

Applications of Optimization Techniques in Active Sensing and Communication Systems

Mohammad Mahdi Naghsh

Isfahan University of Technology, Isfahan, Iran

Web: <https://naghsh.iut.ac.ir/>

Real Worlds Optimization Projects

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Outline

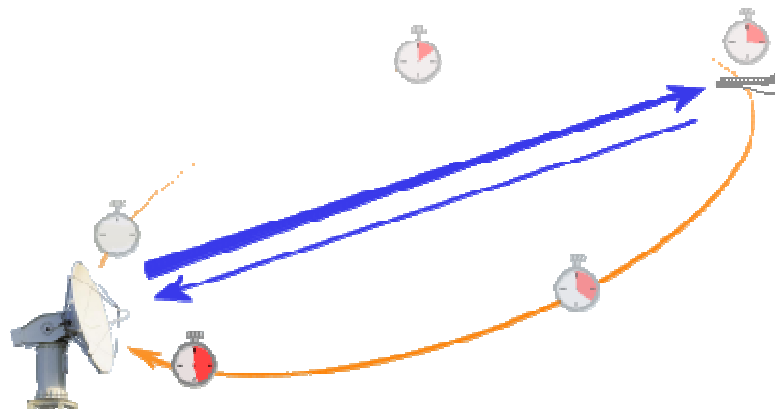
- Introduction
- A radar example
 - Problem formulation
 - The algorithm
- An example for communication systems
 - Problem formulation
 - The algorithm
- Summary and conclusion

Introduction

- Active sensing systems: radars, sonars, etc.
 - Radar: **R**Adio **D**etection **A**nd **R**anging
- Working principle: transmission of waveforms toward medium and process the received echo
- Actively sensing the medium
 - Transmission of signal

Introduction

- Being active: waveform transmission

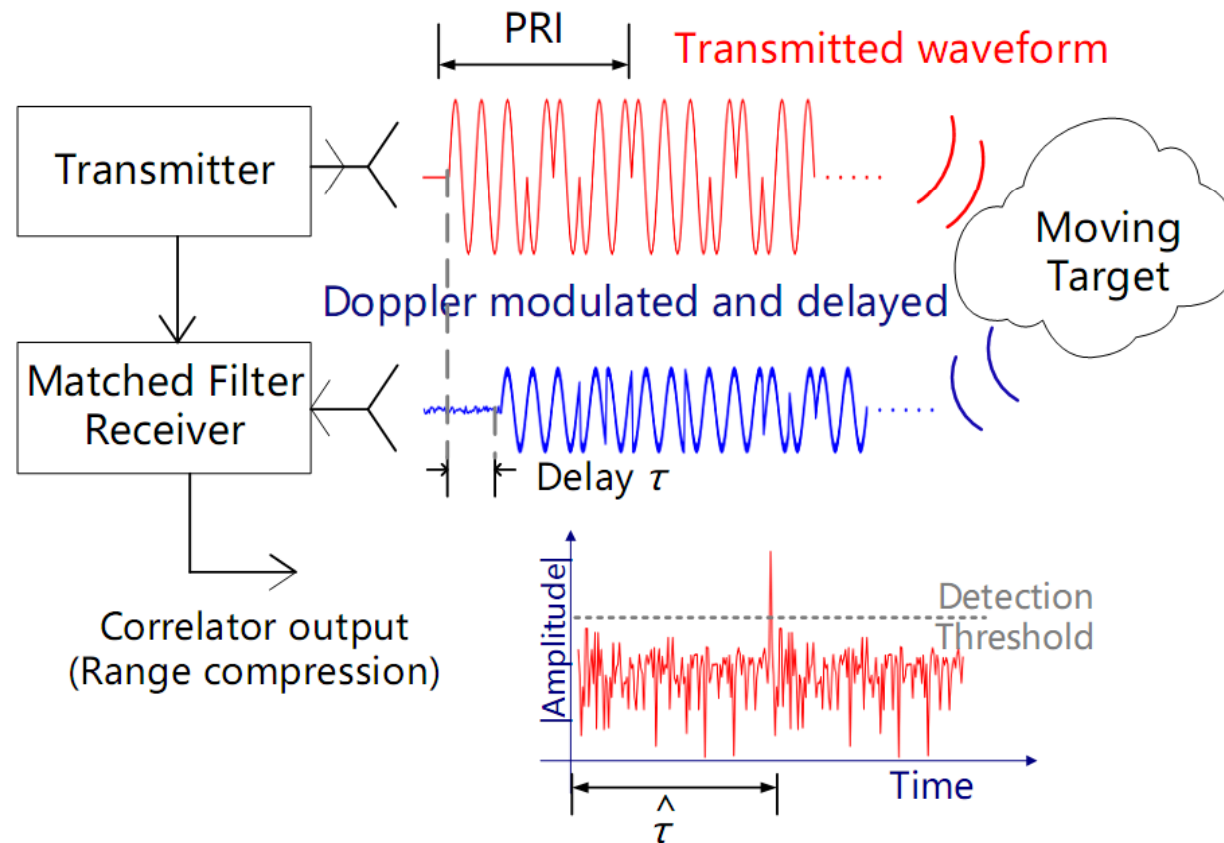


<http://www.radartutorial.eu/01.basics/Radar%20Principle.en.html>

- The system performance & transmit signal

Introduction

- A simplified block diagram

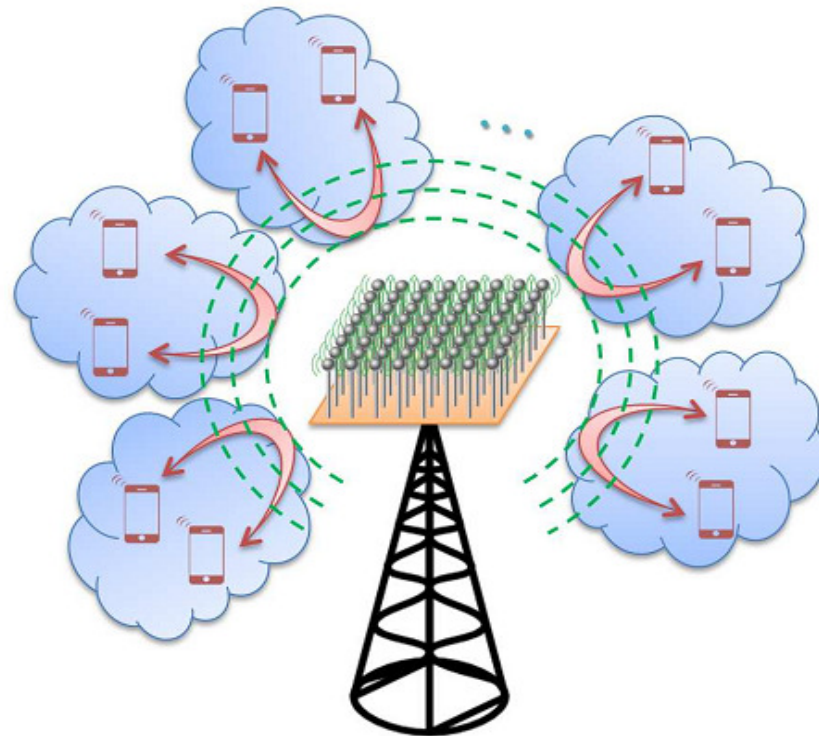


Introduction

- Optimize Tx-Rx pair to improve performance
 - Tx transmit waveform
 - Rx filter
 - Various performance metrics
 - Signal-to-noise-plus-interference (SINR)

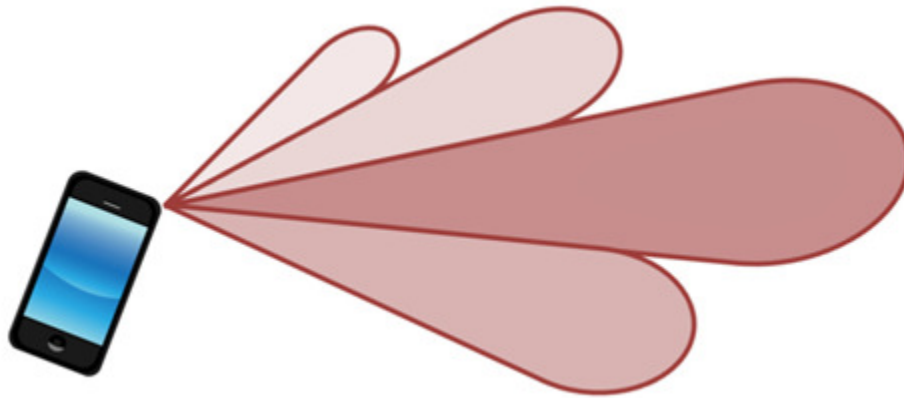
Introduction

- Communication Systems
 - Users communicate with themselves via Base stations, Relays, etc



Introduction

- Optimize Tx-Rx to improve performance
 - User, relay, base station
 - Metrics: user achievable rate



A radar example

- Design Tx transmit signal and Rx filter
 - Improve SINR at the filter output
- Main challenges
 - Clutter: Signal-dependent interference
 - Echo of unwanted targets like mountain, trees, etc.
 - The target speed is unknown
 - Doppler phenomena

$$\mathbf{r} = \alpha_T \mathbf{x} \odot \mathbf{p}(\nu) + \mathbf{c} + \mathbf{n},$$

target

Clutter+interference

A radar example

- SINR expression for Doppler \nu

$$\text{SINR}(\nu) = \frac{|\alpha_T|^2 |\mathbf{w}^H (\mathbf{x} \odot \mathbf{p}(\nu))|^2}{\mathbf{w}^H \Sigma_c(\mathbf{x}) \mathbf{w} + \mathbf{w}^H \mathbf{M} \mathbf{w}}$$

clutter

interference

– Clutter covariance:

$$\Sigma_c(\mathbf{x}) = \sum_{k=0}^{N_c-1} \sum_{i=0}^{L-1} \sigma_{(k,i)}^2 \mathbf{J}_k \Gamma(\mathbf{x}, (k, i)) \mathbf{J}_k^T$$

A radar example

- The design problem: a maxmin
 - Robustifying w.r.t to unknown Doppler

$$\mathcal{P} \left\{ \begin{array}{ll} \max_{\mathbf{x}, \mathbf{w}} \min_{\nu} & \frac{|\mathbf{w}^H (\mathbf{x} \odot \mathbf{p}(\nu))|^2}{\mathbf{w}^H \Sigma_c(\mathbf{x}) \mathbf{w} + \mathbf{w}^H \mathbf{M} \mathbf{w}} \\ \text{subject to} & \|\mathbf{x}\|^2 = e \\ & \|\mathbf{x} - \mathbf{x}_0\|^2 \leq \delta \\ & \nu \in \Omega \end{array} \right.$$



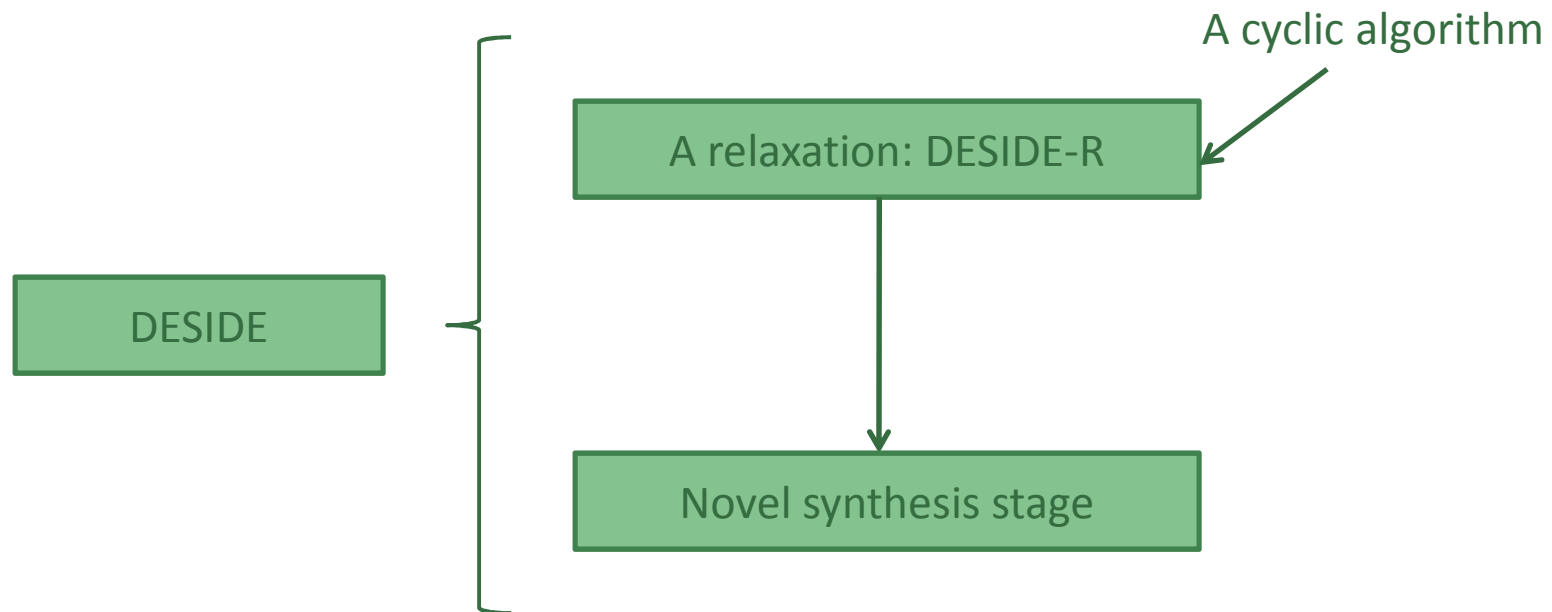
Belongs to a class of NP-Hard problems

A radar example

- A joint work from 2013
 - IUT
 - Prof. P. Stoica, Sweden
 - Prof. A. D Maio, Italy
 - Published as a book chapter in 2019 (by IET)
- Milestones of the devised method

A radar example

- The proposed method: **DESIDE** ✓
 - DopplEr robuSt joint DESign of transmit sequence and receive filter



A radar example

- Step 1: reformulation via rank-1 matrices

$$\begin{array}{l}
 \mathbf{X} = \mathbf{x}\mathbf{x}^H \\
 \mathbf{W} = \mathbf{w}\mathbf{w}^H
 \end{array}
 \left\{ \begin{array}{l}
 \max_{\mathbf{X}, \mathbf{W}} \min_{\nu} \frac{\mathbf{p}(\nu)^H (\mathbf{W} \odot \mathbf{X}^*) \mathbf{p}(\nu)}{\text{tr}\{(\boldsymbol{\Sigma}_c(\mathbf{X}) + \mathbf{M}) \mathbf{W}\}} \\
 \text{subject to} \quad \text{tr}\{\mathbf{X}\} = e \\
 \text{tr}\{\mathbf{X}\mathbf{X}_0\} \geq \epsilon_\delta \\
 \text{rank}(\mathbf{X}) = 1 \\
 \text{rank}(\mathbf{W}) = 1 \\
 \mathbf{X} \succeq \mathbf{0} \\
 \mathbf{W} \succeq \mathbf{0} \\
 \nu \in \Omega
 \end{array} \right.$$

A radar example

- Step 2: SDR and apply alternating optimization

$$\mathcal{P}_X \left\{ \begin{array}{l} \max_{\mathbf{X}, \tilde{t}} \quad \frac{\tilde{t}}{\text{tr} \left\{ \left(\Theta_c(\mathbf{W}) + \left(\frac{\beta}{e} \right) \mathbf{I} \right) \mathbf{X} \right\}} \\ \text{subject to} \quad \mathbf{p}(\nu)^H (\mathbf{W} \odot \mathbf{X}^*) \mathbf{p}(\nu) \geq \tilde{t}, \quad \forall \nu \in \Omega \\ \text{tr}\{\mathbf{X}\} = e \\ \text{tr}\{\mathbf{X}\mathbf{X}_0\} \geq \epsilon_\delta \\ \mathbf{X} \succeq \mathbf{0}. \end{array} \right.$$

Infinitely many constraints: The idea of the trigonometric polynomial/sum of squares to reformulate as finite SDP constraints

A radar example

- Step 3: Obtain Tx transmit vector from the solution to SDP: matrix $\mathbf{X} = \mathbf{x}\mathbf{x}^H$
 - novel synthesis stage via ESD approximation
- Summary of DESIDE

Step 0: Initialize $\mathbf{X}$ with $\mathbf{x}\mathbf{x}^H$ where $\mathbf{x}$ is a random vector in $\mathbb{C}^N$.

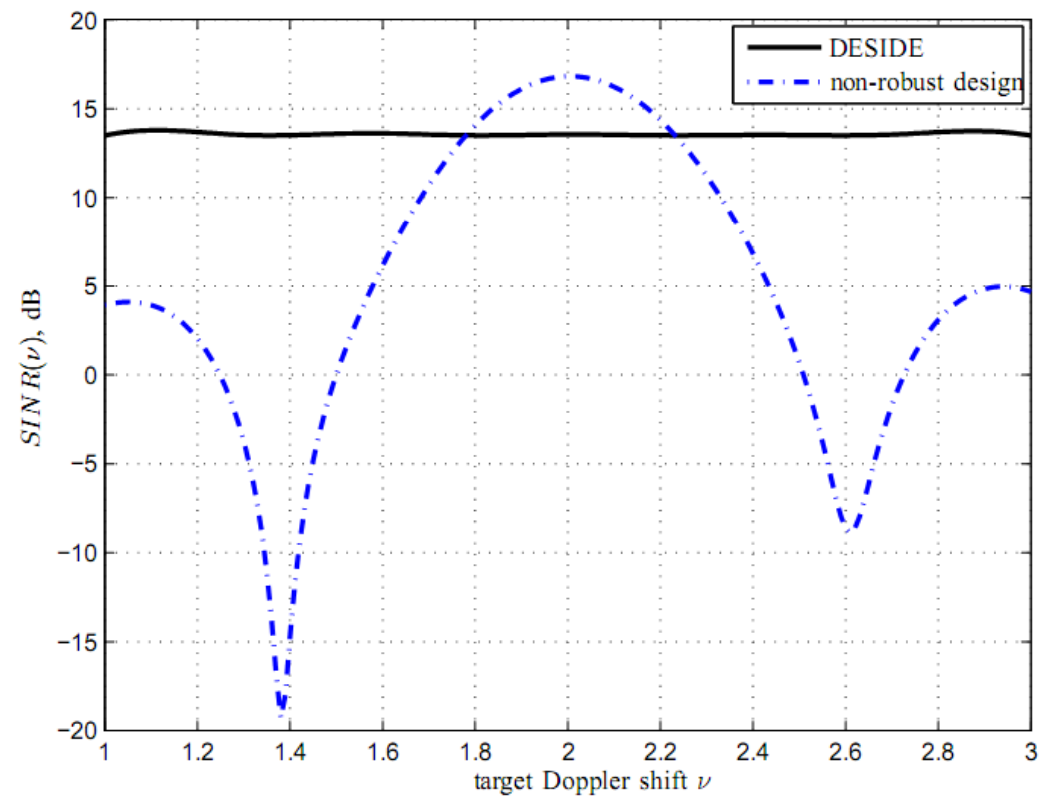
Step 1: Solve the problem $\mathcal{SDP}_W$ in (26) to obtain $\mathbf{W}$.

Step 2: Solve the problem $\mathcal{SDP}_X$ in (24) to obtain $\mathbf{X}$.

Step 3: Repeat steps 1 and 2 until a pre-defined stop criterion is satisfied, e.g. $|\min_{\nu \in \Omega} \widetilde{SINR}_{relax}(\nu)^{(\kappa+1)} - \min_{\nu \in \Omega} \widetilde{SINR}_{relax}(\nu)^{(\kappa)}| \leq \mu$ for a given $\mu > 0$.

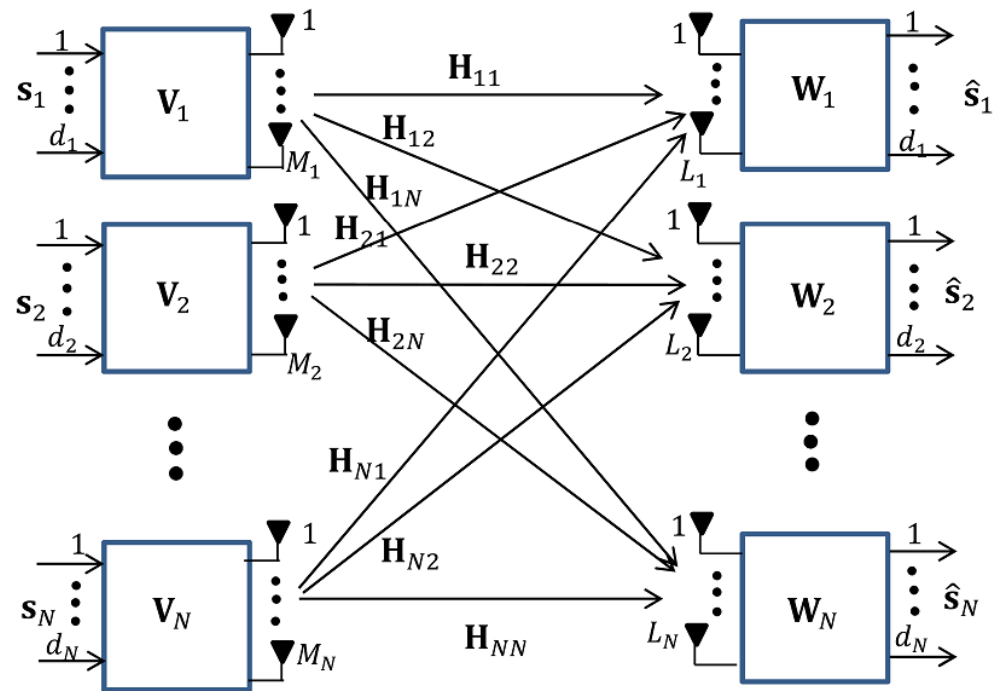
A radar example

- Numerical example: robustness



A communication example

- N pairs in MIMO-IC
 - Tx precoders
 - Rx decoders
 - Users' rates
 - Done in 2019



A communication example

- Received signal at the i -th Rx

$$\mathbf{y}_i = \underbrace{\mathbf{H}_{ii}\mathbf{d}_i}_{\text{desired signal}} + \underbrace{\sum_{j \neq i} \mathbf{H}_{ji}\mathbf{d}_j + \mathbf{n}_i}_{\text{interference plus noise}}$$

- User rate assuming MMSE decoder

$$R_i = \log \det \left(\mathbf{I}_{d_i} + \mathbf{V}_i^H \mathbf{H}_{ii}^H \left[\mathbf{\Gamma}_i + \sum_{j \neq i} \mathbf{H}_{ji} \mathbf{V}_j \mathbf{V}_j^H \mathbf{H}_{ji}^H \right]^{-1} \mathbf{H}_{ii} \mathbf{V}_i \right)$$

A communication example

- The design problem

$$\begin{aligned} \max_{\{\mathbf{Q}_i\}_{i=1}^N} \quad & \min_{i=1,2,\dots,N} R_i \\ \text{s.t.} \quad & \text{tr}\{\mathbf{Q}_i\} \leq p_i \quad \forall i = 1, 2, \dots, N \\ & \mathbf{Q}_i \succeq \mathbf{0} \quad \forall i = 1, 2, \dots, N \end{aligned}$$

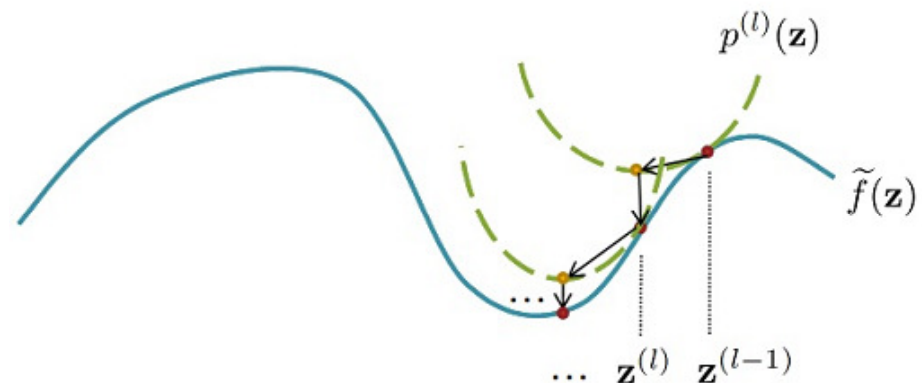
- With Tx covariance matrix $\mathbf{Q}_i \triangleq \mathbf{V}_i \mathbf{V}_i^H$

$$R_i = \log \det \left(\mathbf{I}_{L_i} + \mathbf{H}_{ii} \mathbf{Q}_i \mathbf{H}_{ii}^H \left[\mathbf{\Gamma}_i + \sum_{j \neq i} \mathbf{H}_{ji} \mathbf{Q}_j \mathbf{H}_{ji}^H \right]^{-1} \right)$$

A communication example

- MM framework: Majorization-minimization
 - The problem

$$\begin{cases} \min_{\mathbf{z}} & f(\mathbf{z}) \\ \text{subject to} & c(\mathbf{z}) \leq 0 \end{cases}$$



- Majorization: a proper upper bound

$$\begin{aligned} p^{(l)}(\mathbf{z}) &\geq f(\mathbf{z}), \quad \forall \mathbf{z} \\ p^{(l)}(\mathbf{z}^{(l-1)}) &= f(\mathbf{z}^{(l-1)}) \end{aligned}$$

- Minimization:

$$\begin{cases} \min_{\mathbf{z}} & p^{(l)}(\mathbf{z}) \\ \text{subject to} & c(\mathbf{z}) \leq 0 \end{cases}$$

A communication example

- Trick: reformulation of the objective as a convex function!

– with
$$R_i = \log \det(\mathbf{U}^H \mathbf{B}_i^{-1} \mathbf{U})$$

$$\mathbf{U} \triangleq \begin{bmatrix} \mathbf{I}_{M_i} & \mathbf{0}_{M_i \times L_i} \end{bmatrix}^T$$

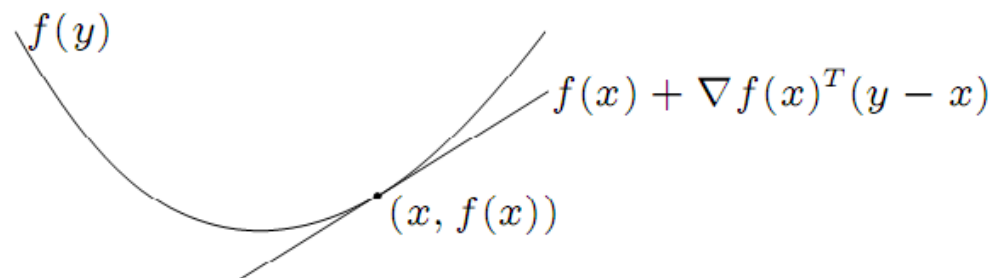
$$\mathbf{B}_i = \begin{bmatrix} \mathbf{I}_{M_i} & \tilde{\mathbf{V}}_i^H \mathbf{H}_{ii}^H \\ \mathbf{H}_{ii} \tilde{\mathbf{V}}_i & \mathbf{\Gamma}_i + \sum_{j=1}^N \mathbf{H}_{ji} \tilde{\mathbf{V}}_j \tilde{\mathbf{V}}_j^H \mathbf{H}_{ji}^H \end{bmatrix}$$

A communication example

- Minorize the convex function via definition of convex functions

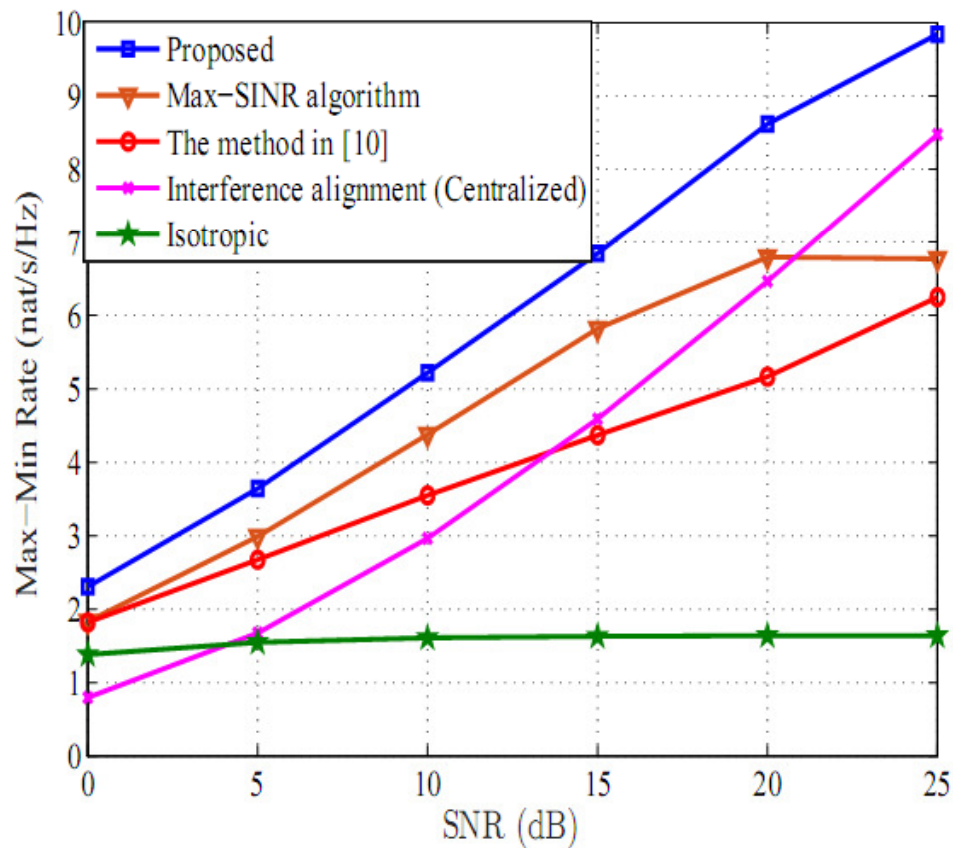
$$\log \det(\mathbf{U}^H \mathbf{B}_i^{-1} \mathbf{U}) \geq \log \det(\mathbf{U}^H \bar{\mathbf{B}}_i^{-1} \mathbf{U}) - \text{tr}\{\mathbf{F}_i(\mathbf{B}_i - \bar{\mathbf{B}}_i)\}$$

- Iterative SOCP



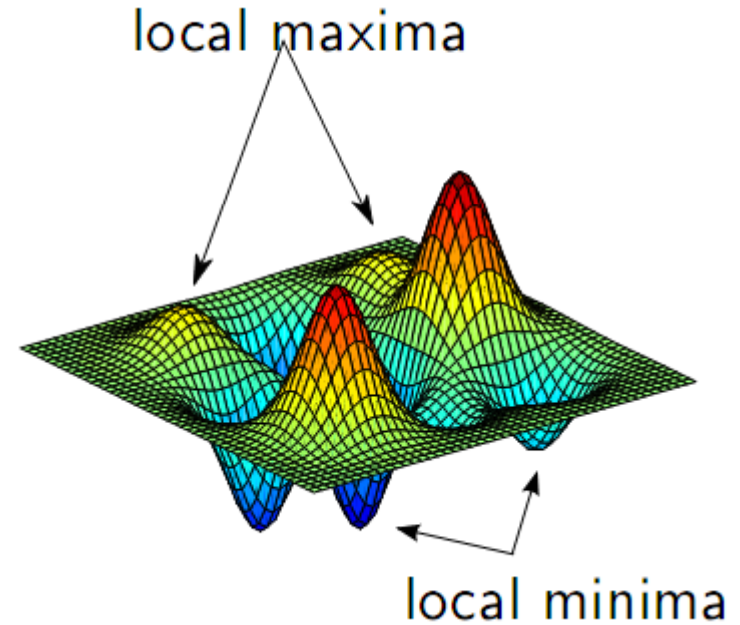
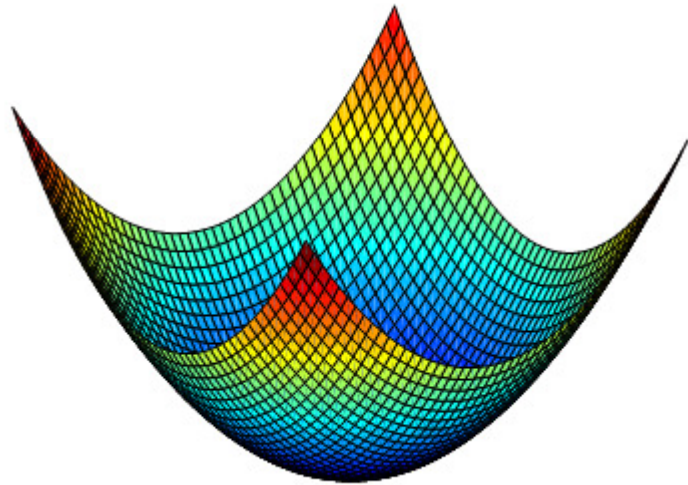
A communication example

- A numerical example



A note on convergence

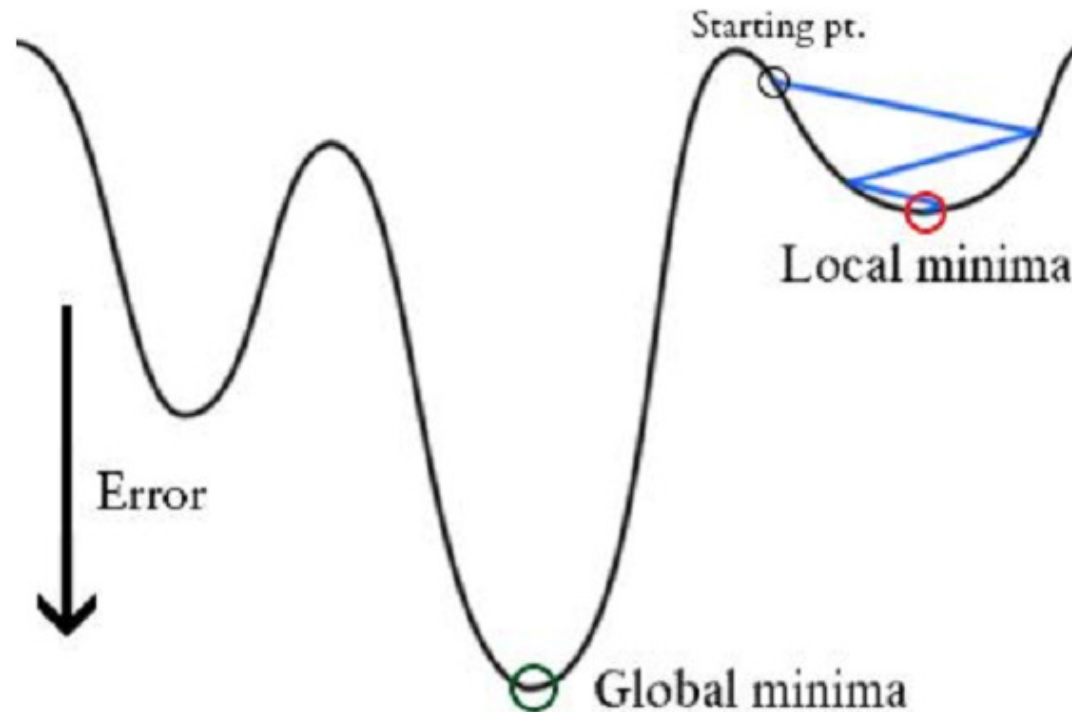
- Convex versus non-convex problems



<http://newport.eecs.uci.edu/anandkumar/slides/icml2016-tutorial.pdf>

A note on convergence

- The effect of the starting point



https://www.cs.ubc.ca/labs/lci/mlrg/slides/non_convex_optimization.pdf

A note on convergence

- Converge to stationary points
 - Not always but under some mild conditions
 - MM, AO
 - Sequence of the objective values are always convergent
- Improvement with respect to starting point
 - Try several initializations
 - Possibility & computational burden

Summary and conclusion

- Active sensing systems: radars
 - Tx-Rx optimization: signal/filter
- Communication systems
 - Tx-Rx optimization: precoder/decoder
- Examples of radar and communication systems
 - Non-convex optimization techniques like SDR and MM