


# MAJORIZATION-MINIMIZATION TECHNIQUE FOR MULTI-STATIC RADAR CODE DESIGN

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# Problem Formulation: Data Modeling

We consider a multi-static pulsed-radar with one transmitter and  $N_r$  widely separated receive antennas. The baseband transmit signal can be formulated as

$$s(t) = \sum_{n=1}^N a_n \phi(t - [n - 1]T_P) \quad (1)$$

where  $\phi(t)$  is the basic unit-energy transmit pulse,  $T_P$  is the pulse repetition period,  $N$  is the number of transmitted pulses, and  $\{a_n\}_{n=1}^N$  are the deterministic coefficients that are to be “optimally” determined. The vector  $\mathbf{a} \triangleq [a_1 \ a_2 \ \dots \ a_N]^T$  is referred to as the code vector of the radar system.

# Problem Formulation: Data Modeling

Therefore, the discrete-time signal corresponding to a certain radar cell for the  $k^{th}$  receiver can be described as:

$$\mathbf{r}_k \triangleq \mathbf{s}_k + \mathbf{c}_k + \mathbf{w}_k = \alpha_k \mathbf{a} + \tilde{\rho}_k \mathbf{a} + \mathbf{w}_k \quad (6)$$

binary hypothesis problem

$$\begin{cases} H_0 : & \mathbf{r} = \mathbf{c} + \mathbf{w} \\ H_1 : & \mathbf{r} = \mathbf{s} + \mathbf{c} + \mathbf{w} \end{cases} \quad (7)$$

$$\mathbf{D}_k \triangleq (\sigma_{c,k}^2 \mathbf{a} \mathbf{a}^H + \mathbf{M}_k)^{-\frac{1}{2}}$$

$$\mathbf{x}_k = \mathbf{D}_k \mathbf{r}_k$$

$$\theta_k \triangleq \mathbf{a}^H \mathbf{D}_k \mathbf{x}_k / \|\mathbf{a}^H \mathbf{D}_k\|_2$$

$$\lambda_k = \sigma_k^2 \mathbf{a}^H (\sigma_{c,k}^2 \mathbf{a} \mathbf{a}^H + \mathbf{M}_k)^{-1} \mathbf{a}$$



detection problem

$$T = \sum_{k=1}^{N_r} \frac{\lambda_k |\theta_k|^2}{1 + \lambda_k} \underset{H_1}{\overset{H_0}{\leq}} \eta$$



# From KL-Divergence to the Design Problem

$$\mathcal{D}(f(\mathbf{r}|\mathbf{H}_0) \| f(\mathbf{r}|\mathbf{H}_1)) = \sum_{k=1}^{N_r} \{\log(1 + \lambda_k) - \lambda_k/(1 + \lambda_k)\}$$



$$\begin{aligned} & \max_{\mathbf{a}, \lambda_k} \sum_{k=1}^{N_r} \{\log(1 + \lambda_k) - \lambda_k/(1 + \lambda_k)\} \\ & \text{subject to} \quad \lambda_k = \sigma_k^2 \mathbf{a}^H (\sigma_{c,k}^2 \mathbf{a} \mathbf{a}^H + \mathbf{M}_k)^{-1} \mathbf{a} \end{aligned}$$

$$\max_{n=1, \dots, N} \{|a_n|^2\} \leq \zeta (e/N)$$

$$\|\mathbf{a}\|_2^2 = e,$$

total transmit energy

PAR-constrained code design

$$\text{PAR}(\mathbf{a}) = \max_n \{|a_n|^2\} / (\frac{1}{N} \|\mathbf{a}\|_2^2) \leq \zeta$$

# & The MaMi!

$$\min_{\mathbf{z}} \tilde{f}(\mathbf{z}) \quad \text{subject to} \quad c(\mathbf{z}) \leq 0$$

- Majorization Step: Finding  $p^{(l)}(\mathbf{z})$  such that its minimization is simpler than that of  $\tilde{f}(\mathbf{z})$ , and that  $p^{(l)}(\mathbf{z})$  majorizes  $\tilde{f}(\mathbf{z})$ , i.e.

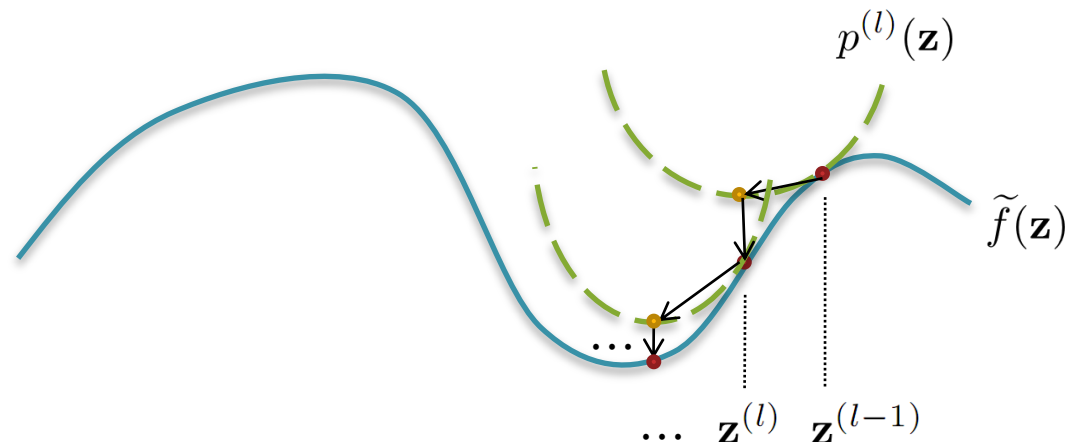
$$p^{(l)}(\mathbf{z}) \geq \tilde{f}(\mathbf{z}), \quad \forall \mathbf{z} \quad \text{and} \quad p^{(l)}(\mathbf{z}^{(l-1)}) = \tilde{f}(\mathbf{z}^{(l-1)}) \quad (13)$$

with  $\mathbf{z}^{(l-1)}$  being the value of  $\mathbf{z}$  at the  $(l-1)^{th}$  iteration.

- Minimization Step: Solving the optimization problem,

$$\min_{\mathbf{z}} p^{(l)}(\mathbf{z}) \quad \text{subject to} \quad c(\mathbf{z}) \leq 0 \quad (14)$$

to obtain  $\mathbf{z}^{(l)}$ .



# The Final Form: QP@ Each Iteration.

$(l + 1)^{th}$  :  
iteration

$$\begin{aligned} \min_{\mathbf{a}} \quad & \mathbf{a}^H \left( \sum_{k=1}^{N_r} \phi_k^{(l)} \mathbf{M}_k^{-1} \right) \mathbf{a} - \text{Real} \left( \sum_{k=1}^{N_r} \mathbf{a}^H \mathbf{d}_k^{(l)} \right) \\ \text{subject to} \quad & \max_{n=1, \dots, N} \{|a_n|^2\} \leq \zeta (e/N) \\ & \|\mathbf{a}\|_2^2 = e \end{aligned} \quad (25)$$

$$\begin{aligned} \mathbf{d}_k^{(l)} &\triangleq (\psi_k^l / \sqrt{y_k^{(l)}}) \mathbf{M}_k^{-1} \mathbf{a}^{(l)} \\ \phi_k^{(l)} &\triangleq \frac{\beta_k}{1 + \beta_k y_k^{(l)}} + \beta_k (1 + \gamma_k) + \frac{\gamma_k}{(1 + \lambda_k^{(l)})^2} \left( \frac{\beta_k}{(1 + \beta_k y_k^{(l)})^2} \right) \\ \psi_k^{(l)} &\triangleq \sqrt{y_k^{(l)}} \left( \frac{2\beta_k (1 + \gamma_k)}{1 + \beta_k y_k^{(l)} (1 + \gamma_k)} + 2\beta_k (1 + \gamma_k) \right) \\ \gamma_k &= \frac{\sigma_k^2}{\sigma_{c,k}^2} \\ \beta_k &= \sigma_{c,k}^2 \end{aligned}$$



# QP with PAR Constraint?

$$\begin{array}{ll} \max_{\mathbf{a}} & \hat{\mathbf{a}}^H \mathbf{K} \hat{\mathbf{a}} \\ \text{subject to} & \max_{n=1, \dots, N} \{|a_n|^2\} \leq \zeta (e/N) \\ & \|\mathbf{a}\|_2^2 = e \end{array}$$

$$\hat{\mathbf{a}} = [\mathbf{a} \ 1]^T, \mathbf{K} = \mu \mathbf{I}_{N+1} - \mathbf{J},$$

$$\mathbf{J} = \begin{bmatrix} \left( \sum_{k=1}^{N_r} \phi_k^{(l)} \mathbf{M}_k^{-1} \right) & -0.5 \left( \sum_{k=1}^{N_r} \mathbf{d}_k^{(l)} \right) \\ -0.5 \left( \sum_{k=1}^{N_r} \mathbf{d}_k^{(l)} \right)^H & 0 \end{bmatrix}$$

$$\mu > \mu_{max} \longrightarrow \text{maximum eigenvalue}$$



# Power Method-Like Iterations

The code vector  $\mathbf{a}$  at the  $(l+1)^{th}$  iteration of MaMi can be obtained from  $\mathbf{a}^{(p)}$  (at convergence), using the power method-like iterations [11]:

$$\max_{\mathbf{a}^{(p+1)}} \|\mathbf{a}^{(p+1)} - \check{\mathbf{a}}^{(p)}\| \quad (27)$$

$$\text{subject to} \quad \max_{n=1, \dots, N} \{|a_n^{(p+1)}|^2\} \leq \zeta(e/N)$$
$$\|\mathbf{a}^{(p+1)}\|_2^2 = e$$

where  $\check{\mathbf{a}}^{(p)}$  represents the vector containing the first  $N$  entries of  $\mathbf{K} \hat{\mathbf{a}}^{(p)}$ .





# Algorithm: Summary

**Table 1.** The MaMi Algorithm for maximizing the KL-divergence with a PAR constraint

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**Step 0:** Initialize  $\mathbf{a}$  with a random vector in  $\mathbb{C}^N$  and set the iteration number  $l$  to 0.

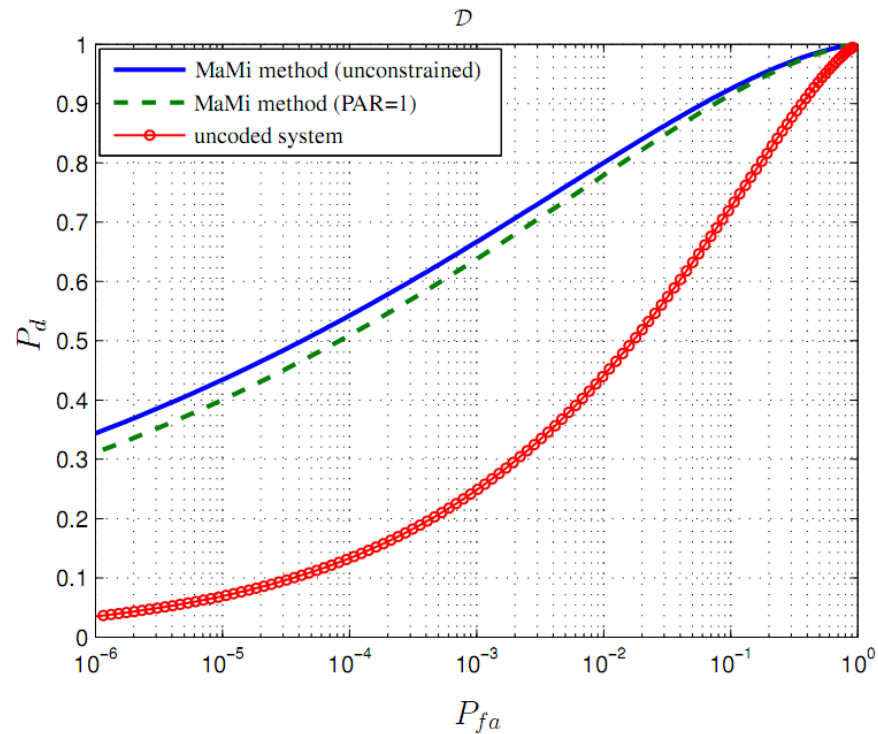
**Step 1:** Solve the problem in (25) iteratively considering the nearest-vector problem in (27); set  $l \leftarrow l + 1$ .

**Step 2:** Compute  $\phi_k^{(l)}$  and  $\mathbf{d}_k^{(l)}$ .

**Step 3:** Repeat steps 1 and 2 until a pre-defined stop criterion is satisfied, e.g.  $\|\mathbf{a}^{(l+1)} - \mathbf{a}^{(l)}\|_2 \leq \xi$  for some  $\xi > 0$ .

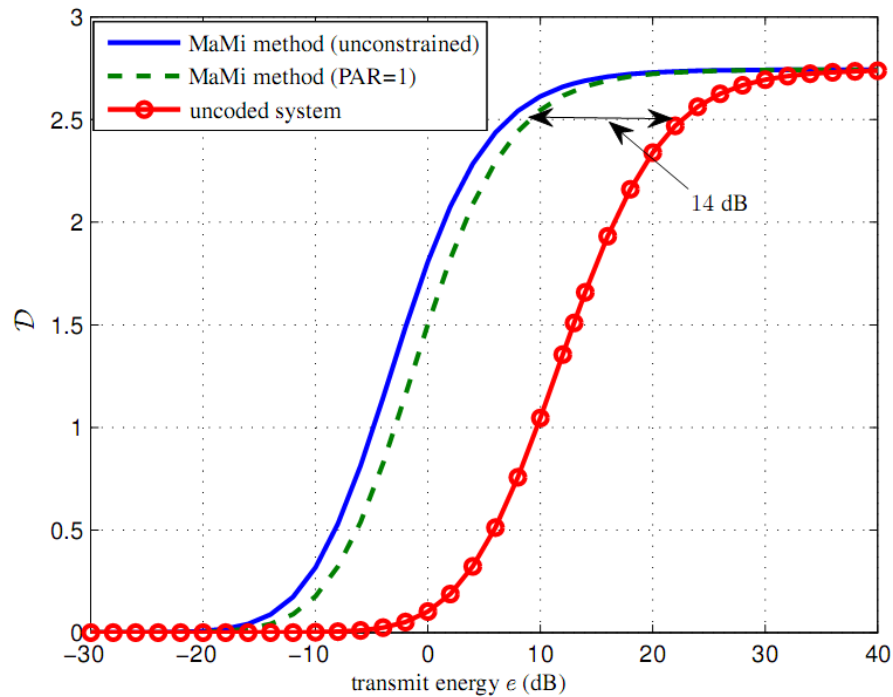
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# Simulation Results



**Fig. 1.** ROCs of optimally coded and the uncoded systems.

# Simulation Results



**Fig. 2.** Behavior of KL-divergence versus transmit energy  $e$  for the coded and uncoded systems.



Thank you for your kind attention!  
-Qs?