Dynamic Waveform Design for Target Tracking Using MIMO Radar

Jun (Jason) Zhang†, Bhavana Manjunath†, Ghassan Maalouli†, Antonia Papandreou-Suppappola†, and Darryl Morrell‡

†Department of Electrical Engineering, Arizona State University, Tempe, AZ
‡Department of Engineering, Polytechnic Campus, Arizona State University, Mesa, AZ

Jun.Zhang.EE@asu.edu, Bhavana.Manjunath@asu.edu, g.maalouli@ieee.org, papandreou@asu.edu, morrell@asu.edu

***Abstract*— In this paper, we investigate waveform design for dynamic target tracking using a multiple-input, multiple-output (MIMO) radar system. The agile tracking application is based on our recently derived Cramér-Rao lower bound (CRLB) for estimating target position and velocity, that is represented in terms of the transmitted waveform parameters. Using the CRLB at high signal-to-noise ratio (SNR), we adaptively select the waveform parameters that minimize the predicted mean-squared error (MSE) at each time step. We demonstrate the improvement in agile tracking using numerical simulations.**

I. Introduction

MIMO radar systems are increasing in popularity as they can expand the degrees of freedom in waveform design provided by their classical phased-array radar counterparts, leading to improved system performance. Their increased detection and estimation performance over conventional radar is due to the fact that MIMO radar can exploit waveform diversity by transmitting multiple waveforms. When the transmission antennas and/or receiver antennas are widely-separated, space-diversity can be obtained [1]–[5] due to multiple, spatially distributed transmitters and receivers. On the other hand, if the antennas are colocated, diversity and beamforming can be achieved by designing a different waveform for each antenna [6]–[14]. Various studies were recently published that compute the CRLB for estimating target parameters given certain assumptions [1], [4], [8]–[10], [15]. Also, the MIMO radar ambiguity function and its relation to the CRLB were discussed in [16], [17]. These studies, however, did not consider estimating attributes of moving targets, such as range-rate or velocity, in a dynamic tracking scenario.

Waveform design for MIMO radar applications was investigated in [9], [10], [18]–[20]. Specifically, in [9], [10], waveform optimization was used to estimate parameters of stationary multiple targets in the presence of spatially colored interference and noise. In [18], waveform design was used to minimize the error in estimating angles-of-arrival, whereas in [19], the authors designed optimized space-time codes to achieve maximum diversity in the presence of correlated clutter. By controlling the space-time (or azimuth-frequency) distribution of the transmitted signal and with knowledge of the clutter and/or target statistics, it was shown in [20] that it is possible to achieve significant improvements in detection performance.

This work was supported in part by the Department of Defense Grant No. AFOSR FA9550-05-1-0443.

In this paper, we investigate waveform design methodologies using MIMO radar systems with widely-separated antennas in order to improve dynamic target tracking. This can be achieved by using our derived waveform-parameterized CRLB for dynamic parameter estimation at high SNR scenarios. In particular, we make the assumption that the observation noise is approximated by the CRLB when the SNR is high. We then use the CRLB to predict the tracker performance for waveforms with varying parameters, and we design the waveform parameters to minimize the trace of the predicted error covariance.

The paper is organized as follows. In Section II, we derive the CRLB for estimating moving target attributes using MIMO radar with widely-separated antennas. We then formulate the dynamic target tracking problem and minimize the predicted MSE by designing the transmit waveform in Section III. In Section IV, we demonstrate the advantage of waveform agility in MIMO radar tracking using simulations.

II. MIMO Radar with Widely-Separated Antennas

A. Signal and Noise Models

We consider a MIMO radar system with widely-separated antennas as depicted in Figure 1. The signal transmitted by the mth antenna, $m \in \{1, \cdots, N_T\}$, and received by the lth antenna, $l \in \{1, \cdots, N_R\}$, can be represented by $r_{l,m}(t) = \beta_{l,m} s_{l,m}(t) + w_{l,m}(t)$. If $s_m(t)$ is the signal transmitted by the mth antenna with carrier frequency f_m, then $s_{l,m}(t) = s_m(t - \tau_{l,m}) e^{j2\pi\nu_{l,m}t}$. The reflection coefficients, time-delay, and Doppler-shift between the (l, m)th radar pair are given by $\beta_{l,m}$, $\tau_{l,m}$, and $\nu_{l,k}$, respectively. We assume that $w_{l,m}(t)$ is additive white Gaussian noise (AWGN) with $\mathrm{E}[w_{l,m}(t) w_{l',m'}(t)] = 0$, $l \neq l'$, $m \neq m'$, where $\mathrm{E}[\cdot]$ denotes statistical expectation. After sampling with period T_s, the signal samples are $r_{l,m}[n] = r_{l,m}(nT_s)$, $n = 1, \ldots, N$. We form the received signal vector $\mathbf{r} = [\mathbf{r}_1^{\mathbb{T}}, \cdots, \mathbf{r}_{N_T}^{\mathbb{T}}]^{\mathbb{T}}$, where $\mathbf{r}_m = [\mathbf{r}_{1,m}^{\mathbb{T}}, \cdots, \mathbf{r}_{N_R,m}^{\mathbb{T}}]^{\mathbb{T}}$, $\mathbf{r}_{l,m} = [r_{l,m}[1], \cdots, r_{l,m}[N]]^{\mathbb{T}}$, and $\mathbb{T}$ denotes vector transpose. Similarly, we define $\mathbf{s}_{l,m} = [s_{l,m}[1], \cdots, s_{l,m}[N]]^{\mathbb{T}}$ and $\mathbf{w}_{l,m} = [w_{l,m}[1], \cdots, w_{l,m}[N]]^{\mathbb{T}}$. Also, $\boldsymbol{\beta} = [\boldsymbol{\beta}_{1,1}^{\mathbb{T}} \cdots \boldsymbol{\beta}_{l,m}^{\mathbb{T}} \cdots \boldsymbol{\beta}_{N_R,N_T}^{\mathbb{T}}]^{\mathbb{T}}$, where $\boldsymbol{\beta}_{l,m} = [\mathrm{Re}\{\beta_{l,m}\} \;\; \mathrm{Im}\{\beta_{l,m}\}]^{\mathbb{T}}$.

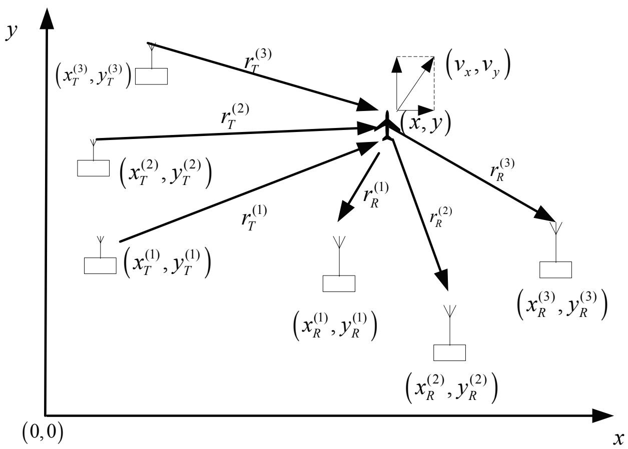

Fig. 1. MIMO radar system with widely-separated antennas.

B. CRLB Computation

Using the above signal model, we obtain the probability density function of the received signal as

$$p(\mathbf{r}|\boldsymbol{\beta}, x, y, v_x, v_y) = (\pi^{NN_RN_T}\det(\mathbf{C}_w))^{-1} \cdot \exp\left(-\sum_{m=1}^{N_T}\sum_{l=1}^{N_R}\left[(\mathbf{r}_{l,m} - \beta_{l,m}\mathbf{s}_{l,m})^{\mathbb{H}}\mathbf{C}_w^{-1}(\mathbf{r}_{l,m} - \beta_{l,m}\mathbf{s}_{l,m})\right]\right),$$

where (x, y) and (v_x, v_y) are the position and velocity of the target in two-dimensional Cartesian coordinates, $\mathbf{C}_w$ is the covariance matrix of $\mathbf{w}_{l,m}$, $\det(\cdot)$ denotes matrix determinant, and $\mathbb{H}$ denotes vector Hermitian. With the AWGN assumption, the noise covariance is given by $\mathbf{C}_w = \sigma_w^2\mathbf{I}_N$, where $\mathbf{I}_N$ is the $N \times N$ identity matrix. We let the unknown parameter vector be given by $\boldsymbol{\Psi} = [x, y, v_x, v_y]^{\mathbb{T}}$. Then, the CRLB for estimating $\boldsymbol{\Psi}$ is given by [15], [21]

$$\text{CRLB}_{\boldsymbol{\Psi}\boldsymbol{\Psi}} = \sigma_w^2\left[2\sum_{m=1}^{N_T}\sum_{l=1}^{N_R}|\beta_{l,m}|^2\mathbf{H}_{l,m}^{\mathbb{T}}\,\mathcal{I}_{l,m}^{\boldsymbol{\Phi}}\,\mathbf{H}_{l,m}\right]^{-1} \quad (1)$$

where

$$\mathcal{I}_{l,m}^{\boldsymbol{\Phi}} = \text{Re}\left\{\left(\frac{\partial\mathbf{s}_{l,m}}{\partial\boldsymbol{\Phi}_{l,m}^{\mathbb{T}}}\right)^{\mathbb{H}}\frac{\partial\mathbf{s}_{l,m}}{\partial\boldsymbol{\Phi}_{l,m}^{\mathbb{T}}} - \left(\frac{\partial\mathbf{s}_{l,m}}{\partial\boldsymbol{\Phi}_{l,m}^{\mathbb{T}}}\right)^{\mathbb{H}}\mathbf{s}_{l,m}(\mathbf{s}_{l,m}^{\mathbb{H}}\mathbf{s}_{l,m})^{-1}\mathbf{s}_{l,m}^{\mathbb{H}}\frac{\partial\mathbf{s}_{l,m}}{\partial\boldsymbol{\Phi}_{l,m}^{\mathbb{T}}}\right\} \quad (2)$$

is the waveform characteristic matrix, and

$$\mathbf{H}_{l,m} = \frac{\partial\boldsymbol{\Phi}_{l,m}}{\partial\boldsymbol{\Psi}^{\mathbb{T}}} = \begin{bmatrix} \frac{\partial\tau_{l,m}}{\partial x} & \frac{\partial\tau_{l,m}}{\partial y} & \frac{\partial\tau_{l,m}}{\partial v_x} & \frac{\partial\tau_{l,m}}{\partial v_y} \\ \frac{\partial\nu_{l,m}}{\partial x} & \frac{\partial\nu_{l,m}}{\partial y} & \frac{\partial\nu_{l,m}}{\partial v_x} & \frac{\partial\nu_{l,m}}{\partial v_y} \end{bmatrix}, \quad (3)$$

which can be determined by the radar geometry. Specifically, if the mth transmission antenna of a MIMO radar system is placed at $(x_T^{(m)}, y_T^{(m)})$, $m = 1, \ldots, N_T$, and the lth receiver antenna is placed at $(x_R^{(l)}, y_R^{(l)})$, $l = 1, \ldots, N_R$, then the time delay $\tau_{l,m}$ and Doppler shift $\nu_{l,m}$ are given by

$$\tau_{l,m} = \frac{r_T^{(m)} + r_R^{(l)}}{c} \text{ and } \nu_{l,m} = \frac{f_m\left(\dot{r}_T^{(m)} + \dot{r}_R^{(l)}\right)}{c}$$

where

$$\begin{aligned} r_T^{(m)} &= \left((x - x_T^{(m)})^2 + (y - y_T^{(m)})^2\right)^{1/2} \\ r_R^{(l)} &= \left((x - x_R^{(l)})^2 + (y - y_R^{(l)})^2\right)^{1/2} \\ \dot{r}_T^{(m)} &= \frac{1}{r_T^{(m)}}(v_x(x - x_T^{(m)}) + v_y(y - y_T^{(m)})) \\ \dot{r}_R^{(l)} &= \frac{1}{r_R^{(l)}}(v_x(x - x_R^{(l)}) + v_y(y - y_R^{(l)}))\,. \end{aligned}$$

As a result, the elements of $\mathbf{H}_{l,m}$ are given by [22]

$$\begin{aligned} \frac{\partial\tau_{l,m}}{\partial x} &= \frac{1}{c}\left(\frac{x - x_T^{(m)}}{r_T^{(m)}} + \frac{x - x_R^{(l)}}{r_R^{(l)}}\right) \\ \frac{\partial\tau_{l,m}}{\partial y} &= \frac{1}{c}\left(\frac{y - y_T^{(m)}}{r_T^{(m)}} + \frac{y - y_R^{(l)}}{r_R^{(l)}}\right) \\ \frac{\partial\tau_{l,m}}{\partial v_x} &= \frac{\partial\tau_{l,m}}{\partial v_y} = 0 \\ \frac{\partial\nu_{l,m}}{\partial x} &= \frac{f_m}{c}\left(\frac{v_x}{r_T^{(m)}} - \dot{r}_T^k\frac{x - x_T^{(m)}}{(r_T^{(m)})^2} + \frac{v_x}{r_R^{(l)}} - \dot{r}_R^l\frac{x - x_R^{(l)}}{(r_R^{(l)})^2}\right) \\ \frac{\partial\nu_{l,m}}{\partial y} &= \frac{f_m}{c}\left(\frac{v_y}{r_T^{(m)}} - \dot{r}_T^k\frac{y - y_T^{(m)}}{(r_T^{(m)})^2} + \frac{v_y}{r_R^{(l)}} - \dot{r}_R^l\frac{y - y_R^{(l)}}{(r_R^{(l)})^2}\right) \\ \frac{\partial\nu_{l,m}}{\partial v_x} &= \frac{f_m}{c}\left(\frac{x - x_T^{(m)}}{r_T^{(m)}} + \frac{x - x_R^{(l)}}{r_R^{(l)}}\right) \\ \frac{\partial\nu_{l,m}}{\partial v_y} &= \frac{f_m}{c}\left(\frac{y - y_T^{(m)}}{r_T^{(m)}} + \frac{y - y_R^{(l)}}{r_R^{(l)}}\right) \end{aligned}$$

where c is the velocity in the propagation medium.

C. CRLB and Transmission Waveforms

The CRLB in (1) can be related to the waveform physical characteristics. Specifically, we note that we can write (2) as

$$\mathcal{I}_{l,m}^{\boldsymbol{\Phi}} = \begin{bmatrix} \xi_{1,1} & \xi_{1,2} \\ \xi_{2,1} & \xi_{2,2} \end{bmatrix}^{-1} \quad (4)$$

which can be shown to be related to the waveform $s_{l,m}(t)$:

$$\xi_{1,1} \approx \int\left|\frac{\partial s_m(t - \tau_{l,m})}{\partial t}\right|^2 dt - \frac{1}{\mathcal{E}_{l,m}}\left|\int s_m(t - \tau)\frac{\partial s_m^*(t - \tau_{l,m})}{\partial t}dt\right|^2$$

$$\xi_{1,2} \approx 2\pi \,\mathrm{Im}\left\{ \int t s_m(t-\tau_{l,m}) \frac{\partial s_m^*(t-\tau_{l,m})}{\partial t} dt - \frac{1}{\mathcal{E}_{l,m}} \int t|s_m(t-\tau_{l,m})|^2 dt \int s_m(t-\tau_{l,m}) \frac{\partial s_m^*(t-\tau_{l,m})}{\partial t} dt \right\}$$

$$\xi_{2,2} \approx 4\pi^2 \left(\int t^2 \left|s_m(t-\tau_{l,m})\right|^2 dt - \frac{1}{\mathcal{E}_{l,m}} \left| \int t \left|s_m(t-\tau_{l,m})\right|^2 dt \right|^2 \right)$$

where

$$\mathcal{E}_{l,m} = \mathbf{s}_{l,m}^{\mathbb{H}} \mathbf{s}_{l,m} \approx \int |s_m(t-\tau_{l,m})|^2 dt \,.$$

Here, $\mathcal{E}_{l,m}$, $\xi_{1,1}$, $\xi_{2,2}$ are proportional to the signal energy, root mean-squared (rms) bandwidth, and rms duration of $s_m(t)$, respectively. Also, it can be shown that (4) is invariant to time and frequency shifts [23], [24]. Note that we also derived the CRLB for moving target parameters using MIMO radars with colocated-antennas [15].

III. Waveform-Agile Target Tracking

A. Tracking Problem Formulation

Our objective is to estimate the motion of a target in two dimensions. The target state is given by $\mathbf{x}_k = [x_k \; y_k \; \dot{x}_k \; \dot{y}_k]^{\mathbb{T}}$, where x_k and y_k correspond to the position, and $\dot{x}_k$ and $\dot{y}_k$ to the velocity of the target, at time k in Cartesian coordinates. The dynamic state space model is then given by

$$\mathbf{x}_k = \mathbf{F}\mathbf{x}_{k-1} + \mathbf{v}_k, \tag{5}$$

where $\mathbf{v}_k$ is a random process representing modeling errors, assumed to be an uncorrelated Gaussian sequence with covariance matrix $\mathbf{Q}$. The matrices $\mathbf{F}$ and $\mathbf{Q}$ are given by

$$\mathbf{F} = \begin{bmatrix} 1 & 0 & \delta t & 0 \\ 0 & 1 & 0 & \delta t \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

and

$$\mathbf{Q} = q \begin{bmatrix} \frac{\delta t^3}{3} & 0 & \frac{\delta t^2}{2} & 0 \\ 0 & \frac{\delta t^3}{3} & 0 & \frac{\delta t^2}{2} \\ \frac{\delta t^2}{2} & 0 & \delta t & 0 \\ 0 & \frac{\delta t^2}{2} & 0 & \delta t \end{bmatrix},$$

where δt is the time interval for the state update and q is a constant that characterizes the intensity of the change in position and velocity. The observation equation is given by

$$\mathbf{z}_k = \mathbf{x}_k + \mathbf{w}_k, \tag{6}$$

where $\mathbf{w}_k$ is the observation noise at time k. Assuming high SNR scenarios, the covariance $\mathbf{R}_k$ of $\mathbf{w}_k$ can be represented in terms of the CRLB of $\mathbf{x}_k$ in (1). Specifically,

$$\mathbf{R}_k = (\mathrm{CRLB}_{\boldsymbol{\Psi}\boldsymbol{\Psi}})_k \;,$$

where $(\mathrm{CRLB}_{\boldsymbol{\Psi}\boldsymbol{\Psi}})_k$ is the CRLB computed using the state vector $\mathbf{x}_k$. The reflection coefficients in (1) vary with time and are denoted by $\beta_{l,m}^{(k)}$. Hence, the dynamic target tracking problem is given by (5) and (6), and since both these equations are linear, the Kalman filter can be used to obtain the optimal state estimate.

B. Kalman Filter Covariance Estimate

We let $\mathbf{P}_{k|k}$ denote the Kalman filter covariance estimate at time k given observations from time $\mathbf{z}_1$ to $\mathbf{z}_k$. Then, $\mathbf{P}_{k+1|k+1}$ can be computed iteratively as

$$\mathbf{P}_{k+1|k+1} = \left[\left(\mathbf{Q} + \mathbf{F}\mathbf{P}_{k|k}\mathbf{F}^{\mathbb{T}} \right)^{-1} + \mathbf{R}_{k+1}^{-1} \right]^{-1}.$$

Note that since $\mathbf{R}_{k+1}$ is a function of the target state $\mathbf{x}_{k+1}$ as well as the reflection coefficients $\beta_{l,m}^{(k)}$ and the waveform physical characteristics, the predicted tracking error covariance $\mathbf{P}_{k+1|k+1}$ is also a function of these parameters.

C. Waveform Design for Dynamic Target Tracking

We investigate next the problem of waveform design for MIMO radar with widely-separated antennas. Specifically, we assume that each antenna of the MIMO radar system transmits one waveform with adjustable parameters. Then, a search over the space of allowable waveform parameters is performed to choose the waveform that optimizes a given cost function, expressed in terms of the waveform parameters.

The following assumptions are made to formulate the waveform design problem. At time k, the mth antenna transmits the Gaussian envelope impulse $s_m^{(k)}(t)$ that is parameterized by the waveform bandwidth parameter $\lambda_{k,m}$ as

$$s_m^{(k)}(t) = \left(\frac{\lambda_{k,m}}{\pi} \right)^{\frac{1}{4}} \exp\left(-\lambda_{k,m}^2 \frac{t^2}{2}\right) \, \exp\left(j2\pi f_m t\right).$$

Here, f_m is the carrier frequency of the mth antenna. Using this waveform, we can show that (4), at time step k, simplifies to

$$\mathcal{I}_{l,m}^{\boldsymbol{\Phi}} = 4\pi^2 \begin{bmatrix} \frac{\lambda_{k,m}^2}{2} & 0 \\ 0 & \frac{1}{2\lambda_{k,m}^2} \end{bmatrix}.$$

It can also be shown that

$$\mathbf{R}_k = \sigma_w^2 \left[2 \sum_{m=1}^{N_T} \sum_{l=1}^{N_R} |\beta_{l,m}|^2 \cdot \mathrm{Re}\left\{ \mathbf{H}_{l,m}^{(k)\mathbb{T}} \left(4\pi^2 \begin{bmatrix} \frac{\lambda_{k,m}^2}{2} & 0 \\ 0 & \frac{1}{2\lambda_{k,m}^2} \end{bmatrix} \right) \mathbf{H}_{l,m}^{(k)} \right\} \right]^{-1},$$

where $\mathbf{H}_{l,m}^{(k)}$ is defined in (3), the superscript k denotes that $\mathbf{H}_{l,m}^{(k)}$ is obtained at each time step k based on the target state $\mathbf{x}_k = [x_k, y_k, \dot{x}_k, \dot{y}_k]^{\mathbb{T}}$.

Using the Kalman filter at time step k, we obtain the target state estimate $\hat{\mathbf{x}}_k$ and error covariance matrix $\widehat{\mathbf{P}}_{k|k}$. Our aim is to design the waveform parameters $\boldsymbol{\lambda}_{k+1} = [\lambda_{k+1,1}\lambda_{k+1,2}\cdots\lambda_{k+1,N_T}]$ by minimizing the trace of the estimation covariance matrix $\mathbf{P}_{k+1|k+1} = \left[\left(\mathbf{Q} + \mathbf{F}\mathbf{P}_{k|k}\mathbf{F}^{\mathbb{T}} \right)^{-1} + \mathbf{R}_{k+1}^{-1} \right]^{-1}$. To compute $\mathbf{P}_{k+1|k+1}$, we need to approximate $\mathbf{H}_{l,m}^{k+1}$ and $\mathbf{R}_{k+1}$ as their direct calculation requires knowledge of the future target state $\mathbf{x}_{k+1}$ and reflection coefficients $\beta_{k+1}^{(k)}$. We can approximate $\mathbf{H}_{l,m}^{(k+1)}$ using the predicted target state $\tilde{\mathbf{x}}_{k+1} = \mathbf{F}\hat{\mathbf{x}}_k$. Also, as we assume that the random reflection coefficient sequence is stationary, the covariance $\mathrm{E}[|\beta_{l,m}|^2]$ remains unchanged. As a result, $\tilde{\mathbf{R}}_{k+1}$ can be obtained using $\tilde{x}_{k+1}$ and $\mathrm{E}[|\beta_{l,m}|^2]$. Then, using $\tilde{\mathbf{R}}_{k+1}$, we can approximate $\mathbf{P}_{k+1|k+1}$ as

$$\tilde{\mathbf{P}}_{k+1|k+1} = \left[\left(\mathbf{Q} + \mathbf{F}\mathbf{P}_{k|k}\mathbf{F}^{\mathbb{T}}\right)^{-1} + \tilde{\mathbf{R}}_{k+1}^{-1}\right]^{-1}.$$

As our numerical results demonstrate, this approximation works well for far-field tracking applications.

We employ sequential quadratic programming (SQP) to minimize the trace of $\tilde{\mathbf{P}}_{k+1|k+1}$ under certain constraints. Specifically,

$$\boldsymbol{\lambda}_k^{\mathrm{opt}} = \min_{\boldsymbol{\lambda}_k} \mathrm{Tr}\left\{\tilde{\mathbf{P}}_{k+1|k+1}\right\}, \text{ subject to } \lambda_{\mathrm{min}} \leq \lambda_{k,m} \leq \lambda_{\mathrm{max}},$$

where λ_{min} and λ_{max} are the minimum and maximum λ values, respectively.

IV. Numerical Results and Discussion

For our numerical simulations, we considered a single target moving in two dimensions. The carrier frequency is $f_c = 10$ GHz, $c = 3 \times 10^8$ m/s, and $\delta t = 1$ s. The waveform bandwidth varies between $\lambda_{\mathrm{min}} = 1$ kHz and $\lambda_{\mathrm{max}} = 10$ kHz. The target moves along a trajectory with a maximum acceleration of 20 m/s^2. The initial position of the target is $(3 \times 10^4, 3 \times 10^4)$ m and its initial velocity is $(100, 100)$ m/s. We assume $N_T = 3$ transmitter antennas located at $(0, 0)$ m, $(10, 0)$ km and $(0, 10)$ km that also act as the receiver antennas. For comparison, we also consider another MIMO radar whose transmitted waveforms are randomly chosen at each time step.

Figure 2 compares the trajectory of the MIMO radar tracker with waveform optimization and the MIMO radar with random waveforms. Figure 3 compares the tracking MSE of 100 Monte Carlo simulations for the two MIMO radar systems. When the waveforms are optimally configured, we observe significant performance improvement in the target positionestimation. Similar improvements can be also observed for the target velocity estimation in Figure 4. Figure 5 shows the optimally selected waveform parameters at each time step, whereas Figure 6 shows the randomly selected waveform parameters at each time step.

V. Conclusions

In this paper, we derived the CRLB for jointly estimating moving target attributes using MIMO radar with widely-separated antennas. We investigated the relationship between the CRLB and the transmission waveform characteristics, and then used this relationship for waveform-agile tracking. Assuming high SNR, the CRLB was used to approximate the predicted error covariance as a function of the transmitted waveform. By selecting the waveform parameters to minimize the predicted tracking error, we demonstrated that we can improve the tracking performance.

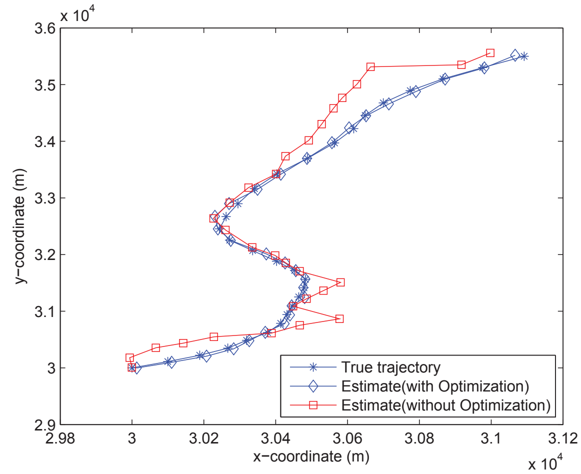

Fig. 2. The true target trajectory and the estimated trajectory.

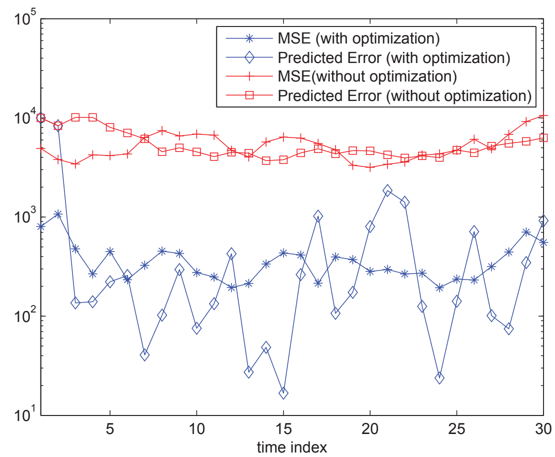

Fig. 3. Tracking MSE for the x-axis position estimate.

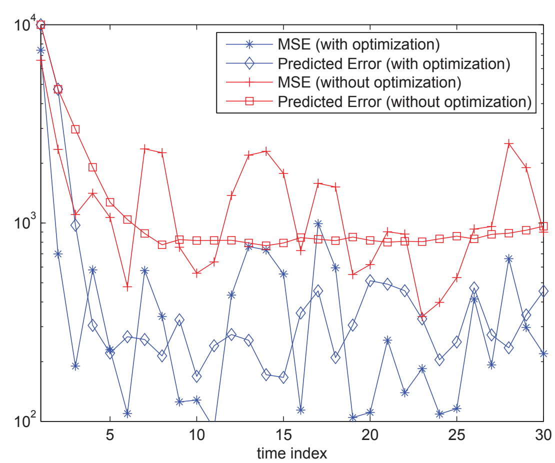

Fig. 4. Tracking MSE for the x-axis velocity estimate.

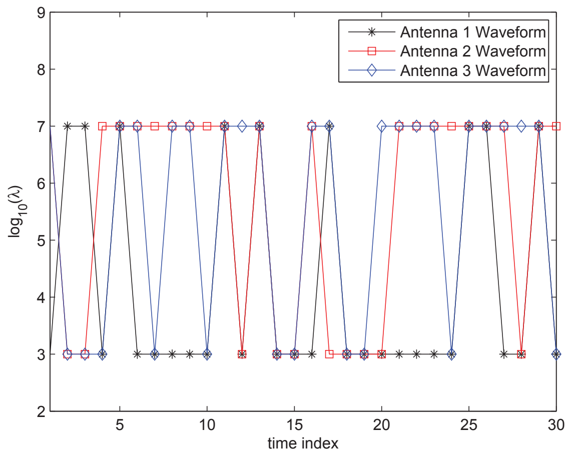

Fig. 5. Optimally selected waveform parameters.

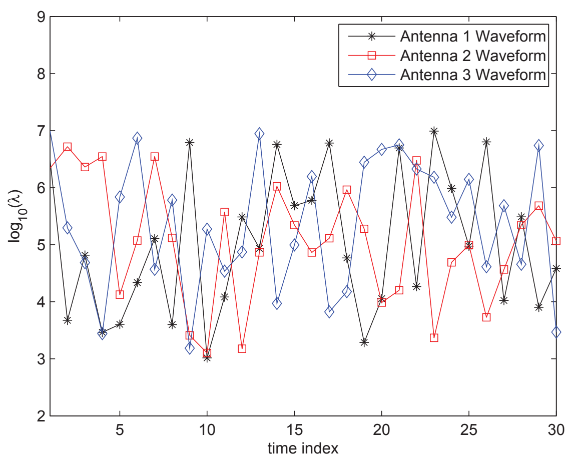

Fig. 6. Randomly selected waveform parameters.

REFERENCES

[1] E. Fishler, A. Haimovich, R. Blum, D. Chizhik, L. Cimini, and R. Valenzuela, "MIMO radar: an idea whose time has come," in *Proceedings of IEEE Radar Conference*, 2004, pp. 71–78.

[2] E. Fishler, A. Haimovich, R. Blum, L. Cimini, D. Chizhik, and R. Valenzuela, "Performance of MIMO radar systems: advantages of angular diversity," in *Proceedings of Asilomar Conference on Signals, Systems and Computers*, vol. 1, 2004, pp. 305–309.

[3] E. Fishler, A. Haimovich, R. Blum, L. J. Cimini, Jr., D. Chizhik, and R. Valenzuela, "Spatial diversity in radars-models and detection performance," *IEEE Transactions on Signal Processing*, vol. 54, no. 3, pp. 823–838, 2006.

[4] N. H. Lehmann, E. Fishler, A. M. Haimovich, R. S. Blum, D. Chizhik, L. J. Cimini, and R. A. Valenzuela, "Evaluation of transmit diversity in MIMO-radar direction finding," *IEEE Transactions on Signal Processing*, vol. 55, no. 5, pp. 2215–2225, 2007.

[5] A. M. Haimovich, R. S. Blum, and L. J. Cimini, "MIMO radar with widely separated antennas," *IEEE Signal Processing Magazine*, vol. 25, no. 1, pp. 116–129, 2008.

[6] J. Li, P. Stoica, and Y. Xie, "On probing signal design for MIMO radar," in *Proceedings of Asilomar Conference on Signals, Systems and Computers*, 2006, pp. 31–35.

[7] J. Li, P. Stoica, L. Xu, and W. Roberts, "On parameter identifiability of MIMO radar," *IEEE Signal Processing Letters*, vol. 14, no. 12, pp. 968–971, 2007.

[8] J. Li, L. Xu, P. Stoica, K. W. Forsythe, and D. W. Bliss, "Range compression and waveform optimization for MIMO radar: A CramérRao bound based study," *IEEE Transactions on Signal Processing*, vol. 56, no. 1, pp. 218–232, 2008.

[9] L. Xu, J. Li, P. Stoica, K. W. Forsythe, and D. W. Bliss, "Waveform optimization for MIMO radar: A Cramér-Rao bound based study," in *Proceedings of IEEE International Conference on Acoustic, Speech and Signal Processing*, vol. 2, 2007, pp. II–917–II–920.

[10] L. Xu and J. Li, "Iterative generalized-likelihood ratio test for MIMO radar," *IEEE Transactions on Signal Processing*, vol. 55, no. 6, pp. 2375–2385, 2007.

[11] L. Xu, J. Li, and P. Stoica, "Adaptive techniques for MIMO radar," in *Proceedings of IEEE Sensor Array and Multichannel Signal Processing Workshop*, 2006, pp. 258–262.

[12] D. R. Fuhrmann and G. San Antonio, "Transmit beamforming for MIMO radar systems using partial signal correlation," in *Proceedings of Asilomar Conference on Signals, Systems and Computers*, vol. 1, 2004, pp. 295–299.

[13] G. San Antonio and D. R. Fuhrmann, "Beampattern synthesis for wideband MIMO radar systems," in *Proceedings of 1st IEEE International Workshop on Computational Advances in Multi-Sensor Adaptive Processing*, 2005, pp. 105–108.

[14] T. Aittomäki and V. Koivunen, "Low-complexity method for transmit beamforming in MIMO radars," in *Proceedings of IEEE International Conference on Acoustic, Speech and Signal Processing*, vol. 2, 2007, pp. II–305–II–308.

[15] J. Zhang, G. Maalouli, A. Papandreou-Suppappola, and D. Morrell, "MIMO radar and joint CRLB for the parameter estimation of moving targets," submitted to *IEEE Signal Processing Letters*, 2008.

[16] G. San Antonio, D. R. Fuhrmann, and F. C. Robey, "MIMO radar ambiguity functions," *IEEE Journal of Selected Topics in Signal Processing*, vol. 1, no. 1, pp. 167–177, 2007.

[17] N. H. Lehmann, A. M. Haimovich, R. S. Blum, and L. Cimini, "High resolution capabilities of MIMO radar," in *Proceedings of Asilomar Conference on Signals, Systems and Computers*, 2006, pp. 25–30.

[18] K. W. Forsythe and D. W. Bliss, "Waveform correlation and optimization issues for MIMO radar," in *Proceedings of Asilomar Conference on Signals, Systems and Computers*, 2005, pp. 1306–1310.

[19] A. De Maio and M. Lops, "Achieving full diversity in MIMO radar: Code construction and performance bounds," in *Proceedings of International Radar Symposium*, 2006, pp. 1–4.

[20] B. Friedlander, "Waveform design for MIMO radars," *IEEE Transactions on Aerospace and Electronic Systems*, vol. 43, no. 3, pp. 1227–1238, 2007.

[21] J. Zhang, "Derivation of the CRLB of mobile target attributes usingMIMO radar," http://www.fulton.asu.edu/~apapand/Research/Zhang_Rept_Nov08.pdf, November 2008.

[22] B. Ristic and S. Arulampalam, *Beyond the Kalman Filter: Particle Filters for Tracking Applications*. Artech House, 2004.

[23] A. Dogandzic and A. Nehorai, "Cramér-Rao bounds for estimating range, velocity, and directionwith a sensor array," *IEEE Transactions on Signal Processing*, vol. 49, pp. 1122 – 1137, 2001.

[24] L. Cohen, *Time Frequency Analysis: Theory and Applications*. Englewood Cliff, New Jersey: Prentice Hall PTR, 1994.