5th Sensor Signal Processing for Defence Conference (SSPD 2015)



Low Complexity Parameter Estimation For Off-the-Grid Targets

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September, 2015

Objectives

- Estimate the radar parameters of a moving target, namely the reflection coefficient, angular location, and Doppler shift using the collocated MIMO-radar setting.
- Reduce the computational complexity of the algorithm by exploiting 2D-FFT to jointly estimate the angular location and Doppler shift.
- Enhance the resolution of the 2D-FFT estimates by applying a steepest decent algorithm to obtain off-the-grid estimates.



2 Iterative Method



System Model:

• A MIMO radar system with uniform linear arrays at the transmitter and the receiver intercepts the following reflected signal:

$$\mathbf{y}(n) = \overbrace{\beta_t e^{j2\pi f_{dt}n} \mathbf{a}_R(\theta_t) \mathbf{a}_T^T(\theta_t) \mathbf{x}(n)}^{\text{reflection from target}} + \sum_{\substack{i=1\\ i=1}^L \beta_i \mathbf{a}_R(\theta_i) \mathbf{a}_T^T(\theta_i) \mathbf{x}(n) + \underbrace{\mathbf{v}(n)}_{\text{noise}}, n = 1, 2, \dots, N,$$
(1)
reflection from interferers

where

- $\beta_t, \theta_t, f_{dt}$: the target's reflection coefficient, angular location, and Doppler shift.
- $\mathbf{a}_T(\theta_p)$, $\mathbf{a}_R(\theta_p)$: transmit and receive steering vectors at a location θ_p
- $\mathbf{x}(n):$ the vector of linearly independent symbols transmitted at time index n
- $\mathbf{v}(n)$: vector of complex white Gaussian noise samples

• The Signal to Interference plus Noise Ratio (SINR) is maximized using the Capon beamformer \mathbf{w} defined as

$$\mathbf{w}(\theta) = \frac{\mathbf{R}_{in}^{-1} \mathbf{a}_R(\theta)}{\mathbf{a}_R^H(\theta) \mathbf{R}_{in}^{-1} \mathbf{a}_R(\theta)},\tag{2}$$

where

$$\mathbf{R}_{in} = \mathbf{E} \left\{ \left(\sum_{i=1}^{L} \beta_i \mathbf{a}_R(\theta_i) \mathbf{a}_T^T(\theta_i) \mathbf{x}(n) \right) \left(\sum_{i=1}^{L} \beta_i \mathbf{a}_R(\theta_i) \mathbf{a}_T^T(\theta_i) \mathbf{x}(n) \right)^H \right\} + \sigma_n^2 \mathbf{I}_{n_R},$$

is the covariance matrix of the interference plus noise term. Using prior information of the interference' parameters, the covariance matrix \mathbf{R}_{in} can be computed. Otherwise, the methods proposed in [1,2] can be used to reconstruct it.

¹Yujie Gu; Leshem, A., "Robust Adaptive Beamforming Based on Interference Covariance Matrix Reconstruction and Steering Vector Estimation," *IEEE Transactions on Signal Processing*, vol.60, no.7, pp. 3881-3885, July 2012.

²Lei Huang; Jing Zhang; Xu Xu; Zhongfu Ye, "Robust Adaptive Beamforming With a Novel Interference-Plus-Noise Covariance Matrix Reconstruction Method," *IEEE Transactions on Signal Processing*, vol.63, no.7, pp. 1643-1650, Aprill, 2015

• To estimate the value of f_{dt} , θ_t , and β_t , the cost-function to be minimized can be written as

$$\{f_{dt}, \theta_t, \beta_t\} = \underset{f_d, \theta, \beta}{\operatorname{argmin}} \operatorname{E}\left\{ \left| \mathbf{w}^H(\theta) \mathbf{y}(n) - \beta e^{j2\pi f_d n} \mathbf{a}_T^T(\theta) \mathbf{x}(n) \right|^2 \right\}.$$
(3)

• By differentiating the above cost-function with respect to β^* and equating it to 0, the minimizing value $\hat{\beta}$ can be found as

$$\hat{\beta}(f_d, \theta) = \frac{1}{n_T} \mathbb{E} \Big\{ e^{-j2\pi f_d n} \mathbf{w}^H(\theta) \mathbf{y}(n) \mathbf{x}^H(n) \mathbf{a}_T^*(\theta) \Big\}.$$
 (4)

• Thus, the cost function to be minimized in order to estimate f_{dt} and θ_t becomes

$$J_{1}(f_{d},\theta) = \mathbf{w}^{H}(\theta)\mathbf{R}_{y}\mathbf{w}(\theta) - \frac{1}{n_{T}} \frac{\left| \mathbf{E} \left\{ e^{-j2\pi f_{d}n} \mathbf{a}_{R}^{H}(\theta)\mathbf{R}_{in}^{-1}\mathbf{y}(n)\mathbf{x}^{H}(n)\mathbf{a}_{T}^{*}(\theta) \right\} \right|^{2}}{\left| \mathbf{a}_{R}^{H}(\theta)\mathbf{R}_{in}^{-1}\mathbf{a}_{R}(\theta) \right|^{2}}.$$
(5)

• In the absence of interferers, i.e., $\mathbf{R}_{in} = \sigma_n^2 \mathbf{I}_{n_R}$, minimizing J_1

$$J_1(f_d, \theta) = \mathbf{w}^H(\theta) \mathbf{R}_y \mathbf{w}(\theta) - \frac{1}{n_T} \frac{\left| \mathbf{E} \left\{ e^{-j2\pi f_d n} \mathbf{a}_R^H(\theta) \mathbf{R}_{in}^{-1} \mathbf{y}(n) \mathbf{x}^H(n) \mathbf{a}_T^*(\theta) \right\} \right|^2}{\left| \mathbf{a}_R^H(\theta) \mathbf{R}_{in}^{-1} \mathbf{a}_R(\theta) \right|^2},$$

becomes equivalent to maximizing the following simplified cost function

$$J_{2} = \left| \mathbb{E} \underbrace{\left\{ e^{-j2\pi f_{d}n} \mathbf{a}_{R}^{H}(\theta) \mathbf{R}_{in}^{-1} \mathbf{y}(n) \mathbf{x}^{H}(n) \mathbf{a}_{T}^{*}(\theta) \right\}}_{a(n)} \right|^{2}.$$
 (6)

• Assuming $\mathbf{r}(n) = \mathbf{R}_{in}^{-1} \mathbf{y}(n)$, the term inside the expectation operator can be written as

$$\begin{aligned} \mathbf{a}(n) &= e^{-j2\pi f_d n} \mathbf{a}_R^H(\theta) \mathbf{r}(n) \mathbf{x}^H(n) \mathbf{a}_T^*(\theta) \\ &= e^{-j2\pi f_d n} \sum_{p=1}^{n_T} \sum_{q=1}^{n_R} r_q(n) x_p^*(n) e^{-j2\pi \frac{d_R}{\lambda} (q-1)\sin(\theta)} e^{-j2\pi \frac{d_T}{\lambda} (p-1)\sin(\theta)} \\ &= e^{-j2\pi f_d n} \sum_{p=1}^{n_T} \sum_{q=1}^{n_R} r_q(n) x_p^*(n) e^{-j2\pi f_s (q-1+\gamma(p-1))}, \end{aligned}$$
(7)

where $f_s = \frac{d_R}{\lambda} \sin(\theta)$ and $\gamma = \frac{d_T}{d_R}$. • By combining the same frequency terms, we can write

$$\mathbf{E}\{a(n)\} = \frac{1}{N} \sum_{n=0}^{N-1} \sum_{m=0}^{n_R-1+\gamma(n_T-1)} f(n,m) e^{-j2\pi f_d n} e^{-j2\pi f_s m},$$
(8)

where
$$f(n,m) = \sum_{i=1}^{n_T} x_i^*(n) r_{m+1-\gamma(i-1)}(n).$$

$$f(n,m) = \sum_{i=1}^{n_T} x_i^*(n) r_{m-i+2}(n).$$
(9)

$$\hat{f}_{dt}, \hat{f}_{st} = \operatorname*{argmax}_{f_d, f_s} \left| \sum_{n=0}^{N-1} \sum_{m=0}^{\gamma(n_T-1)} f(n,m) e^{-j2\pi f_d n} e^{-j2\pi f_s m} \right|^2.$$
(10)

$$f(n,m) = \sum_{i=1}^{n_T} x_i^*(n) r_{m-i+2}(n).$$
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(10)

• If interferers are present, as J_2 exactly estimates \hat{f}_{dt} , a search method is applied to find the estimate $\hat{\theta}_t$ that minimizes the cost function J_1 ,

$$J_1(\hat{f}_{dt}, \hat{\theta}_t) = \underset{\theta}{\operatorname{argmin}} \mathbf{w}^H(\theta) \mathbf{R}_y \mathbf{w}(\theta) - \frac{1}{n_T} \frac{J_2(\hat{f}_{dt}, \frac{d_R}{\lambda} \sin(\theta))}{\left|\mathbf{a}_R^H(\theta) \mathbf{R}_{in}^{-1} \mathbf{a}_R(\theta)\right|^2}.$$

• To reduce the computational cost, instead of evaluating the cost function J_1 over all grid points, we can restrict the search method over the region centered around the maximum of J_2 .

The low resolution estimates f̂_{dt} and f̂_{st} will be used to initialize the steepest decent algorithm and optimize the appropriate objective function J₁ or J₂ depending on whether the interferes are present or not.
Thus, the first order derivatives with respect to θ and f_d of the following two expressions

$$J_2(\theta, f_d) = \frac{\left|\sum_{n=0}^{N-1} e^{-j2\pi f_d n} \mathbf{a}_R^H(\theta) \mathbf{r}(n) \mathbf{x}^H(n) \mathbf{a}_T^*(\theta)\right|^2}{N^2},$$
(11)

and

$$A(\theta) = \mathbf{a}_{R}^{H}(\theta) \mathbf{G} \mathbf{a}_{R}(\theta), \qquad (12)$$

are required. Here, **G** is a generic Hermitian positive semidefinite matrix of size n_R .

• Using matrix transformation, we can reformulate J_2 as

$$J_{2}(\theta, f_{d}) = \frac{1}{N^{2}} \left| \sum_{n=0}^{N-1} e^{-j2\pi f_{d}n} \mathbf{x}^{H}(n) \mathbf{M}_{r}(n) \mathbf{a}_{S}^{*}(\theta) \right|^{2},$$
(13)

where the i^{th} row of the $n_T \times (n_R + \gamma (n_T - 1))$ matrix $\mathbf{M}_r(n)$ is defined as

$$(\mathbf{M}_{r}(n))_{i} = \begin{bmatrix} \underbrace{0 \cdots 0}_{(i-1)\gamma} \mathbf{r}^{T}(n) & 0 \cdots 0 \end{bmatrix}, \ i = 1, 2, \dots, n_{T},$$

and $\mathbf{a}_{S}(\theta) = \begin{bmatrix} 1 & e^{j2\pi \frac{d_{R}}{\lambda}\sin(\theta)} & \cdots & e^{j2\pi \frac{d_{R}}{\lambda}\sin(\theta)(n_{R}-1+\gamma(n_{T}-1))} \end{bmatrix}^{T}.$

• Considering the symmetry of **G**, the expression $A(\theta)$ is reformulated as

$$A(\theta) = \sum_{l=1}^{n_R} \mathbf{G}_{l,l} + 2\Re \left(\sum_{l=1}^{n_R-1} \sum_{k>l}^{n_R} \mathbf{G}_{l,k} e^{j2\pi f_s(k-l)} \right) = 2\Re \left(\mathbf{g}^T \mathbf{a}_R(\theta) \right), \quad (14)$$

where $\mathbf{g} = \left[\frac{1}{2} \sum_{l=1}^{n_R} \mathbf{G}_{l,l} \quad \sum_{l=1}^{n_R-1} \mathbf{G}_{l,l+1} \quad \cdots \quad \mathbf{G}_{1,n_R} \right]^T.$

• Hence, the first order derivatives of $J_2(\theta, f_d)$ with respect to f_d and θ are respectively

$$\frac{\partial J_2}{\partial f_d} = -\frac{4\pi}{N^2} \Im \left(\sum_{n=0}^{N-1} e^{-j2\pi f_d n} \mathbf{x}^H(n) \mathbf{M}_r(n) \mathbf{a}_S^*(\theta) \sum_{n=0}^{N-1} n e^{j2\pi f_d n} \mathbf{a}_S^T(\theta) \mathbf{M}_r^H(n) \mathbf{x}(n) \right), \tag{15}$$

and

$$\begin{aligned} \frac{\partial J_2}{\partial \theta} &= -\frac{4\pi d_R \cos(\theta)}{\lambda N^2} \times \\ & \Im \bigg(\sum_{n=0}^{N-1} e^{-j2\pi f} d^n \mathbf{x}^H(n) \mathbf{M}_r(n) \mathbf{a}_S^*(\theta) \sum_{n=0}^{N-1} e^{j2\pi f} d^n \mathbf{a}_S^T(\theta) \mathbf{D}_0^{+nR^{-1}} \mathbf{M}_r^H(n) \mathbf{x}(n) \bigg). \end{aligned}$$
(16)

• The first order derivative of $A(\theta)$ can be expressed as below

$$\frac{\partial A}{\partial \theta} = -4\pi \frac{d_R}{\lambda} \cos(\theta) \Im \left(\mathbf{g}^T \mathbf{D}_0^{n_R - 1} \mathbf{a}_R(\theta) \right).$$
(17)



Fig. 1: Comparison of the processing time needed to compute the cost function J_2 for N=32 samples using 2D-FFT (blue) and direct method (red).



Fig. 2: Convergence behavior of the steepest descent algorithm for the estimation of the Doppler shift (left) and the spatial location (right) at SNR=0 dB.

No Iterferers:



Fig. 3: Comparison of the 128 point 2D-FFT (dash-dot lines) and the iterative algorithm (solid lines) with the CRLB (dashed lines) of β_t , f_d , and θ_t . Here, $\beta_t = -1 + 2j$ and $\theta_t = 10^{\circ}$.

With Iterferers:



Fig. 4: Comparison of the 128 point 2D-FFT (dash-dot lines) and the iterative algorithm (solid lines) with the CRLB (dashed lines) of β_t , f_d , and θ_t . Here, $\beta_t = -1 + 2j$, $\theta_t = 10^\circ$, and INR=20 dB.



(dashed lines) method derived in [1]. Here, $\beta_t = -1 + 2j$, $\theta_t = 10^\circ$, and INR=20 dB.

¹Luzhou Xu, Jian Li, and Petre Stoica, "Target detection and parameter estimation for MIMO radar systems," *IEEE Transactions on Aerospace and Electronic Systems*, vol.44, no. 3, pp. 927-939, July 2008.

Conclusion:

- An iterative algorithm estimates the reflection coefficient, the Doppler shift, and the spatial location of an off-the-grid target
- The low resolution 2D-FFT is used to find an initial point for the steepest descent algorithm
- The simulation results showed that the MSEE of the derived estimators matches the CRLB

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