Sensor Scheduling with Waveform Design for Dynamic Target Tracking Using MIMO Radar

Bhavana Manjunath†, Jun J. Zhang†, Antonia Papandreou-Suppappola†, and Darryl Morrell‡

†School of Electrical, Computer and Energy Engineering, Arizona State University, Tempe, AZ
‡Department of Engineering, Polytechnic Campus, Arizona State University, Mesa, AZ

***Abstract*—Multiple-input, multiple-output (MIMO) radar systems have gained significant attention as they can enhance target detection, identification and parameter estimation performance. In this paper, we consider the problem of optimizing the target tracking performance of a widely-separated MIMO radar system by scheduling the transmitter sensors and adaptively designing their waveforms. Specifically, for a tracking scenario consisting of a large number of MIMO radars, we propose: (a) a transmitter scheduling algorithm to achieve tracking performance gains based on resource constraints; and (b) an adaptive waveform optimization algorithm that further improves tracking performance. Under an ideal receiver assumption, we evaluate the predicted tracking mean-squared error using the derived Cramér-Rao lower bound (CRLB) on the estimation of the target states. The scheduling algorithm is then formulated as a mixed boolean-convex optimization problem to minimize the CRLB. The optimum waveform parameters are adaptively obtained using sequential quadratic programming. The effectiveness of combining the MIMO radar technology with adaptive waveform design and sensor scheduling was demonstrated with simulations.**

I. Introduction

MIMO radar systems have been gaining in popularity since their introduction in [1]. When compared to conventional radar systems, which suffer from large fluctuations in the received signal power, MIMO radar systems were shown to exhibit (almost) constant average signal-to-noise ratios (SNRs). There were also shown to demonstrate performance gains over their conventional phased array counter-parts as well as improvements in detection performance, angular resolution, and direction finding [2]–[4]. Waveform optimization was also considered using several criteria on the Cramér-Rao lower bound (CRLB) matrix in [5]. In [6], beamforming was used by designing random transmission waveforms to improve the output SNR and increase detection and estimation performance for MIMO radars with collocated antennas. Specifically, the covariance matrix of the transmitted waveforms was optimized by considering various optimization criteria and the CRLB matrix of the target parameters. Note that although different beam patterns were considered, the same transmit waveform was used by all antennas. Note, however, that one of the main advantages of MIMO radar systems is their characteristic ability to transmit a different waveform by each radar sensor.

We couple the flexibility of transmitting a completely different waveform by each transmitter radar with optimal waveform design to obtain performance gains in a tracking application. As the design of radar transmission waveforms for traditional monostatic and multistatic radar systems was studied extensively [9]–[11], we now use this design for each transmit radar of a widely-separated MIMO radar system. Most of the work on MIMO radar with widely-separated antennas has been directed towards improving the performance in detection of a stationary target and estimating its parameters. As we propose an adaptive waveform design algorithm for a target in motion, we incorporate both delay and Doppler shifts due to the moving target in the receiver model, and we optimize waveform parameters to estimate the target's position and velocity at every time step.

We integrate the waveform agile sensing with a radar scheduling algorithm to further increase the tracking performance while meeting the serious trade-offs in resource utilization costs. Some examples where sensor scheduling was shown to result in large performance improvements include selecting sensors for data gathering [12], sensor management to efficiently use limited resources [13], and selectively tasking waveforms and pointing direction in sensors [14]. Our proposed system is a tracking system which incorporates a scheduler that activates a selected set of radars based on some criteria and then obtains the optimum transmission waveforms for those radars using a waveform design algorithm.

This paper is organized as follows. In Section II, we provide the signal model for the widely-separated MIMO radar system and the derivation of the CRLB for estimating the position and velocity of the target. The tracking problem is formulated in Section III. The proposed scheduling and adaptive waveform design methods are discussed in Sections IV and V, respectively. Using simulation results in Section VI, we demonstrate the effectiveness of the proposed MIMO radar tracking system.

II. MIMO Radar System Signal Model

A. Signal Model

We assume that the MIMO radar system have widely-separated sensors so that the reflection coefficients between each transmit-receive radar pair are uncorrelated [4]. This results in reduced radar cross section (RCS) fluctuations and aid in maintaining a constant averaged SNR [15].

Specifically, we consider a system with N_T transmitter radars and N_R receiver radars. We assume that the mth transmitter, $m = 1, \ldots, N_T$, transmits signal $s_m(t)$ with carrier frequency f_m. The baseband received signal due to the transmitter-receiver pair (l, m), $l = 1, \ldots, N_R$, can be represented by $r_{l,m}(t) = \beta_{l,m} s_{l,m}(t) + w_{l,m}(t)$, where $s_{l,m}(t) =$

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

$s_m(t-\tau_{l,m})e^{j2\pi\nu_{l,m}t}$ is the received waveform of radar pair (l,m). The complex reflection coefficient, time-delay, and Doppler-shift between the (l,m)th radar pair are $\beta_{l,m}$, $\tau_{l,m}$, and $\nu_{l,m}$, respectively. We assume that $w_{l,m}(t)$ is additive white Gaussian noise (AWGN) with $\mathrm{E}[w_{l,m}(t)w_{l',m'}(t)]=0$, $\forall\ l \neq l'$, $m \neq m'$, where $\mathrm{E}[\cdot]$ denotes statistical expectation. After uniform sampling with sampling 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 matrix 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 $\boldsymbol{\beta}_{l,m}=[\mathrm{Re}\{\beta_{l,m}\}\ \ \mathrm{Im}\{\beta_{l,m}\}]^{\mathbb{T}}$.

B. CRLB Computation

Let the vector $\boldsymbol{\Psi}=[x,y,\dot{x},\dot{y}]^{\mathbb{T}}$ denote the unknown position (x,y) and velocity $(\dot{x},\dot{y})$ of the target in two-dimensional (2-D) Cartesian coordinates. The radar configuration incorporates an activation parameter $\mathbf{a}=[a_1,a_2,\cdots,a_{N_T}]$, where $\mathbf{a}$ is a binary vector in which $a_m=1$ denotes the activation of the mth radar. An activated radar transmits signals and receives returns from the target; the returns originated from activated radars like itself). The CRLB for estimating $\boldsymbol{\Psi}$ is then

$$\mathrm{CRLB}_{\boldsymbol{\Psi}\boldsymbol{\Psi}}=\left[2\sum_{m=1}^{N_T}\sum_{l=1}^{N_R}a_m|\beta_{l,m}|^2\frac{1}{\sigma^2_{w_{l,m}}}\mathbf{H}_{l,m}^{\mathbb{T}}\ \mathcal{I}_{l,m}^{\boldsymbol{\Phi}}\mathbf{H}_{l,m}\right]^{-1} \tag{1}$$

where

$$\mathcal{I}_{l,m}^{\boldsymbol{\Phi}} = \mathrm{Re}\Big\{\Big(\frac{\partial\mathbf{s}_{l,m}}{\partial\boldsymbol{\Phi}_{l,m}^{\mathbb{T}}}\Big)^{\mathbb{H}}\frac{\partial\mathbf{s}_{l,m}}{\partial\boldsymbol{\Phi}_{l,m}^{\mathbb{T}}}-\Big(\frac{\partial\mathbf{s}_{l,m}}{\partial\boldsymbol{\Phi}_{l,m}^{\mathbb{T}}}\Big)^{\mathbb{H}} \cdot\mathbf{s}_{l,m}(\mathbf{s}_{l,m}^{\mathbb{H}}\mathbf{s}_{l,m})^{-1}\mathbf{s}_{l,m}^{\mathbb{H}}\frac{\partial\mathbf{s}_{l,m}}{\partial\boldsymbol{\Phi}_{l,m}^{\mathbb{T}}}\Big\}$$

is the waveform characteristic matrix, and

$$\mathbf{H}_{l,m}=\frac{\partial\boldsymbol{\Phi}_{l,m}}{\partial\boldsymbol{\Psi}^{\mathbb{T}}}=\begin{bmatrix}\frac{\partial\tau_{l,m}}{\partial x} & \frac{\partial\tau_{l,m}}{\partial y} & \frac{\partial\tau_{l,m}}{\partial\dot{x}} & \frac{\partial\tau_{l,m}}{\partial\dot{y}}\\ \frac{\partial\nu_{l,m}}{\partial x} & \frac{\partial\nu_{l,m}}{\partial y} & \frac{\partial\nu_{l,m}}{\partial\dot{x}} & \frac{\partial\nu_{l,m}}{\partial\dot{y}}\end{bmatrix}$$

is determined by the geometry relationship between the radars and the target. Specifically, if the mth transmitter is placed at $(x_T^{(m)},y_T^{(m)})$, $m=1,\ldots,N_T$, and the lth receiver is placed at $(x_R^{(l)},y_R^{(l)})$, $l=1,\ldots,N_R$, then the time delay is given by $\tau_{l,m}=(r_T^{(m)}+r_R^{(l)})/c$ and Doppler shift is given by $\nu_{l,m}=f_m\Big(\dot{r}_T^{(m)}+\dot{r}_R^{(l)}\Big)/c$, where $r_T^{(m)}=((x-x_T^{(m)})^2+(y-y_T^{(m)})^2)^{1/2}$, $r_R^{(l)}=((x-x_R^{(l)})^2+(y-y_R^{(l)})^2)^{1/2}$, $\dot{r}_T^{(m)}=(\dot{x}(x-x_T^{(m)})+\dot{y}(y-y_T^{(m)}))/r_T^{(m)}$, and $\dot{r}_R^{(l)}=(\dot{x}(x-x_R^{(l)})+\dot{y}(y-y_R^{(l)}))/r_R^{(l)}$.

III. Tracking Problem Formulation

For the tracking problem, we assume that a single target is moving in 2-D space. At time step k, 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 in Cartesian coordinates. The dynamic state space model is given by $\mathbf{x}_k=\mathbf{F}\mathbf{x}_{k-1}+\mathbf{v}_k$, where $\mathbf{v}_k$ is a random process representing modeling errors, assumed to be an uncorrelated Gaussian sequence with covariance matrix $\mathbf{Q}$, where

$$\mathbf{F}=\begin{bmatrix}1&0&\delta t&0\\0&1&0&\delta t\\0&0&1&0\\0&0&0&1\end{bmatrix},\quad \mathbf{Q}=q\begin{bmatrix}\frac{\delta t^3}{3}&0&\frac{\delta t^2}{2}&0\\0&\frac{\delta t^3}{3}&0&\frac{\delta t^2}{2}\\\frac{\delta t^2}{2}&0&\delta t&0\\0&\frac{\delta t^2}{2}&0&\delta t\end{bmatrix},$$

and δt is the time interval for the state update and q is a constant characterizing the intensity of the change in position and velocity. The observation equation is given by $\mathbf{z}_k=\mathbf{x}_k+\mathbf{w}_k$, where $\mathbf{w}_k$ is the observation noise at time k. In the case of a multisensor or multistatic radar system, we obtain measurements from each of the active radars such that $\mathbf{z}_k=\Big[\mathbf{z}_k^1,\mathbf{z}_k^2\ \cdots,\mathbf{z}_k^{N_T}\Big]$. In the MIMO radar case, we obtain the position and velocity in the x and y coordinates directly. It is evident that the dynamic target tracking problem given by the state space model are linear, and the Kalman filter can be used to obtain the optimal state estimate.

In order to formulate a predictive scheduling algorithm, i.e., perform optimization and schedule sensors at time $k+1$ using information at time k, we consider the iterative computation of the Kalman filter covariance estimate $\mathbf{P}_{k+1|k+1}$. We let $\mathbf{P}_{k|k}$ denote the Kalman filter covariance estimate at time k given observations from time $\mathbf{z}_1$ to $\mathbf{z}_k$. From the classical Kalman filter equations [16], we have, $\mathbf{P}_{k+1|k+1}=\Big[\big(\mathbf{Q}+\mathbf{F}\mathbf{P}_{k|k}\mathbf{F}^{\mathbb{T}}\big)^{-1}+\mathbf{R}_{k+1}^{-1}\Big]^{-1}$. The assumption of high SNR allows us to express the measurement noise covariance matrix in terms of the CRLB on the unbiased estimates of the receiver estimation parameter vector [9], [10]. We incorporate the CRLB in (1) as the measurement noise covariance,

$$\begin{aligned}\mathbf{R}_k &= (\mathrm{CRLB}_{\boldsymbol{\Psi}\boldsymbol{\Psi}})_k\\ &=\left[2\sum_{m=1}^{N_T}\sum_{l=1}^{N_R}a_{m,k}|\beta_{l,m,k}|^2\frac{1}{\sigma^2_{w_{l,m,k}}}\mathbf{H}_{l,m,k}^{\mathbb{T}}\ \mathcal{I}_{l,m,k}^{\boldsymbol{\Phi}}\ \mathbf{H}_{l,m,k}\right]^{-1},\end{aligned}$$

where the subscript k indicates that all the variables are obtained at time step k. Thus, the predicted state covariance is in terms of the selected radars and the waveform parameters.

IV. Radar Sensor Scheduling

In this section, we consider the scheduling problem for the MIMO radar system for target tracking. We use the trace of the estimated error covariance as the performance metric to quantify the tracking accuracy. Specifically, the trace of the predicted error covariance $\mathbf{P}_{k+1|k+1}$ is used as the performance metric to quantify the tracking accuracy. To compute $\mathbf{P}_{k+1|k+1}$, we first need to approximate $\mathbf{H}_{l,m,k+1}$ and $\mathbf{R}_{k+1}$, as their direct calculation requires the future target state $\mathbf{x}_{k+1}$ and reflection coefficients β_{k+1}, which are impossible to obtain at time step k. We can approximate $\mathbf{H}_{l,m,k+1}$ using the predicted target state $\tilde{\mathbf{x}}_{k+1}=\mathbf{F}\hat{\mathbf{x}}_k$, where $\hat{\mathbf{x}}_k$ is the estimate of target state $\mathbf{x}_k$. Also, as we assume that the random reflection coefficient sequence is stationary, the covariance $\sigma^2_{\beta_{l,m}}=\mathrm{E}[|\beta_{l,m,k+1}|^2]$ remains unchanged. As our numerical results demonstrate, this approximation works well for far-field tracking applications. As a result, $\tilde{\mathbf{R}}_{k+1}$ can be obtained using $\tilde{\mathbf{x}}_{k+1}$ and $\mathrm{E}[|\beta_{l,m}|^2]$. Then, using $\tilde{\mathbf{R}}_{k+1}$, we can obtain $\tilde{\mathbf{P}}_{k+1|k+1} = \left[\left(\mathbf{Q} + \mathbf{F}\mathbf{P}_{k|k}\mathbf{F}^{\mathbb{T}}\right)^{-1} + \tilde{\mathbf{R}}_{k+1}^{-1}\right]^{-1}$. Using $\mathbf{P}_{k+1|k} = \mathbf{Q} + \mathbf{F}\mathbf{P}_{k|k}\mathbf{F}^{\mathbb{T}}$ and $\left(\tilde{\mathbf{R}}_{k+1}\right)^{-1} = \sum_{m=1}^{N_T} a_{m,k+1}\mathbf{J}_{k+1}^{m}$ where $\mathbf{J}_{k+1}^{m} = 2\sum_{l=1}^{N_R} \sigma_{\beta_{l,m}}^2 \frac{1}{\sigma_{w_{l,m}}^2} \tilde{\mathbf{H}}_{l,m,k+1}^{\mathbb{T}} \mathcal{I}_{l,m,k+1}^{\mathbf{\Phi}} \tilde{\mathbf{H}}_{l,m,k+1}$, then $\tilde{\mathbf{P}}_{k+1|k+1} = \left[\mathbf{P}_{k+1|k}^{-1} + \sum_{m=1}^{N_T} a_{m,k+1}\mathbf{J}_{k+1}^{m}\right]^{-1}$. We also denote its trace as $\rho(\mathbf{a}_{k+1}) = \mathrm{Tr}\left\{\tilde{\mathbf{P}}_{k+1|k+1}\right\}$.

We can formulate the scheduling problem as a mixed boolean convex (MBC) optimization. This is a class of constrained optimization problems with convex objective and constraint equations, where the optimization variable attains discrete values. In our case, the integer valued constraint variables are due to the radar activation vector. The branch and bound algorithm is one of the methods that can be used to solve this class of constrained optimization problems and obtain a global optimum solution.

We consider the scheduling problem for two tracking scenarios. In the first case, the objective is to minimize the number of active radars such that a predefined tracking accuracy is maintained. In the second case, the objective is to minimize the tracking error subject to constraints on the number of radars that can be used.

a) Scheduling to minimize resource utilization: We seek to activate the minimum number of sensors for which $\rho(\mathbf{a}_{k+1}) < \gamma$, where γ is a preset threshold. This minimization problem can be formulated as

$$\begin{aligned} &\underset{a_{k+1}}{\text{minimize}} \quad \mathbf{1}^{\mathbb{T}}\mathbf{a}_{k+1} \\ &\text{subject to} \quad \rho(\mathbf{a}_{k+1}) < \gamma \text{ and } a_{m,k+1} \in \{0, 1\} \end{aligned} \tag{2}$$

where $m = 1, \ldots, N_T$, $\rho(\mathbf{a}_{k+1})$ is convex with respect to $\mathbf{a}_{k+1}$, $\mathbf{1}$ is a vector of ones, and $\mathbf{1}^{\mathbb{T}}\mathbf{a}_{k+1}$ is an affine function of $\mathbf{a}_{k+1}$. The discrete values assumed by the sensor activation vector makes the problem non-convex, however, a suitable candidate for an MBC optimization problem. We solve the problem using the branch and bound method.

b) Scheduling to minimize the predicted tracking MSE: We consider the problem of scheduling the radars to minimize the tracking MSE. We constrain the minimum number N_l and maximum number N_u of transmitters that can be activated at each time step. The minimization problem is given by

$$\begin{aligned} &\underset{a_{k+1}}{\text{minimize}} \quad \rho(\mathbf{a}_{k+1}) \\ &\text{subject to } N_l \leq \mathbf{1}^{\mathbb{T}}\mathbf{a}_{k+1} \leq N_u \text{ and } a_{m,k+1}^{m} \in \{0, 1\} \end{aligned} \tag{3}$$

where $m = 1, \ldots, N_T$. The objective (trace of the predicted tracking MSE $\mathbf{P}_{k+1|k+1}$) is formulated as a function of the Boolean vector $\mathbf{a}_{k+1}$ and can be shown to be convex. The constraints specify the minimum (N_l) and maximum (N_u) number of sensors that can be activated at any time step, and these constraints are affine functions of $\mathbf{a}_{k+1}$ and hence convex. Thus, this problem can also be solved using the branch and bound algorithm. Forming a binary tree and finding the bounds on the optimal solution follows from the previous problem. We expect the algorithm to choose the maximum number of sensors at all time steps as the information obtained is proportional to the number of sensors. However, the optimum combination of those sensors is a critical step for efficient tracking performance.

V. Adaptive Waveform Design

The problem of waveform design for MIMO radar sensors is chosen by the scheduling algorithm in that we assume that each chosen radar 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.

If we let $\hat{m} \in \{1, \cdots, \hat{N}_T\}$ be the index of one of the radars activated by the scheduling algorithm, then the following assumptions are made to formulate the waveform design problem. At time $k+1$, the $\hat{m}$th radar transmits the Gaussian envelope waveform $s_{\hat{m}}^{(k+1)}(t) = (\lambda_{k+1,\hat{m}}/\pi)^{1/4} \exp\left(-\lambda_{k+1,\hat{m}}^2 t^2/2\right) \exp\left(j2\pi f_{\hat{m}} t\right)$ that is parameterized by the bandwidth parameter $\lambda_{k+1,\hat{m}}$. Here, $f_{\hat{m}}$ is the carrier frequency of the $\hat{m}$th radar. Using this waveform, the waveform characteristic matrix, at time step $k+1$, is the diagonal matrix $\mathcal{I}_{l,\hat{m},k+1}^{\mathbf{\Phi}}$=$4\pi^2\,\mathrm{diag}(\lambda_{k+1,\hat{m}}^2/2, 1/(2\lambda_{k+1,\hat{m}}^2))$. Using the scheduled radars, the approximate measurement noise covariance at time step $k+1$ is $\tilde{\mathbf{R}}_{k+1}^{*}$=$\sigma_w^2[2\sum_{\hat{m}=1}^{\hat{N}_T}\sum_{l=1}^{N_R}\sigma_{\beta_{l,m}}^2 \tilde{\mathbf{H}}_{l,\hat{m},k+1}^{\mathbb{T}} \mathcal{I}_{l,\hat{m},k+1}^{\mathbf{\Phi}} \tilde{\mathbf{H}}_{l,\hat{m},k+1}]^{-1}$. Our aim is to design the parameters $\boldsymbol{\lambda}_{k+1}$=$[\lambda_{k+1,1}\lambda_{k+1,2}\cdots\lambda_{k+1,N_T}]$ to minimize the trace of the estimation covariance matrix $\tilde{\mathbf{P}}_{k+1|k+1}^{*}$=$[(\mathbf{Q} + \mathbf{F}\mathbf{P}_{k|k}\mathbf{F}^{\mathbb{T}})^{-1} + (\tilde{\mathbf{R}}_{k+1}^{*})^{-1}]^{-1}$ under certain constraints. This is achieved using sequential quadratic programming. Specifically,

$$\boldsymbol{\lambda}_{k+1}^{*} = \min_{\boldsymbol{\lambda}_{k+1}} \mathrm{Tr}\{\tilde{\mathbf{P}}_{k+1|k+1}^{*}\}, \quad \lambda_{\min} \leq \lambda_{k+1,\hat{m}} \leq \lambda_{\max},$$

where $\lambda_{\min}$, $\lambda_{\max}$ are the minimum and maximum λ values, respectively.

We note that, in order to initiate the scheduling algorithm, all sensors require transmission waveform parameters. As a result, at time $k = 0$, we initialize all the radars to transmit using waveforms with the maximum possible bandwidth. We then proceed with the scheduling and waveform design algorithms.

VI. Simulation Results

We consider a widely-separated $N_T = 6$ transmitter and $N_R = 6$ receiver MIMO radar system in order to demonstrate tracking performance improvements using sensor scheduling and waveform design. Specifically, we track a single target moving along the simulated trajectory shown in Figure 1 during 30 time steps. For the scheduling, we consider the problem formulated in Equation (2), where the objective is to minimize the number of radars such that the predicted MSE is below a preset threshold. The minimum number of sensors

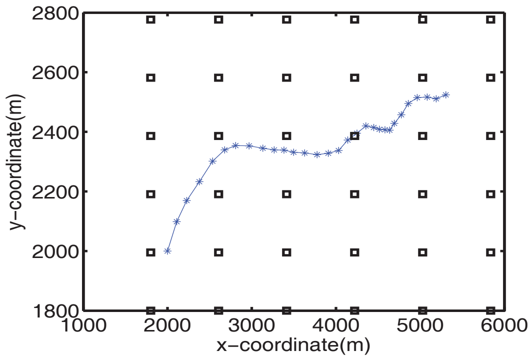


Fig. 1. Simulation setup.

that can be used was set to $N_l = 3$ and the threshold was set to $\gamma = 1300$. The algorithm chooses a different number of radars at each time step, as demonstrated in Figure 2.

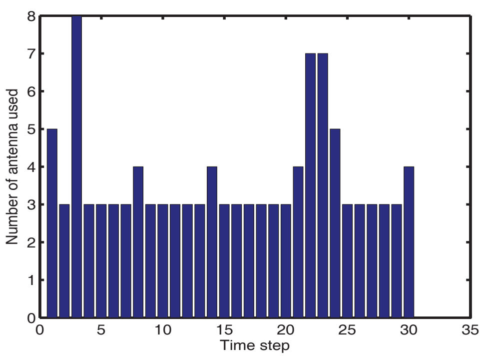
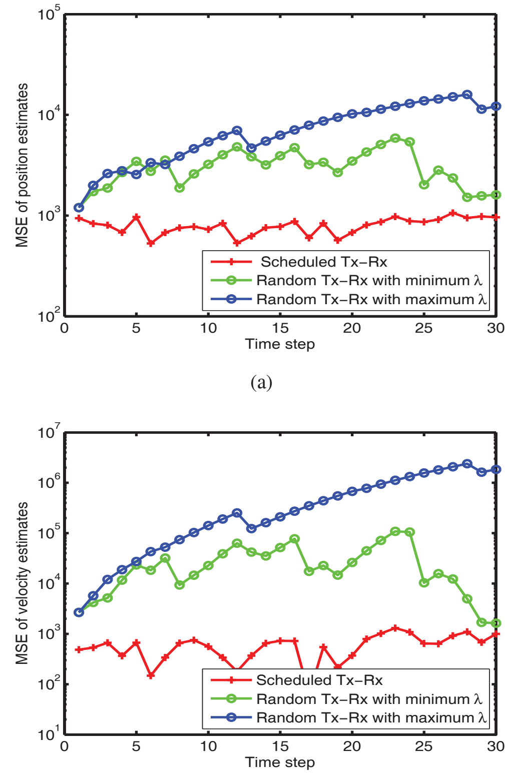


Fig. 2. Radars configured by the scheduling algorithm.

For the selected radars, the waveform parameters are then designed to further increase the tracking performance. In the simulations, we used $\lambda_{\min} = 1$ kHz and $\lambda_{\max} = 10$ MHz, and the carrier frequency was set to 2 GHz. As we observed that, on average, 3 radars were sufficient to attain the MSE below γ, we compared the tracking performance when we randomly chose 3 radars. The bandwidth of the waveform on all the radars was set to $\lambda_{\min}$ or $\lambda_{\max}$, a common choice in systems without waveform design. As it can be seen in Figure 3, the tracking performance (in terms of the MSE in position and velocity) has improved when the waveform bandwidth was designed than when only the minimum or maximum bandwidth was used.

We also simulated the second scheduling scenario in (3), where the scheduling algorithm activates those radars which minimize the predicted tracking MSE. Here, the minimum and maximum number of sensors were chosen to be N_l=2 and N_u=4. As expected, the algorithm chose N_u radars every time as the MSE is inversely proportional to the number of radars. The tracking MSE for position and velocity estimates are shown in Figure 4; they are compared with a choice of 4 randomly chosen radars with transmission waveform param-



(a)

(b)

Fig. 3. Tracking MSE corresponding to the scheduling method in Equation (2) for: (a) position estimates, and (b) velocity estimates.

eters chosen with either minimum or maximum bandwidth.

The choice of the bandwidth parameter for each of the radars at every time step is shown in Figure 5. We observe that the chosen bandwidth parameters for the optimum radar configuration are either $\lambda_{\min}$ or $\lambda_{\max}$. This choice aids in eliminating the range-Doppler estimation trade-off [7], [8].

VII. Conclusions

We proposed a tracking system with an integrated sensor scheduling and waveform design algorithm for a widely-separated MIMO radar system. We considered two different scheduling algorithms. The first algorithm schedules the MIMO radar sensors to minimize the cost of resource utilization. Specifically, the algorithm chooses the minimum number of radar sensors such that the tracking mean-squared error (MSE) is below a specified threshold. The second algorithm selects the minimum number of radar sensors such that the predicted tracking MSE is minimized. Given a maximum number of available radar sensors, the algorithm activates only those radars that result in minimizing the MSE. For both algorithms, we assumed high SNR and used the derived CRLB to estimate the position and velocity of a target based on the location of the radar sensors and the parameters of the transmit waveform. The waveform design algorithm optimally selects

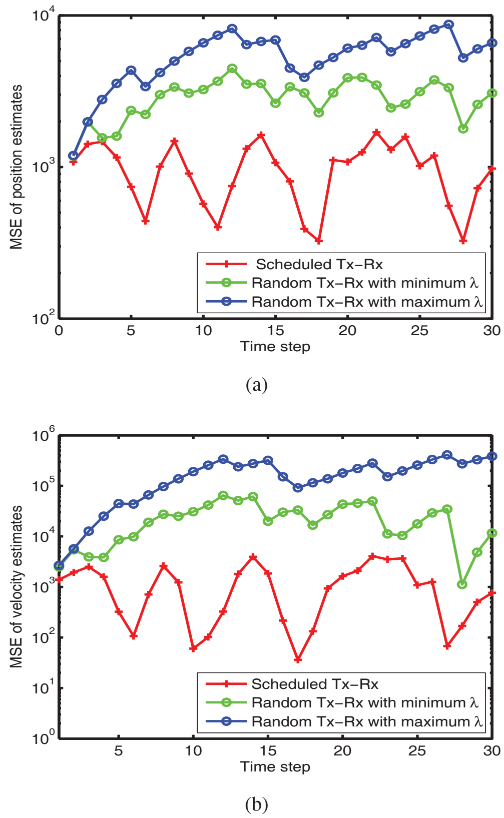


Fig. 4. Tracking MSE corresponding to the scheduling method in Equation (3) for: (a) position estimates, and (b) velocity estimates.

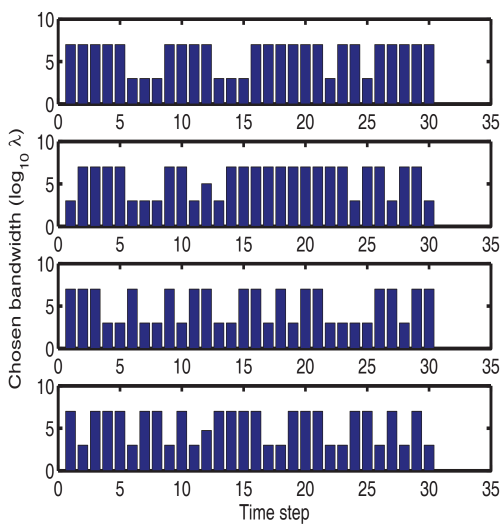


Fig. 5. Optimum waveforms selected.

the parameters of the waveforms that the scheduled radar sensors need to transmit in order to either minimize resource usage or minimize estimation MSE. Our simulation results demonstrated that the proposed new algorithms significantly outperformed traditional tracking by overcoming the range-Doppler coupling trade-off.

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