

Robust Adaptive Beamforming: Evolution of Approaches, Analysis and Comparison

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156th Meeting of the Acoustic Society of America, 2008



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- 1 Introduction
- 2 Worst-Case Performance Optimization Approach
- 3 Probabilistically-Constrained Optimization Approach
- 4 Analysis of Approaches and a New One
- 5 Robust Adaptive Beamforming Using SQP
- 6 Comparison

Introduction

- Adaptive Beamforming finds applications in many areas such as **radar, sonar, wireless communications**, etc.
- Conventional beamforming techniques assume
 - *the steering vector of the desired signal is known precisely*
 - *large number of snapshots (training sample size)*
 - *stationary training data set*
- **In many practical situations there is mismatch** between the presumed steering vector and the actual one!

Signal Model

The output of a narrowband beamformer

$$y(k) = \mathbf{w}^H \mathbf{x}(k)$$

where

$$\mathbf{x}(k) = \underbrace{s(k)\mathbf{p}}_{\text{signal}} + \underbrace{i(k)}_{\text{interference}} + \underbrace{n(k)}_{\text{noise}}$$

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Actual steering vector

$$\underbrace{\mathbf{a}}_{\text{actual}} = \underbrace{\mathbf{p}}_{\text{presumed}} + \underbrace{\mathbf{e}}_{\text{unknown mismatch}}$$

Maximum SINR criterion

$$\max_{\mathbf{w}} \text{SINR}, \quad \text{SINR} = \frac{\sigma_s^2 |\mathbf{w}^H(\mathbf{p} + \mathbf{e})|^2}{\mathbf{w}^H \mathbf{R}_{i+n} \mathbf{w}}$$

Interference-plus-noise covariance matrix

$$\mathbf{R}_{i+n} = \text{E} \left\{ (\mathbf{i}(k) + \mathbf{n}(k)) (\mathbf{i}(k) + \mathbf{n}(k))^H \right\}$$

Note

- In practice, \mathbf{R}_{i+n} is unavailable
- Sample estimate $\hat{\mathbf{R}} \triangleq \frac{1}{N} \sum_{k=1}^N \mathbf{x}(k) \mathbf{x}^H(k)$ is used

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Worst-Case Performance Optimization

The essence of this approach is to

- **Maintain a distortionless response** towards a continuum of steering vectors that belong to a certain uncertainty set
- Guarantee that the distortionless response is maintained in the worst case
- **Model the uncertainty** about the mismatch vector using
 - spherical uncertainty set [Vorobyov, Gershman, Luo '03]
 - elliptical uncertainty set [Lorenz and Boyd '05]



Problem Formulation and Main Result

- The spherical uncertainty set is (for some known $\varepsilon > 0$)

$$\|\mathbf{e}\| \leq \varepsilon$$

The robust MVDR beamforming problem is formulated as

$$\min_{\mathbf{w}} \mathbf{w}^H \hat{\mathbf{R}} \mathbf{w} \quad \text{s. t.} \quad |\mathbf{w}^H (\mathbf{p} + \mathbf{e})| \geq 1, \quad \forall \quad \|\mathbf{e}\| \leq \varepsilon$$

- *Result 1* [Vorobyov, Gershman, Luo '03]: Infinite number of non-convex constraints

$$|\mathbf{w}^H (\mathbf{p} + \mathbf{e})| \geq 1, \quad \forall \quad \|\mathbf{e}\| \leq \varepsilon$$

is equivalent to a single convex constraint

$$\varepsilon \|\mathbf{w}\| \leq \mathbf{w}^H \mathbf{p} - 1$$



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Robust MVDR Beamforming

The robust MVDR beamforming problem is equivalent to

$$\min_{\mathbf{w}} \mathbf{w}^H \hat{\mathbf{R}} \mathbf{w} \quad \text{s. t.} \quad \varepsilon \|\mathbf{w}\| \leq \mathbf{w}^H \mathbf{p} - 1$$

This is so-called convex second order cone (SOC) programming problem! It can be easily solved!

Problem Formulation and Main Results

- The probabilistically-constrained beamformer guarantees that the distortionless response is maintained *with a certain “sufficient” probability*

$$\min_{\mathbf{w}} \mathbf{w}^H \hat{\mathbf{R}} \mathbf{w} \quad \text{s. t.} \quad \Pr\{|\mathbf{w}^H(\mathbf{p} + \mathbf{e})| \geq 1\} \geq \rho_0$$

- *Result 2* [Vorobyov, Chen, Gershman '08]: For Gaussian mismatch

$$\mathbf{e} \sim \mathcal{N}_C(\mathbf{0}, \mathbf{C}_e)$$

the probabilistic constraint is tightly approximated by the deterministic constraint

$$\sqrt{-\ln(1 - \rho_0)} \|\mathbf{C}_e^{1/2} \mathbf{w}\| \leq \mathbf{w}^H \mathbf{p} - 1$$



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Probabilistically-Constrained Beamformer

- **Result 3** [Vorobyov, Chen, Gershman '08]: For mismatch with the worst-case distribution the probabilistic constraint is tightly approximated by the deterministic constraint

$$\frac{1}{\sqrt{1-p_0}} \|\mathbf{C}_e^{1/2} \mathbf{w}\| \leq \mathbf{w}^H \mathbf{p} - 1$$

Moreover, the worst-case distribution is discrete.

- *The problem is equivalent to that of the worst-case based robust adaptive beamforming* if $\mathbf{C}_e = (\sigma_e^2/M)\mathbf{I}$.

For the worst-case mismatch distribution: $\varepsilon = \sigma_e \sqrt{\frac{1}{M(1-p_0)}}$

For Gaussian mismatch: $\varepsilon = \sigma_e \sqrt{\frac{-\ln(1-p_0)}{M}}$



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Analysis and a New Idea

Problems with previous approaches

- If mismatch is Gaussian, its norm is Chi-square distributed (not norm bounded)
- Over/under estimation of the parameters, e.g. ε , may lead to degradation in performance

Essence of a new approach

Estimate the mismatch vector and form the beam using the corrected steering vector [Hassanien, Vorobyov, Wong '08]

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Estimate the mismatch vector and form the beam using the corrected steering vector [Hassanien, Vorobyov, Wong '08]

Problem Formulation

- First maximize the beamformer output SINR by solving the optimization problem

$$\min_{\mathbf{w}} \mathbf{w}^H \hat{\mathbf{R}} \mathbf{w} \quad \text{subject to} \quad \mathbf{w}^H (\mathbf{p} + \mathbf{e}) = 1$$

- Solution

$$\mathbf{w}(\mathbf{e}) = \frac{\hat{\mathbf{R}}^{-1} (\mathbf{p} + \mathbf{e})}{(\mathbf{p} + \mathbf{e})^H \hat{\mathbf{R}}^{-1} (\mathbf{p} + \mathbf{e})}$$

- *The beamformer output power*

$$P(\mathbf{e}) = \frac{1}{(\mathbf{p} + \mathbf{e})^H \hat{\mathbf{R}}^{-1} (\mathbf{p} + \mathbf{e})}$$

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Problem Formulation and Difficulties

Estimate the unknown mismatch vector \mathbf{e} by maximizing the beamformer output power

$$\min_{\mathbf{e}} (\mathbf{p} + \mathbf{e})^H \hat{\mathbf{R}}^{-1} (\mathbf{p} + \mathbf{e}) \quad \text{s. t.} \quad \|\mathbf{p} + \mathbf{e}\| = \sqrt{M}$$

Two difficulties

- The corrected vector $\mathbf{p} + \hat{\mathbf{e}}$ might converge to a vector associated with interference
- Non-convex constraint!

Problem Formulation and Difficulties

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Robust Adaptive Beamforming Using SQP

- To avoid first difficulty, enforce $\mathbf{p} + \mathbf{e}$ to belong to a subspace that is spanned by the actual steering vector

$$\mathbf{P}_p^\perp (\mathbf{p} + \mathbf{e}) = \mathbf{0}$$

$\mathbf{P}_p^\perp \triangleq \mathbf{I} - \mathbf{U}\mathbf{U}^H$ is a projection onto a subspace that is orthogonal to the actual steering vector

- $\mathbf{U} \triangleq [\mathbf{u}_1, \mathbf{u}_2, \dots, \mathbf{u}_K]$, $\{\mathbf{u}_k\}_{k=1}^K$ are K principal eigenvectors of

$$\mathbf{C} \triangleq \int_{\Theta} \mathbf{p}(\theta)\mathbf{p}^H(\theta) d\theta$$

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Robust Adaptive Beamforming Using SQP (Cont'd)

- **Result 4** [Hassanien, Vorobyov, Wong '08]: The initial optimization problem is equivalent to the problem

$$\begin{aligned} \min_{\mathbf{e}} \quad & (\mathbf{p} + \mathbf{e})^H \hat{\mathbf{R}}^{-1} (\mathbf{p} + \mathbf{e}) \\ \text{subject to} \quad & \mathbf{P}_{\mathbf{p}}^{\perp} (\mathbf{p} + \mathbf{e}) = \mathbf{0} \\ & \|\mathbf{p} + \mathbf{e}\| = \sqrt{M} \end{aligned}$$

- How to get rid of non-convexity?



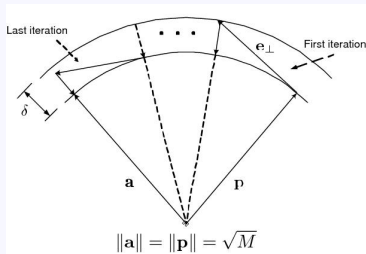
Robust Adaptive Beamforming Using SQP (Cont'd)

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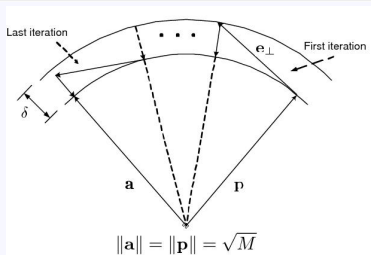
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Iterative Solution



Iterative Solution



$$\begin{aligned} \min_{\mathbf{e}_{\perp}} \quad & (\mathbf{p} + \mathbf{e}_{\perp})^H \hat{\mathbf{R}}^{-1} (\mathbf{p} + \mathbf{e}_{\perp}) \\ \text{subject to} \quad & \mathbf{P}_p^{\perp} (\mathbf{p} + \mathbf{e}) = \mathbf{0} \\ & \|\mathbf{p} + \mathbf{e}_{\perp}\| \leq \sqrt{M} + \delta \\ & \mathbf{p}^H \mathbf{e}_{\perp} = 0 \end{aligned}$$

Iterative Algorithm

Algorithm:

- 1 Estimate \mathbf{e}_\perp by solving the problem in previous slide
- 2 If $\|\mathbf{e}_\perp\| = \text{"small"}$, go to Step 5.
- 3 Update the presumed steering vector $\mathbf{p} = \mathbf{p} + \mathbf{e}_\perp$.
- 4 Project the updated steering vector back to the sphere
 $\mathbf{p} = \left(\sqrt{M}/\|\mathbf{p}\| \right) \mathbf{p}$, then go to Step 1.
- 5 Calculate the robust adaptive beamformer weights

$$\mathbf{w}_{\text{SQP}} = \frac{\hat{\mathbf{R}}^{-1} \mathbf{p}}{\mathbf{p}^H \hat{\mathbf{R}}^{-1} \mathbf{p}},$$

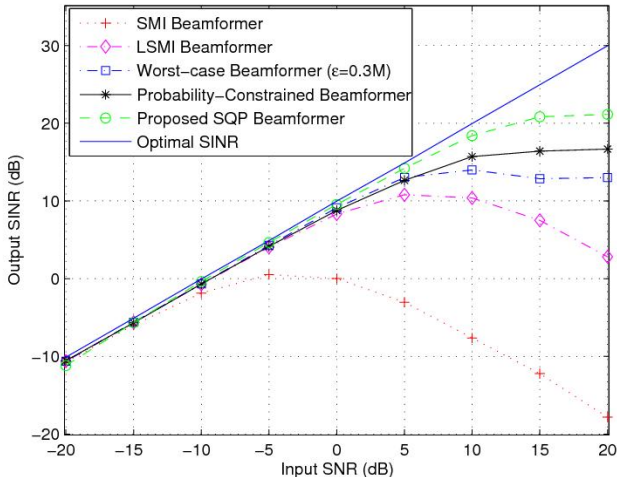


Simulation Setup

- $M = 10$ sensors spaced half wavelength apart. $N = 100$ data snapshots.
- Desired signal is assumed to impinge on the array from direction $\theta_p = 5^\circ$
- Two interfering sources with DOAs -50° and -20° ; INR = 30 dB.
- **Look direction mismatch:**
actual DOA is uniformly drawn from $[1^\circ 9^\circ]$
- **Array perturbation:**
Sensors are assumed to be displaced from its original location and the displacement is drawn uniformly from the set $[-0.05, 0.05]$ measured in wavelength.



Simulation Results



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