the mobile sensor is positioned at $\mathbf{z}_j = [z_{j1}\ z_{j2}]^T$ with a velocity ν_j and angle α_j to the positive horizontal axis, and the target locates at $\mathbf{y}_j = [y_{j1}\ y_{j2}]^T$ with a velocity μ_j and angle β_j to the positive horizontal axis. The radial line that connects the mobile sensor and the target is denoted by r_j, with angle ϕ_j to the positive horizontal axis.

In polar coordinates, the mobile sensor and target move according to the following kinematics:

$$\dot{z}_{j1} = \nu_j \cos\alpha_j, \quad \dot{z}_{j2} = \nu_j \sin\alpha_j, \tag{4}$$

$$\dot{y}_{j1} = \mu_j \cos\beta_j, \quad \dot{y}_{j2} = \mu_j \sin\beta_j, \tag{5}$$

respectively. Since $\tan\phi_j = \frac{y_{j2}-z_{j2}}{y_{j1}-z_{j1}}$, the decomposition of the relative velocity gives the following relative kinematics equations between the mobile sensor and the target [12]

$$\dot{r}_j = \mu_j \cos(\beta_j - \phi_j) - \nu_j \cos(\alpha_j - \phi_j), \tag{6}$$

$$r_j\dot{\phi}_j = \mu_j \sin(\beta_j - \phi_j) - \nu_j \sin(\alpha_j - \phi_j). \tag{7}$$

If $\dot{r}_j < 0$, then the distance between the mobile sensor and the target is decreasing, i.e., the mobile sensor is approaching the target. In [13], a cubic navigation strategy has been proposed, where

$$\alpha_j = \phi_j + K\phi_j^3. \tag{8}$$

Assuming $\nu_j > \mu_j$, it has been proven that under this cubic law, the corresponding $\dot{r}_j < 0$, and the mobile sensor will reach the target successfully. Because of the simplicity of this navigation law, we will apply this strategy in our work.

Alternatively, we may be interested in keeping the mobile sensor at a given distance away from the target for surveillance purpose without being discovered. In such applications, we need to set $\dot{r}_j = 0$. Combining (6) and (8), we have

$$\mu_j \cos(\beta_j - \phi_j) = \nu_j \cos(K\phi_j^3), \tag{9}$$

which gives the mobile sensor speed as

$$\nu_j = \frac{\mu_j \cos(\beta_j - \phi_j)}{\cos(K\phi_j^3)}. \tag{10}$$

4 Tracking Algorithm

4.1 Target Localization

The first step of tracking is to estimate positions of both target and mobile sensor. Since the measurement in the form of TOA information collected at the data fusion center is the same for both the target and the mobile sensor, we, therefore, focus our discussion on how to estimate the location vector $\mathbf{y}_j$ of the target at a given time instant T_j.

We can modify the TOA model by rewriting (1) into

$$t_{ji} - t_{j0} = \frac{1}{c}\|\mathbf{x}_i - \mathbf{y}_j\| + \frac{1}{c}\|\mathbf{x}_i - \mathbf{y}_j\|n_{ji} + \delta_j. \tag{11}$$

Squaring both sides, we get

$$\begin{aligned}(t_{ji} - t_{j0})^2 &- \frac{1}{c^2}\|\mathbf{x}_i - \mathbf{y}_j\|^2 \\ &= \underbrace{\left(\frac{1}{c}\|\mathbf{x}_i - \mathbf{y}_j\|n_{ji} + \delta_j\right)\left(\frac{1}{c}\|\mathbf{x}_i - \mathbf{y}_j\|(2 + n_{ji}) + \delta_j\right)}_{\omega_{ji}},\end{aligned} \tag{12}$$

for $i = 1, \ldots, N$.

The right-hand side of (12) is a noise term ω_{ji} that is independent for different indices i. If n_{ij} and δ_j are zero, then the right-hand side of (12) would be zero. Therefore, one way to estimate the optimum $\mathbf{y}_j$ without assuming any particular characteristics on ω_{ji} is to minimize the ℓ_∞ norm of ω_{ji}. This approach makes no assumption on the noise distribution or on the noise dependency. It simply tries to minimize the peak error. Therefore, its performance is expected to be less sensitive to the noise distribution or correlation. Thus, we propose to adopt the min-max criterion for location estimation via

$$\hat{\mathbf{y}}_j = \arg\min_{\mathbf{y}_j} \max_{i=1,\ldots,N} \left| (t_{ji} - t_{j0})^2 - \frac{1}{c^2}\|\mathbf{x}_i - \mathbf{y}_j\|^2 \right|. \tag{13}$$

The min-max formulation (13) is nonconvex, but is quite amenable to semidefinite relaxations as shown below. We first introduce two auxiliary variables $y_{js} = \mathbf{y}_j^T\mathbf{y}_j$ and $t_{js} = t_{j0} \cdot t_{j0}$, and define the following function:

$$\begin{aligned}&\psi(t_{js}, t_{ji}, t_{j0}, y_{js}, \mathbf{x}_i, \mathbf{y}_j)\\&= t_{js} - 2t_{ji}^2 + t_{ji}^2 - \frac{1}{c^2}\left(y_{js} - 2\mathbf{x}_i^T\mathbf{y}_j + \mathbf{x}_i^T\mathbf{x}_i\right).\end{aligned} \tag{14}$$

Then, (13) can be rewritten as

$$\hat{\mathbf{y}}_j = \arg\min_{\mathbf{y},\, y_{js},\, t_{j0},\, t_{js}} \max_{i=1,\dots,N} |\psi(t_{js}, t_{ji}, t_{j0}, y_{js}, \mathbf{x}_i, \mathbf{y}_j)|, \tag{15}$$

which is a convex function of $\mathbf{y}_j$, y_{js}, t_{j0}, and t_{js}.

However, the two equalities $y_{js} = \mathbf{y}_j^T\mathbf{y}_j$ and $t_{js} = t_{j0} \cdot t_{j0}$ are not affine. In order to make the whole formulation convex, we relax the two equalities $y_{js} = \mathbf{y}_j^T\mathbf{y}_j$ and $t_{js} = t_{j0} \cdot t_{j0}$ to inequalities $y_{js} \succeq \mathbf{y}_j^T\mathbf{y}_j$ and $t_{js} \succeq t_{j0} \cdot t_{j0}$, respectively. These inequalities can also be expressed in linear matrix inequalities, i.e.,

$$\begin{bmatrix} \mathbf{I} & \mathbf{y}_j \\ \mathbf{y}_j^T & y_s \end{bmatrix} \succeq 0, \quad \begin{bmatrix} 1 & t_{j0} \\ t_{j0} & t_{js} \end{bmatrix} \succeq 0. \tag{16}$$

In addition, based on the location estimate at time instant T_{j-1}, we can obtain an approximate location vector for the target at time instant T_j. Let $\Delta T_j = T_j - T_{j-1}$ and μ_{j-1} be the estimated velocity vector of the target at time instant T_{j-1}. Then the location change can be approximated as $\Delta\mathbf{y}_j = \mathbf{y}_j - \mathbf{y}_{j-1} \approx \Delta T_j \mu_{j-1}$. This can be used as additional constraints for the target location estimation at time instant T_j. Considering in 2D, the location change vector $\Delta\mathbf{y}_j$ is restricted to a box, then the corresponding $\mathbf{y}_j$ will also be constrained to a box, i.e.,

$$y_{jl} \le y_{j1} \le y_{jr}, \quad y_{jd} \le y_{j2} \le y_{ju}. \tag{17}$$

Define $\mathbf{a}_j = [y_{jl}\ y_{jd}]^T$, $\mathbf{b}_j = [y_{jr}\ y_{ju}]^T$, and $y_{js} = \mathbf{y}_j^T\mathbf{y}_j$. We can apply the Reformulation-Linearization-Technique (RLT) [16] to (17) in order to obtain some extra constraints. In fact, based on RLT, (17) can be relaxed as

$$\begin{aligned}\mathbf{a}_j^T\mathbf{a}_j - \mathbf{a}_j^T\mathbf{y}_j - \mathbf{a}_j^T\mathbf{y}_j + y_{js} \ge 0,\\ \mathbf{b}_j^T\mathbf{b}_j - \mathbf{b}_j^T\mathbf{y}_j - \mathbf{b}_j^T\mathbf{y}_j + y_{js} \ge 0,\\ -\mathbf{a}_j^T\mathbf{b}_j + \mathbf{a}_j^T\mathbf{y}_j + \mathbf{b}_j^T\mathbf{y}_j - y_{js} \ge 0,\end{aligned} \tag{18}$$

which can be rewritten in the following matrix form

$$\begin{bmatrix} \|\mathbf{a}_j\|^2 & -2\mathbf{a}_j^T & 1 \\ \|\mathbf{b}_j\|^2 & -2\mathbf{b}_j^T & 1 \\ -\mathbf{a}_j^T\mathbf{b}_j & \mathbf{a}_j^T + \mathbf{b}_j^T & -1 \end{bmatrix} \begin{bmatrix} 1 \\ \mathbf{y}_j \\ y_{js} \end{bmatrix} \ge 0. \tag{19}$$

Here "≥ 0"' denotes that each element in the vector is nonnegative.

Combining the above constraints, we obtain the following SDP optimization formulation:

$$\begin{aligned}&\min_{\mathbf{y}_j, y_{js}, t_{j0}, t_{js}} \theta_j\\ &\text{s.t. } -\theta_j < \psi(t_{js}, t_{ji}, t_{j0}, y_{js}, \mathbf{x}_i, \mathbf{y}_j) < \theta_j,\\ &\begin{bmatrix} \mathbf{I} & \mathbf{y}_j \\ \mathbf{y}_j^T & y_{js} \end{bmatrix} \succeq 0, \quad \begin{bmatrix} 1 & t_{j0} \\ t_{j0} & t_{js} \end{bmatrix} \succeq 0,\\ &\begin{bmatrix} \|\mathbf{a}_j\|^2 & -2\mathbf{a}_j^T & 1 \\ \|\mathbf{b}_j\|^2 & -2\mathbf{b}_j^T & 1 \\ -\mathbf{a}_j^T\mathbf{b}_j & \mathbf{a}_j^T + \mathbf{b}_j^T & -1 \end{bmatrix} \begin{bmatrix} 1 \\ \mathbf{y}_j \\ y_{js} \end{bmatrix} \ge 0.\end{aligned} \tag{20}$$

The SDP problem of (20) can be solved using some common tools such as SeDuMi [17].

4.2 Mobile Sensor Localization

Similar to estimating the location of the target, we can reformulate the mobile sensor localization problem into an SDP relaxation problem. More specifically, we can estimate the mobile sensor location $\mathbf{z}_j$ via the similar formulation based on the TOA measurements at the anchor nodes from the signal received from the mobile sensor (2).

Define $z_{js} = \mathbf{z}_j^T\mathbf{z}_j$ and $\tau_{js} = \tau_{j0} \cdot \tau_{j0}$. Similarly, based on the input velocity vector ν_{j-1} of the mobile sensor from the controller at time instant T_{j-1}, we can approximate the location change of the mobile sensor as $\Delta\mathbf{z}_j = \mathbf{z}_j - \mathbf{z}_{j-1} \approx \Delta T_j \nu_{j-1}$. Then the corresponding $\mathbf{z}_j$ will also be constrained to a box, i.e.,

$$z_{jl} \le z_{j1} \le z_{jr}, \quad z_{jd} \le z_{j2} \le z_{ju}. \tag{21}$$

Let $\mathbf{d}_j = [z_{jl}\ z_{jd}]^T$ and $\mathbf{e}_j = [z_{jr}\ z_{ju}]^T$. By applying the similar relaxations, we obtain the following SDP formulation:

$$\begin{aligned}&\min_{\mathbf{z}_j, z_{js}, \tau_{j0}, \tau_{js}} \theta_j\\ &\text{s.t. } -\theta_j < \psi(\tau_{js}, \tau_{ji}, \tau_{j0}, z_{js}, \mathbf{x}_i, \mathbf{z}_j) < \theta_j,\\ &\begin{bmatrix} \mathbf{I} & \mathbf{z}_j \\ \mathbf{z}_j^T & z_{js} \end{bmatrix} \succeq 0, \quad \begin{bmatrix} 1 & \tau_{j0} \\ \tau_{j0} & \tau_{js} a \end{bmatrix} \succeq 0,\\ &\begin{bmatrix} \|\mathbf{d}_j\|^2 & -2\mathbf{e}_j^T & 1 \\ \|\mathbf{e}_j\|^2 & -2\mathbf{e}_j^T & 1 \\ -\mathbf{d}_j^T\mathbf{e}_j & \mathbf{d}_j^T + \mathbf{e}_j^T & -1 \end{bmatrix} \begin{bmatrix} 1 \\ \mathbf{z}_j \\ z_{js} \end{bmatrix} \ge 0.\end{aligned} \tag{22}$$

4.3 Joint Target and Mobile Sensor Localization

Note, however, that the mobile sensor also receives target signal information and can obtain an additional measurement of TOA from the target to the mobile sensor in (3). This TOA information provides a connection between the target and the mobile sensor locations. If $\mathbf{z}_j$ is known in (3), we can treat the mobile sensor as another anchor node, and add one more inequality in (20). This additional information can be obtained by solving (22) first and then using the output $\mathbf{z}_j$ in (3). However, since we are not able to obtain the accurate $\mathbf{z}_j$, this will induce error propagation. Therefore, we propose to solve both $\mathbf{y}_j$ and $\mathbf{z}_j$ simultaneously in order to better utilize the TOA measurement information in (3).

To do so, we first need to introduce one more variable to make the whole problem convex. Let $q_j = \mathbf{y}_j^T\mathbf{z}_j$, then $\|\mathbf{y}_j - \mathbf{z}_j\|^2 = y_{js} - 2q_j + z_{js}$. And we have the following constraint:

$$-\frac{1}{2}(y_{js} + z_{js}) \le q_j \le \frac{1}{2}(y_{js} + z_{js}). \tag{23}$$

By combining the above formulation and constraints, we arrive at the following joint optimization formulation:

$$\begin{aligned}
&\min_{\mathbf{y}_j, y_{js}, t_{j0}, t_{js}, \mathbf{z}_j, z_{js}, \tau_{j0}, \tau_{js}, q_j} \quad \theta_j \\
&\text{s.t. } -\theta_j < \psi(t_{js}, t_{ji}, t_{j0}, y_{js}, \mathbf{x}_i, \mathbf{y}_j) < \theta_j, \\
&-\theta_j < \psi(\tau_{js}, \tau_{ji}, \tau_{j0}, z_{js}, \mathbf{x}_i, \mathbf{z}_j) < \theta_j, \\
&-\theta_j < t_{js} - 2\varphi_j t_{j0} + \varphi_j^2 - \frac{1}{c^2}(y_{js} - 2q_j + z_{js}) < \theta_j, \\
&\begin{bmatrix} \mathbf{I} & \mathbf{y}_j \\ \mathbf{y}_j^T & y_{js} \end{bmatrix} \succeq 0, \quad \begin{bmatrix} 1 & t_{j0} \\ t_{j0} & t_{js} \end{bmatrix} \succeq 0, \\
&\begin{bmatrix} \|\mathbf{a}_j\|^2 & -2\mathbf{a}_j^T & 1 \\ \|\mathbf{b}_j\|^2 & -2\mathbf{b}_j^T & 1 \\ -\mathbf{a}_j^T\mathbf{b}_j & \mathbf{a}_j^T + \mathbf{b}_j^T & -1 \end{bmatrix} \begin{bmatrix} 1 \\ \mathbf{y}_j \\ y_s \end{bmatrix} \geq 0, \\
&-\frac{1}{2}(y_{js} + z_{js}) \leq q_j \leq \frac{1}{2}(y_{js} + z_{js}), \\
&\begin{bmatrix} \mathbf{I} & \mathbf{z}_j \\ \mathbf{z}_j^T & z_{js} \end{bmatrix} \succeq 0, \quad \begin{bmatrix} 1 & \tau_{j0} \\ \tau_{j0} & \tau_{js} \end{bmatrix} \succeq 0, \\
&\begin{bmatrix} \|\mathbf{d}_j\|^2 & -2\mathbf{e}_j^T & 1 \\ \|\mathbf{e}_j\|^2 & -2\mathbf{e}_j^T & 1 \\ -\mathbf{d}_j^T\mathbf{e}_j & \mathbf{e}_j^T + \mathbf{e}_j^T & -1 \end{bmatrix} \begin{bmatrix} 1 \\ \mathbf{z}_j \\ z_{js} \end{bmatrix} \geq 0.
\end{aligned} \tag{24}$$

Using SeDuMi [17], we can simultaneously obtain estimates for the target and the mobile sensor locations.

More generally, multiple mobile sensors can be deployed and multiple TOA measurements can be utilized. Expanding the single mobile sensor formulation of (24), we have multiple $\mathbf{z}_j$'s to estimate. Without having to present the formulation in detail, we can see that it is straightforward to generalize the formation (24) to include multiple measurements of multiple mobile sensors.

4.4 Conditions for Localization

We note that source localization is not unconditional and depends on the sensor geometry. As shown in [18], in 2D spaces, if all the anchored sensor nodes lie on a single line, i.e., they are collinear, then the problem of source location becomes ill-conditioned and the result surfers from an ambiguity. In fact, there can be multiple location candidates when no additional information is provided beyond the TOA measurements. Naturally, during the course of target tracking, we may occasionally encounter such collinear scenarios. However, since we have other a priori information about the location of the target (17) from the previous time instant(s) as well as from its mobile velocity, these prior knowledges enable us to resolve the location ambiguity caused by the collinear sensors. Indeed, we actually combine such priori information in our formulation (24). Therefore, the ambiguity can be resolved in our solution (24).

5 Weighted Tracking Error and Iterative Tracking

For the particular TOA model of (11), because the noise due to multipath propagation is often much greater than the noise due to sensing error [3], the dominant noise term of ω_{ji} in (12) is $\frac{2}{c^2}\|\mathbf{x}_i - \mathbf{y}_j\|^2 n_{ji}$ after we neglect the smaller noise from sensing error and second order noise terms. By focusing on the dominant noise term, we can rewrite equality of (12) as

$$\frac{c^2}{2\|\mathbf{x}_i - \mathbf{y}_j\|^2}\left((t_{ji} - t_{j0})^2 - \frac{1}{c^2}\|\mathbf{x}_i - \mathbf{y}_j\|^2\right) = n_{ji}. \tag{25}$$

Thus, the right-hand side of (25) is only related to the noise factor n_{ij} for all the anchor sensors.

Observe that, in the TOA model (1)-(3), the noise from multipath propagation is proportional to the propagation time. As a result, the TOA measurement of shorter propagation time is less noisy and should be more dependable. In addition, the right side of (12) is expected to be lower if the measurement $\frac{1}{c}\|\mathbf{x}_i - \mathbf{y}_j\|$ is smaller. For this reason, it is more sensible to place more emphasis on those TOA measurements of higher confidence. Similar ideas have been explored for localization algorithms in [15] and [19]. Since we have mobile sensors moving towards the target, measurements collected by mobile sensors are more reliable than other sensing nodes. We, therefore, advocate a weighted tracking error to improve target tracking performance. Thus, we can add a weighting factor to the min-max criterion (13) to estimate the target location via

$$\hat{\mathbf{y}}_j = \arg\min_{\mathbf{y}_j} \max_{i=1,\ldots,N} \gamma_{ji}\left|(t_{ji} - t_{j0})^2 - \frac{1}{c^2}\|\mathbf{x}_i - \mathbf{y}_j\|^2\right|, \tag{26}$$

where γ_{ji} is the weighting factor.

Using the similar semidefinite relaxation technique we discussed in Section 3, we obtain the following SDP formulation for weighted tracking:

$$\begin{aligned}
&\min_{\mathbf{y}_j, y_{js}, t_{j0}, t_{js}, \mathbf{z}_j, z_{js}, \tau_{j0}, \tau_{js}, q_j} \quad \theta_j \\
&\text{s.t. } -\theta_j < \gamma_{ji}^{(1)} \cdot \psi(t_{js}, t_{ji}, t_{j0}, y_{js}, \mathbf{x}_i, \mathbf{y}_j) < \theta_j, \\
&-\theta_j < \gamma_{ji}^{(2)} \cdot \psi(\tau_{js}, \tau_{ji}, \tau_{j0}, z_{js}, \mathbf{x}_i, \mathbf{z}_j) < \theta_j, \\
&-\theta_j < \gamma_j^{(3)}\left(t_{js} - 2\varphi_j t_{j0} + \varphi_j^2 - \frac{1}{c^2}(y_{js} - 2q_j + z_{js})\right) < \theta_j, \\
&\begin{bmatrix} \mathbf{I} & \mathbf{y}_j \\ \mathbf{y}_j^T & y_{js} \end{bmatrix} \succeq 0, \quad \begin{bmatrix} 1 & t_{j0} \\ t_{j0} & t_{js} \end{bmatrix} \succeq 0, \\
&\begin{bmatrix} \|\mathbf{a}_j\|^2 & -2\mathbf{a}_j^T & 1 \\ \|\mathbf{b}_j\|^2 & -2\mathbf{b}_j^T & 1 \\ -\mathbf{a}_j^T\mathbf{b}_j & \mathbf{a}_j^T + \mathbf{b}_j^T & -1 \end{bmatrix} \begin{bmatrix} 1 \\ \mathbf{y}_j \\ y_s \end{bmatrix} \geq 0, \\
&-\frac{1}{2}(y_{js} + z_{js}) \leq q_j \leq \frac{1}{2}(y_{js} + z_{js}), \\
&\begin{bmatrix} \mathbf{I} & \mathbf{z}_j \\ \mathbf{z}_j^T & z_{js} \end{bmatrix} \succeq 0, \quad \begin{bmatrix} 1 & \tau_{j0} \\ \tau_{j0} & \tau_{js} \end{bmatrix} \succeq 0, \\
&\begin{bmatrix} \|\mathbf{d}_j\|^2 & -2\mathbf{d}_j^T & 1 \\ \|\mathbf{e}_j\|^2 & -2\mathbf{e}_j^T & 1 \\ -\mathbf{d}_j^T\mathbf{e}_j & \mathbf{d}_j^T + \mathbf{e}_j^T & -1 \end{bmatrix} \begin{bmatrix} 1 \\ \mathbf{z}_j \\ z_{js} \end{bmatrix} \geq 0,
\end{aligned} \tag{27}$$

where $\gamma_{ji}^{(1)}$, $\gamma_{ji}^{(2)}$, and $\gamma_j^{(3)}$ are weighting factors. We note again that it is straightforward to generalize the formation (27) to include multiple mobile sensors.

The remaining issue is the optimum choice of the weighting factors in (27). Our way is to consider (25), according to which the weighting factors can be set as

$$\gamma_{ji}^{(1)} = \frac{1}{\|\mathbf{x}_i - \mathbf{y}_j\|^2},$$
$$\gamma_{ji}^{(2)} = \frac{1}{\|\mathbf{x}_i - \mathbf{z}_j\|^2}, \tag{28}$$
$$\gamma_{j}^{(3)} = \frac{1}{\|\mathbf{y}_j - \mathbf{z}_j\|^2}.$$

Alternatively, we may consider a singe-side i.i.d. multipath propagation noise from a truncated Gaussian distribution. By neglecting the noise from sensing errors, the joint conditional probability density function of the measurement data in (1) follows equality

$$p\big(t_{j1}, t_{j2}, \ldots, t_{jN}|\mathbf{y}, t_{j0}\big) = \prod_{i=1}^{N} \frac{\sqrt{2}c}{\sqrt{\pi}\sigma_p\|\mathbf{x}_i - \mathbf{y}_j\|} \exp\left(-\frac{c^2}{2\sigma_p^2} \sum_{i=1}^{N} \frac{(t_{ji} - \frac{1}{c}\|\mathbf{x}_i - \mathbf{y}\| - t_0)^2}{\|\mathbf{x}_i - \mathbf{y}_j\|^2} \right), \tag{29}$$

where σ_p is the variance of n_{ij}. We can see that the choices of weighting factors (28) are consistent with the maximum likelihood (ML) criteria.

Nevertheless, neither $\mathbf{y}_j$ and $\mathbf{z}_j$ is known a priori. As a result, we can not find the optimum weighting factor in (28) without first estimating the target and mobile sensor locations. Thus, we propose an iterative approach by estimating the target and sensor locations before determining the new weighting factors, which in turn, will be used to estimate the target and mobile sensor locations in the next iteration. To begin with, in the first iteration, we set the default weighting factors all to unity, for obtaining initial estimates of $\mathbf{y}_j$ and $\mathbf{z}_j$. By performing iterative weighted tracking, we can get a better performance.

6 The Posterior Cramer-Rao Bound

In this section, we derive the Cramer-Rao Bound for the tracking process. Suppose that a target is moving in the area according to a dynamic model:

$$\mathbf{S}_{j+1} = \mathbf{G}_{j+1}\mathbf{S}_j + \mathbf{N}_j, \tag{30}$$

where $\mathbf{S}_j$ is the target state vector defined as $\mathbf{S}_j = [\mathbf{y}_{j1}, \mathbf{y}_{j2}, \dot{\mathbf{y}}_{j1}, \dot{\mathbf{y}}_{j2}]^T$, $\mathbf{G}_j$ is the motion matrix, and $\mathbf{N}_j$ is the process noise which can be approximately assumed to be Gaussian with zero mean and covariance matrix $\mathbf{Q}$.

Denote the total measurement sequence up to time instant T_j as $t_{1:j} = [t_1, t_2, \ldots, t_j]^T$, where $t_j = [t_{j1}, t_{j2}, \ldots, t_{jN}]^T$, and denote the continuous state sequence $\mathbf{S}_{1:j} = [\mathbf{S}_1, \mathbf{S}_2, \ldots, \mathbf{S}_j]^T$. The optimal Bayesian solution to the problem cannot be computed analytically since the measurement equation is nonlinear. Let $\hat{\mathbf{S}}_j$ be an unbiased estimator of the state vector $\mathbf{S}_j$, based on the set of measurements $t_{1:j}$. Then, the estimate covariance W_j is bounded by

$$W_j = E\{[\hat{\mathbf{S}}_j - \mathbf{S}_j][\hat{\mathbf{S}}_j - \mathbf{S}_j]^T\} \geq F_j^{-1}, \tag{31}$$

where F_j is the posterior Fisher information matrix (FIM):

$$F_j = E\{-\nabla_{\mathbf{S}_j}\nabla_{\mathbf{S}_j}^T \log p(\mathbf{S}_j, \mathbf{t}_j)\}, \tag{32}$$

and $\nabla_{\mathbf{S}_j}$ is the first-order partial derivative operator with respect to $\mathbf{S}_j$.

According to Tichavsky et al. [20], the Fisher information matrix F_j can be recursively calculated as

$$F_{j+1} = U_j^{22} - U_j^{21}(F_j + U_j^{11})^{-1}U_j^{12}, \tag{33}$$

where

$$U_j^{11} = E\big\{ -\nabla_{\mathbf{S}_j}\nabla_{\mathbf{S}_j}^T \log p(\mathbf{S}_{j+1}/\mathbf{S}_j)\big\},$$

$$U_j^{12} = \big[U_j^{21}\big]^T = E\big\{ -\nabla_{\mathbf{S}_j}\nabla_{\mathbf{S}_{j+1}}^T \log p(\mathbf{S}_{j+1}/\mathbf{S}_j)\big\},$$

$$U_j^{22} = E\big\{ -\nabla_{\mathbf{S}_{j+1}}\nabla_{\mathbf{S}_{j+1}}^T \log p(\mathbf{S}_{j+1}/\mathbf{S}_j)\big\}.$$

The recursive equation (33) can be initialized as

$$F_0 = E\big\{ -\nabla_{\mathbf{S}_0}\nabla_{\mathbf{S}_0}^T \log p(\mathbf{S}_0)\big\}. \tag{34}$$

Based on (30), we have

$$U_j^{11} = \mathbf{G}_{j+1}^T\mathbf{Q}^{-1}\mathbf{G}_{j+1},$$

$$U_j^{12} = \big[U_j^{21}\big]^T = -\mathbf{G}_{j+1}^T\mathbf{Q}^{-1},$$

$$U_j^{22} = \mathbf{Q}^{-1}.$$

Using the above equations, we can numerically compute the posterior Cramer-Rao Bound at different time instants.

7 Numerical Results

In this section, we provide examples to illustrate the tracking performance of the proposed algorithm. For tracking comparison, we include the performance of classic TDOA algorithm [2] in combination with a Kalman filter (labeled as "Kalman") in our simulation examples. We denote our proposed tracking performance with and without weighting factors as "MMA," "WMMA," respectively. In addition, the cubic navigation strategy is used for mobile sensor navigation. For simplicity, we convert the noise in (1)-(3) into to the distance domain in our examples.

Example 1. In this example, we place $N = 15$ anchor sensor nodes in an area $[-20, 20] \times [-20, 20]$ as shown in Fig. 3. The target moves from $[-16, 1]^T$ following a sinusoidal trajectory while the mobile sensor initially sits at $[-16, -16]^T$ with the navigation parameter $K = 2$. The multipath propagation noise and the sensing error noise in (1), (2), and (3) are all Gaussian variables with variance $1/\sigma_p^2 = 16$ dB, $1/\sigma_s^2 = 20$ dB, respectively. The transmission start time t_0, τ_0 are randomly chosen with normal distribution of zero mean and variance of 4. For the WMMA algorithm, we only need two iterations. We illustrate the estimated target trajectories using both the Kalman and our proposed algorithms. The resulting navigation trajectories of the mobile sensor are also shown in Fig. 3. Moreover, we provide the average RMSE of the target location in Fig. 4. From these results, we can see that the proposed MMA algorithm gives a more

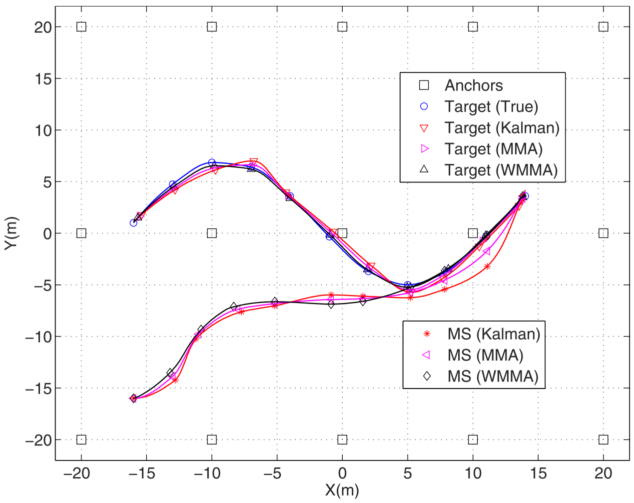

Fig. 3. Comparison of the tracking under different trajectory estimation algorithms.

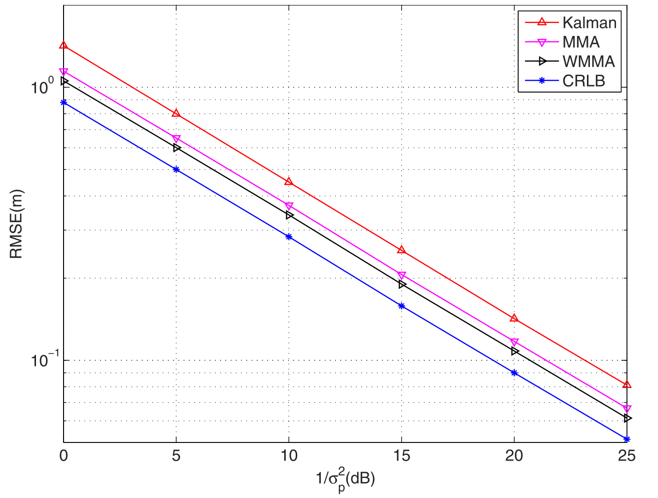

Fig. 5. The average RMSE of the target trajectory estimation under Kalman, MMA, and WMMA algorithm.

accurate trajectory estimate than the Kalman algorithm. In addition, the WWMA algorithm improves over the MMA algorithm, at the cost of one more iteration. We can also find that the navigation based on the more accurate target trajectory can reach the target faster.

To further compare the tracking algorithms, we compare the average root mean squared error (RMSE) of the location estimate as standard deviation of the multipath propagation noise varies in Fig. 5, where the sensing error noise is set to $1/\sigma_s^2 = 20$ dB. By processing the measurement data directly and using the additional RLT constraints, we can see that MMA and WMMA offer about 2 and 2.5 dB performance gain over the Kalman algorithm, respectively. Hence, navigation based on the estimated target trajectory from MMA and WMMA algorithms should be better.

Example 2. In this example, we control the mobile sensor to keep it at a constant distance $r = 4$ away from the target. We again place $N = 15$ nodes in an area of $[-20, 20] \times [-20, 20]$. Here the multipath propagation noise and the sensing error noise are all Gaussian distributed variables, and are set to $1/\sigma_p^2 = 16$ dB, $1/\sigma_s^2 = 20$ dB, respectively. The transmission start time t_0, τ_0 are randomly chosen with normal distribution of zero mean and variance of 4. The trajectories of the target and the mobile sensor under different algorithms are shown in Fig. 6. From the results, we can see that the proposed tracking algorithms work well with the navigation strategy and the mobile sensor is able to keep a certain distance away from the target much faster under the WMMA algorithm. This example shows that our algorithm can be used in surveillance applications such as battlefield.

Example 3. In this example, we reduce the number of anchor sensor nodes but increase the number of mobile sensors to test the difference in tracking performance. All conditions are identical to those in Example 1 except that we turn off six anchor nodes and add one more mobile sensor. We show the estimated trajectories, the RMSE of the target location, of different algorithms and the posterior Cramer-Rao bound in Figs. 7 and 8,

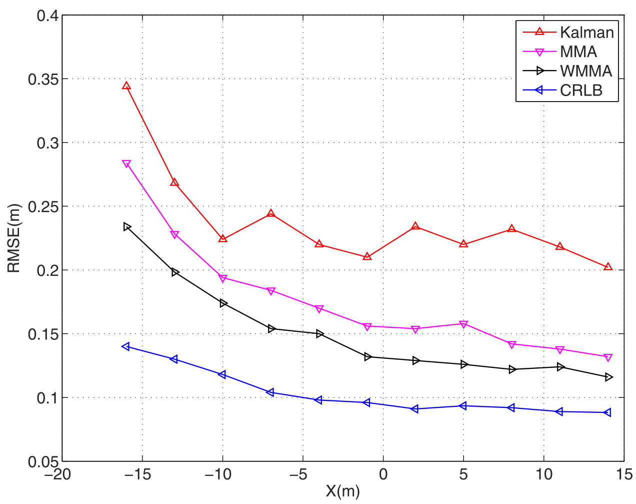

Fig. 4. RMSE of target location and posterior Cramer-Rao bound.

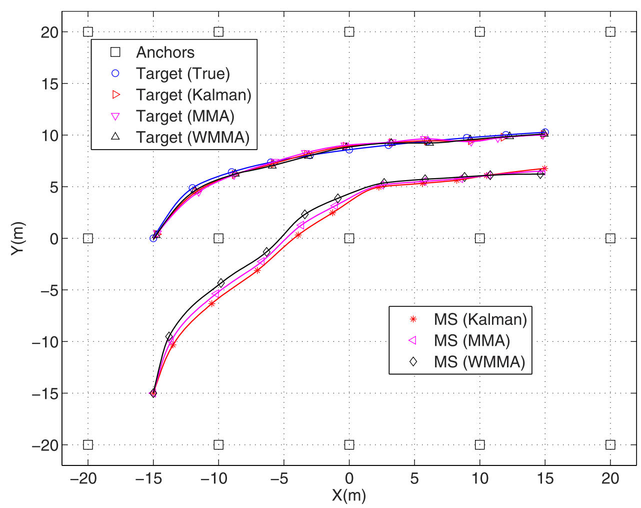

Fig. 6. Navigation to keep a constant distance under different trajectory estimation algorithms.

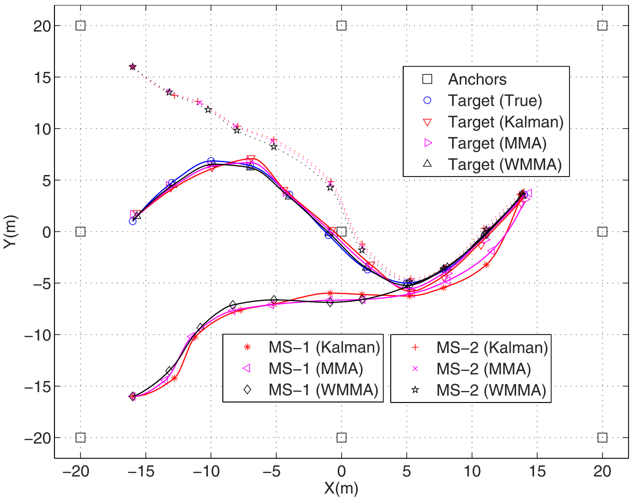

Fig. 7. Comparison of the tracking under different trajectory estimation algorithms.

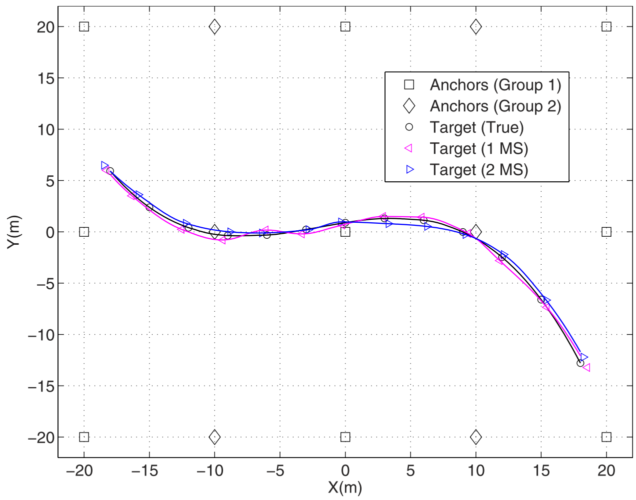

Fig. 9. Comparison of the tracking under different number of mobile sensors and cubic trajectory.

respectively. From the numerical results, we can find that although fewer anchor nodes are used than Example 1, we can still obtain almost the same performance by relying on one more mobile sensor since the mobile sensor can provide more reliable measurements and our weighted tracking algorithm can utilize the measurements more effectively in the scenario. In addition, we only use 3/5 of anchor nodes compared with Example 1 by adding one mobile sensor, thus we can save the commutation overhead between the anchor nodes and the data fusion center.

Example 4. In this example, we test our proposed WMMA tracking algorithms under different number of anchors and mobile sensors. Unlike the previous examples, the trajectory of the target is cubic. The multipath propagation noise and the sensing error noise in (1), (2), and (3) are all Gaussian variables, with variance $1/\sigma_p^2 = 15$ dB, $1/\sigma_s^2 = 20$ dB, respectively. The transmission start time t_0, τ_0 are randomly chosen with normal distribution of zero mean and variance of 4. We simulate two cases. In the first case, we use one mobile sensor and all the 15 anchor sensors (Groups 1 and 2 in Fig. 9), and in the second case we use two mobile sensors and part of the anchor sensors (Group 1 in Fig. 9). The tracking trajectories under these two cases are shown in Fig. 9. It can be observed that our algorithm can provide good tracking accuracy under the cubic trajectory in the two cases, which demonstrates that the proposed WMMA approach is robust to different trajectories. Once again, with one additional mobile sensor, we can obtain good performance with 2/5 of the anchor sensors off since the WMMA algorithm can yield good tracking accuracy by using the measurement information more efficiently.

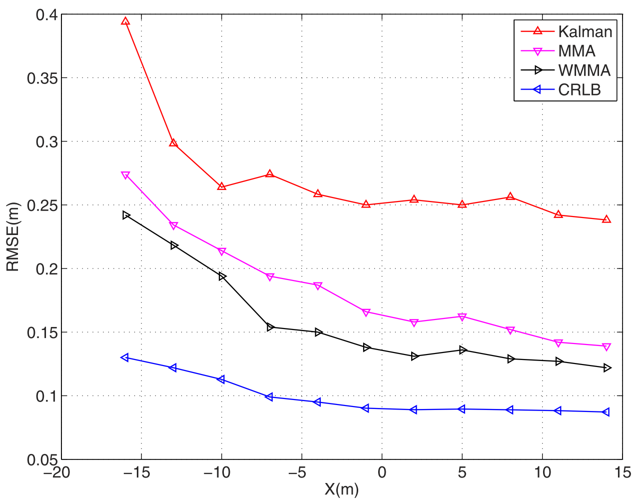

Fig. 8. RMSE of target location and posterior Cramer-Rao bound.

Example 5. The previous examples are based on Gaussian noise in the measurement model. To test the robustness of our algorithm to different noise distributions, this example considers uniformly distributed noise. We test our proposed WMMA tracking algorithms with different numbers of anchors and mobile sensors. We assume that the target trajectory follows a semicircular path. We let the multipath propagation noise and the sensing error noise in (1), (2), and (3) all be uniformly distributed variables, with variance $1/\sigma_p^2 = 15$ dB, $1/\sigma_s^2 = 20$ dB. We chose the unknown transmission start time t_0, τ_0 randomly with normal distribution of zero mean and variance of 4. We also test two simulation cases. In the first case, we use one mobile sensor and all the 10 anchor sensors marked as Groups 1 and 2 in Fig. 10. In the second test case, we use two mobile sensors and part of the anchor sensors marked as Group 1 in Fig. 10. Our mobile sensors try to keep a constant distance $r = 20$ away from the target. In Fig. 10, we provide the tracking trajectories of these two cases. From these results, we can see a close tracking performance by our proposed algorithms in both cases. Even when the noise distributions vary, our proposed WMMA algorithm continues to work well for different numbers of anchor sensors and mobile sensors. This example demonstrates the robustness of our algorithm to different noise distributions and sensor configurations.

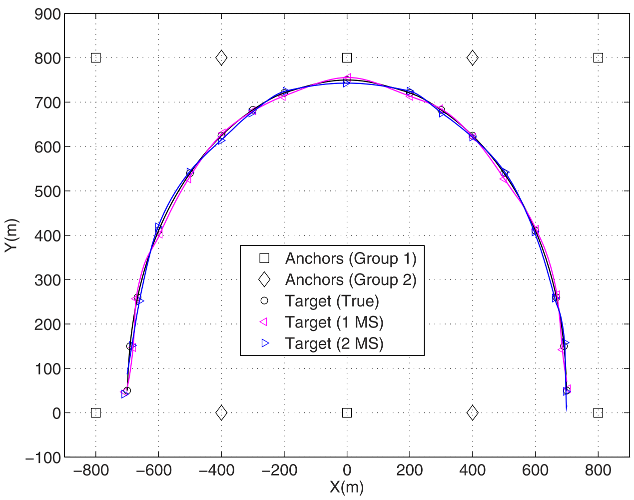

Fig. 10. Comparison of the tracking under different number of mobile sensors under circular trajectory.

8 Conclusion

We study the problem of tracking a moving target using navigated mobile sensors in wireless sensor networks. With unknown target and mobile sensor locations, we need to estimate the locations of the target and the mobile sensors first. Based on a more general TOA measurement model, convex optimization algorithms through SDP relaxation are developed for localization. We provide a sequential algorithm and a joint weighted localization algorithm before controlling the mobile sensor movement to follow the target. For the navigation of mobile sensors, the cubic law is applied. Simulation results illustrate successful tracking and navigation performance for the proposed algorithms under different trajectories and noises.

Acknowledgments

This work is supported by National Science Foundation Grants CCF-0830706, CCF-0803747, and CCF-0729025. Enyang Xu was with the Department of Electrical and Computer Engineering, University of California, Davis, at the time this work was completed.

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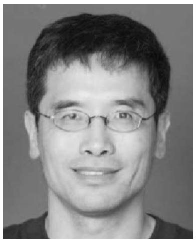

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