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COMSATS

Adaptive Minimum Entropy Beamforming Algorithms for Narrowband Signals

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Contents

Introduction

Adaptive Filters

Definition

A filter that self-adjusts its coefficients according to an algorithm driven by an error signal.

Types

There are two types of adaptive filters

- Blind Adaptive Filters
- Non-Blind Adaptive Filters

Non-Blind Adaptive Filters

Adaptive Filters that require a desired signal for their operation. Such filters try to minimize the error between the filter output and the desired signal.

Examples

- Least Mean Square (LMS) Algorithm
- Recursive Least Squares (RLS) Algorithm
- Least Mean Fourth (LMF) Algorithm

Blind Adaptive Filters

Adaptive Filters that do not require a desired signal for their operation. Such Algorithms try to restore certain signal properties hence they rely on signal statistics.

Examples

- Constant Modulus Algorithm (CMA)
- Multiple Signal Classification (MUSIC) Algorithm
- Multi-Modulus Algorithm (MMA)

Beamforming

Definition

A signal processing technique used in sensor arrays for directional signal transmission or reception.

Adaptive Beamforming

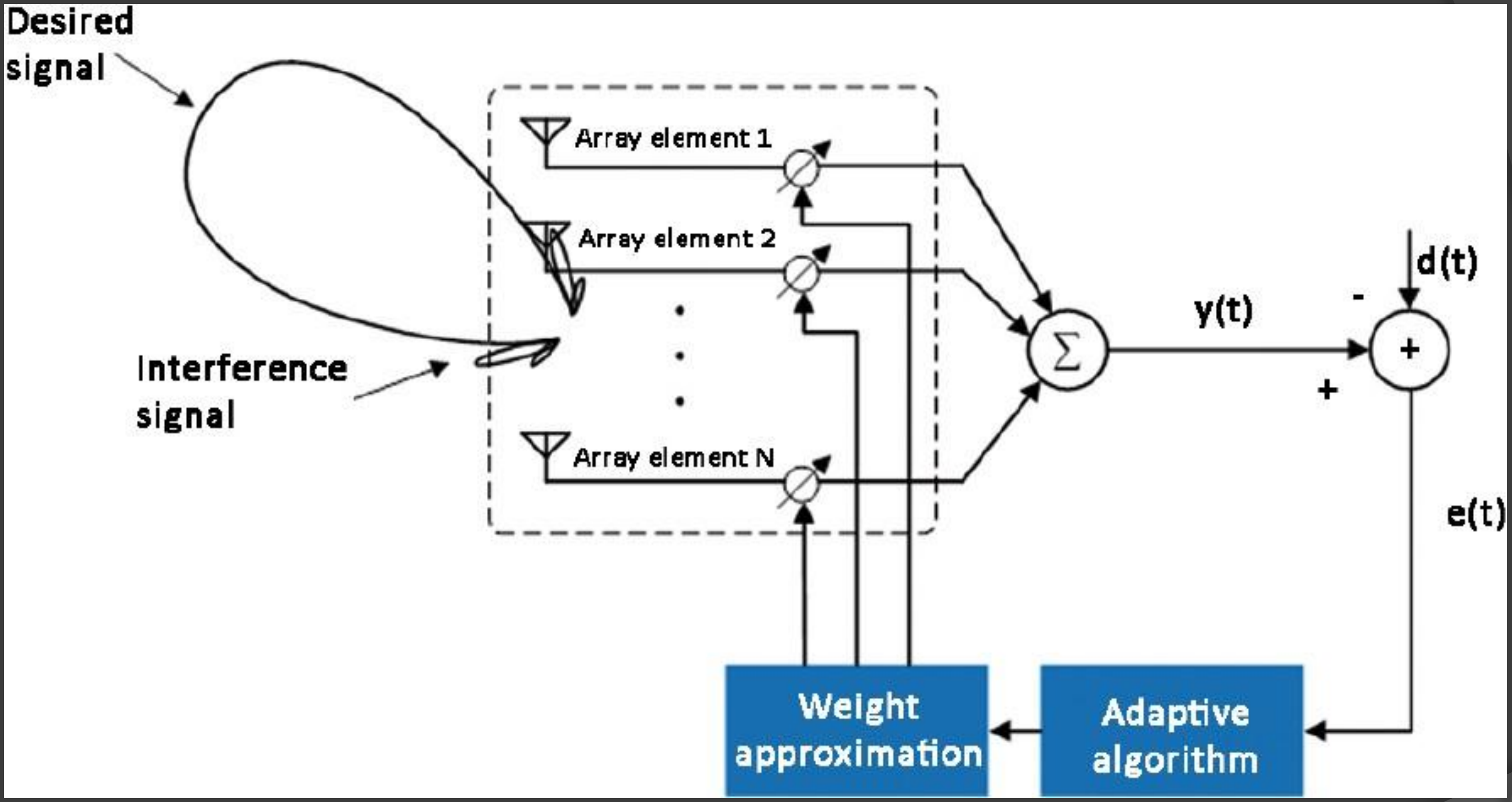
Transmission or reception of signals in different directions without having to mechanically steer the array

Blind Adaptive Beamforming

Adaptive Beamforming realized with the help of blind adaptive filters is called Blind Adaptive Beamforming.

Narrowband Signals

For purpose of beamforming 'narrowband' means that the bandwidth of the impinging signal should be narrow enough to make sure that the signals received by the opposite ends of the array are still correlated with each other.



Adaptive Beamforming System

Existing Solutions for Blind Beamforming

Constant Modulus Algorithm (CMA)

- CMA/Godard Algorithm Forces output to have a constant Modulus
- CMA has the following cost function

$$J_{\text{cma}} = E\{(|y_n|^p - R)^q\}$$

- In special case of $\mathrm{p} = \mathrm{q} = 2$ CMA has the following weight update equation

$$w_{n+1} = w_n + \mu\, y_n^* (R - |y_n|^2) x_n$$

$\mu :=$ step size parameter, $y_n :=$ output, $R :=$ Dispersion Constant, $x_n :=$ Regressor

Multi Modulus Algorithm (MMA)

- MMA utilizes the dispersion of real and imaginary parts separately
- The cost function of MMA is given as

$$J_{\text{mma}} = E[(y_{n,R}^2 - R_R^2)^2 + (y_{n,I}^2 - R_I^2)^2]$$

- The weight update equation of MMA is given as

$$w_{n+1} = w_n + \mu[y_{n,R}(R_R - y_{n,R}^2) + \jmath\, y_{n,I}(R_I - y_{n,I}^2)]^* x_n$$

$y_{n,R}, y_{n,I}$:= Real and Imaginary Part of Output

R_R, R_I := Real and Imaginary Part of Dispersion Constant

Minimum Entropy Deconvolution Criteria

- One of the earliest principle for designing blind cost functions
- Proposed by Wiggins in 1977
- He suggested to maximize the following cost for seismic data (Super Gaussian)

$$\frac{\frac{1}{B}\sum_{b=1}^{B}|y_{n-b+1}|^4}{\left(\frac{1}{B}\sum_{b=1}^{B}|y_{n-b+1}|^2\right)^2}$$

$B :=$ Number of Equalized Samples

- Gray generalized Wiggins idea to two degrees of freedom in 1979 as follows

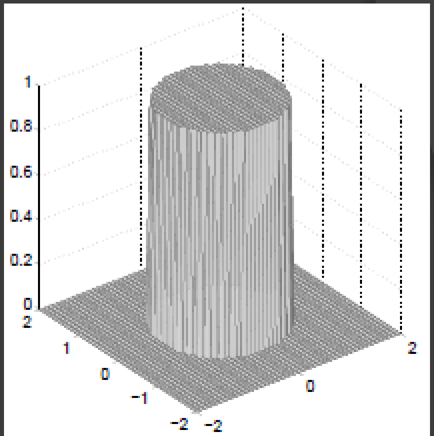
$$\mathrm{J}_{\text{med}}^{(p,q)} \equiv \frac{\frac{1}{B}\sum_{b=1}^{B}|y_{n-b+1}|^{p}}{\left(\frac{1}{B}\sum_{b=1}^{B}|y_{n-b+1}|^{q}\right)^{\frac{p}{q}}}$$

- Donoho then developed general rules for designing MED type estimators
- Several cases of MED have appeared in context of blind deconvolution of seismic data have appeared in literature

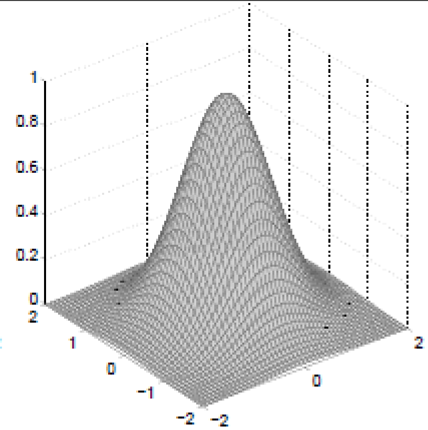
Designing Blind Cost Function

We use following in the design of cost function for Advanced Phase Shift Keying (APSK) constellations

- MED principle
- The probability density function (PDF) of transmitted (APSK)
- PDF of noisy received signal



PDF of
Continous APSK



Gaussian PDF
(Received Signal)

- Using MED principle along with PDFs of APSK constellation and noisy received signal results in the following cost function

$$w^{\dagger} = \arg\max_{w} = \frac{E\left[\left|y_n\right|^2\right]}{\left(\max\left\{\left|y_n\right|\right\}\right)^2}$$

- Maximizing the above cost can be interpreted as finding weights that
  - Drive the distribution of y_n away from Gaussian towards uniform
  - This results in removal of interference from received APSK signal

Proposed Algorithms

- Stchochastic Gradient Based implementation of the equation

$$w^{\dagger} = \arg\max_{w} E\left[|y_n|^2 \right] \text{ s.t. } \max\{|y_n|\} \le R_a$$

requires inclusion of a differentiable constraint: one possibility is given below

$$w^{\dagger} = \arg\max_{w} E\left[|y_n|^2 \right] \text{ s.t. } \mathrm{fmax}(R_a, |y_n| \overset{w^{\dagger}}{)} = R_a$$

- By optimizing the given expression for the following update equations are obtained

$$w_{n+1} = w_n + \mu \, \mathrm{f}(y_n) \, y_n^* \, x_n,$$

$$\mathrm{f}(y_n) = \begin{cases} 1, & \text{if } |y_n| \le R_a \\ -\beta, & \text{if } |y_n| > R_a. \end{cases}$$

- Where $\beta = 2MM_L / (P_a R_a^2) - 1$

$M :=$ Total Number of Signal Alphabets

$M_L :=$ Alphabets on Modulus R_a

$P_a :=$ Average Signal Energy

$R_a :=$ Outermost Modulus

- The given algorithm is called β-CMA

- To obtain an adaptive blind beamforming algorithm for Square-QAM we note that
  - In-phase and quadrature components of square-QAM are statistically independent of each other
  - Exploiting this independence and applying MED we get the following cost function

$$\max_{w} E\left[\left|y_n\right|^2\right], \text{s.t. } \max\left\{\left|y_{R,n}\right|\right\} = \max\left\{\left|y_{I,n}\right|\right\} \leq R$$

- Optimization of the given equation yields the following algorithm which is termed β-MMA

$$w_{n+1} = w_n + \mu\left(\mathrm{f}_R\, y_{R,n} + \jmath\, \mathrm{f}_I\, y_{I,n}\right)^* x_n$$

$$\mathrm{f}_L = \begin{cases} 1, & \text{if } |y_{L,n}| \leq R \\ -\beta, & \text{if } |y_{L,n}| > R \end{cases}$$

$$\beta = (R^2 + 2)/(3R), R = \max\left\{\left|a_{R,n}\right|\right\} = \max\left\{\left|a_{I,n}\right|\right\}$$

Simulation Results

Signal to Interference Plus Noise Ratio (SINR)

We Define

$$\mathrm{SINR}_k = \frac{w_n^H h(\theta_k)\sigma_k^2 h(\theta_k)^H w_n}{w_n^H R_k w_n}$$

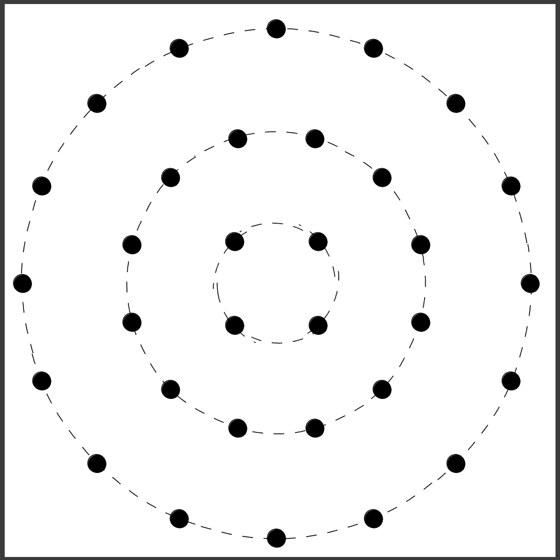
$h(\theta_k) :=$ Steering Vector for k^{th} source

$\sigma_k^2 :=$ Energy of the k^{th} source

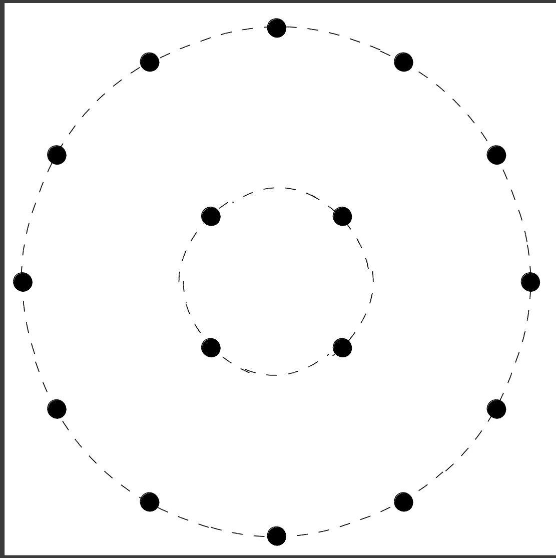
$R_k :=$ True autocorrelation of the interference

Simulation Parameters for β-CMA

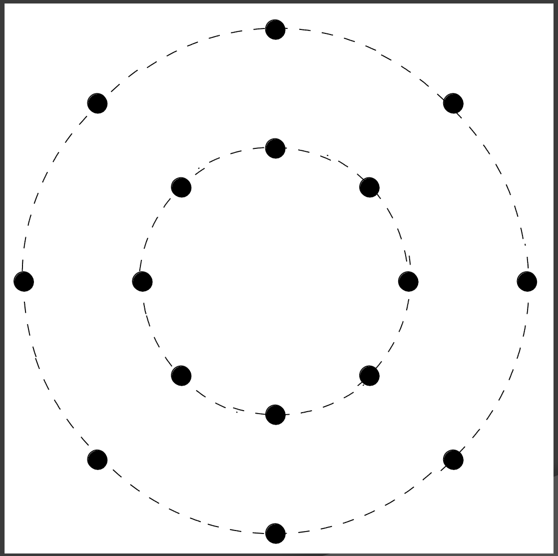
- Signal to Noise Ratio (SNR)=30dB
- Signal to Interference Ratio (SIR)=10dB
- Interference1 = 16 APSK (8,8), impinging angle $\theta_1 = 5^\circ$
- Interference2 = 16 APSK (4,12), impinging angle $\theta_2 = 50^\circ$
- Desired Signal = 32 APSK, impinging angle $\theta_d = -40^\circ$
- Antenna Array Elements =9
- Distance between antenna elements=λ/2 where λ is wavelength of signal



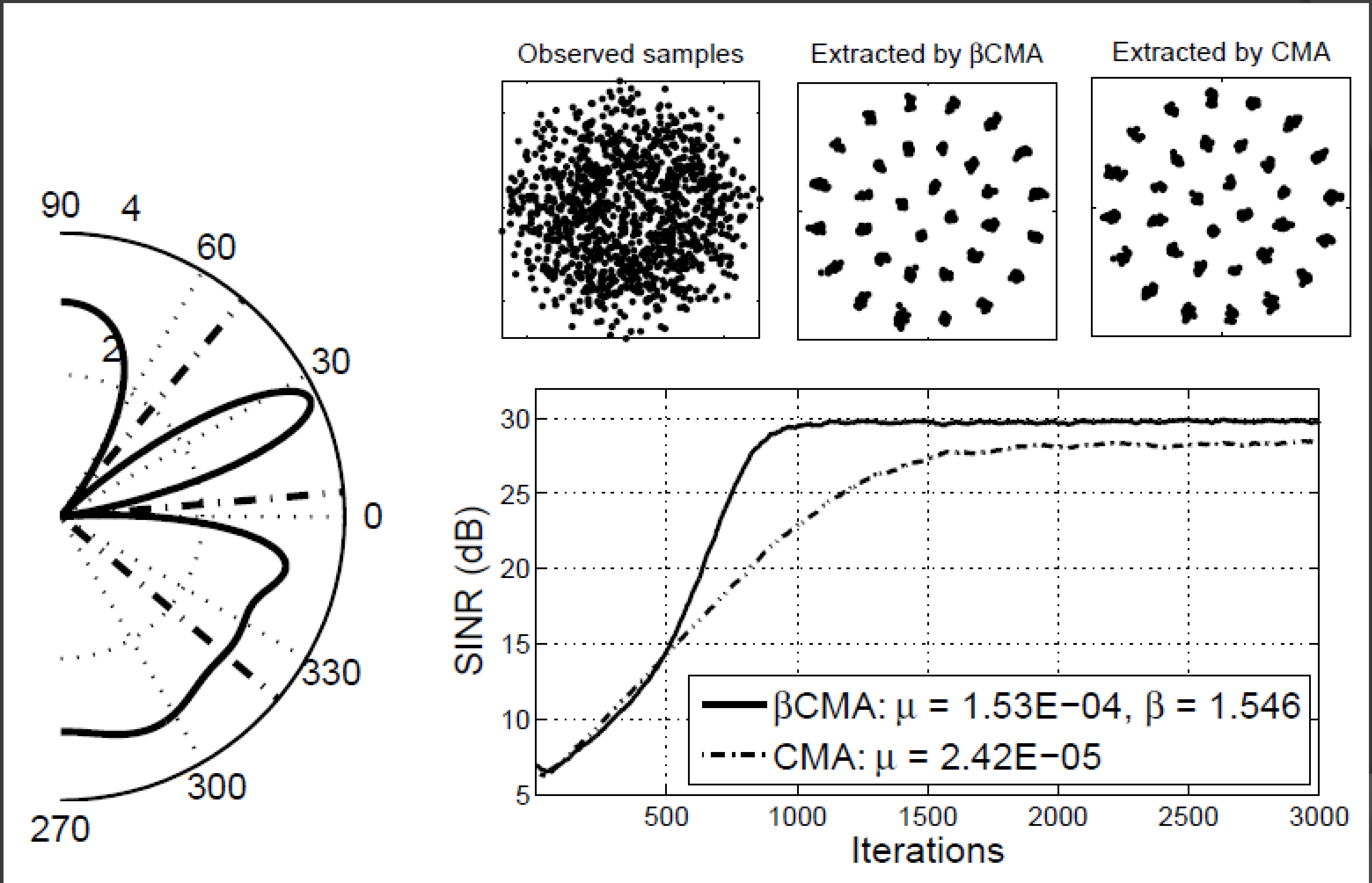
32 APSK



16 APSK (4,12)



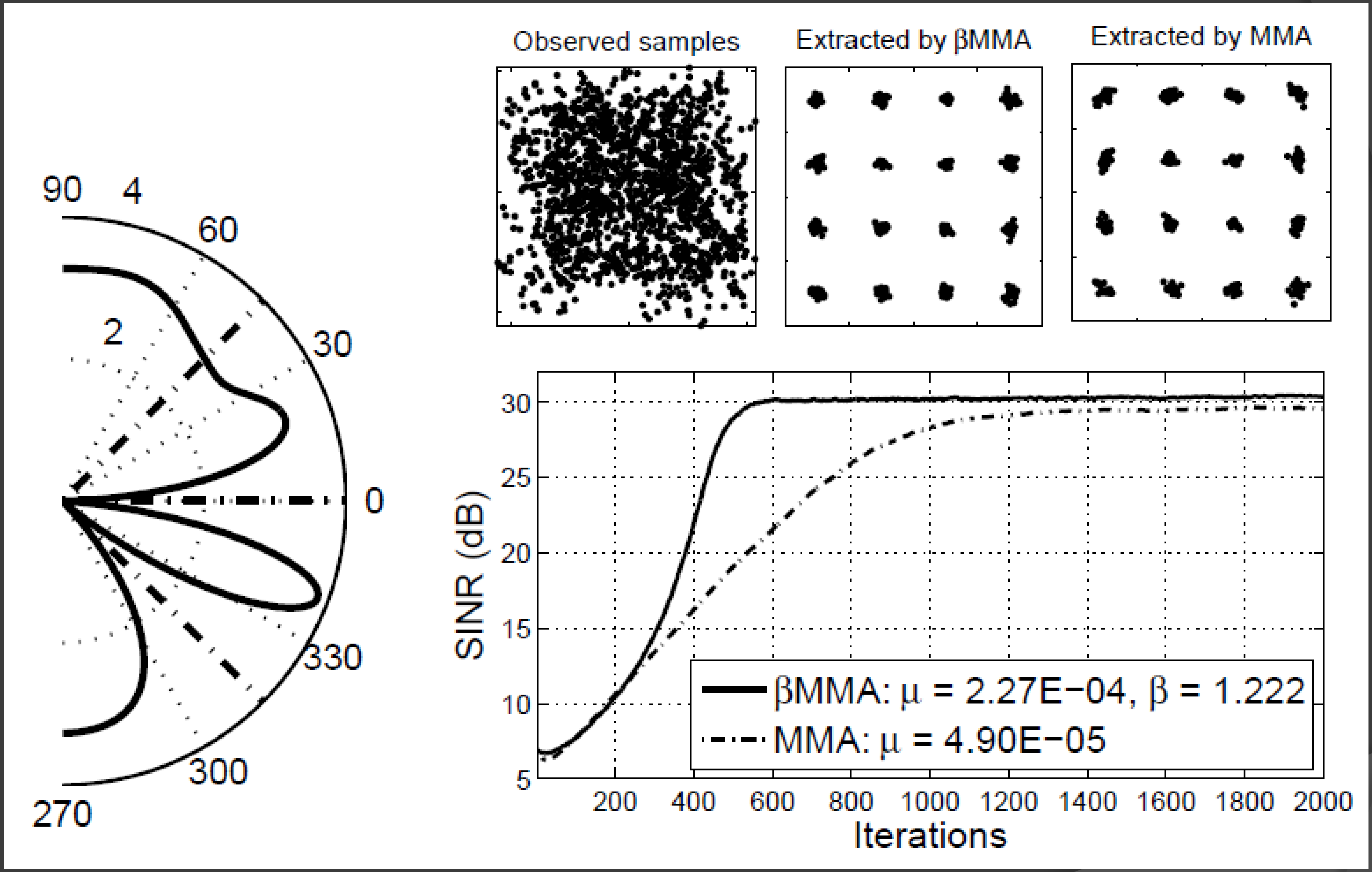
16 APSK (8,8)



Simulation Results

Simulation Parameters for β-MMA

- Interference1 = 4 QAM (8,8), impinging angle $\theta_1 = 0^\circ$
- Interference2 = 16 QAM (4,12), impinging angle $\theta_2 = 45^\circ$
- Desired Signal = 64 QAM, impinging angle $\theta_d = -45^\circ$
- Antenna Array elements, Inter element spacing, SNR and SIR values are same as for β-CMA



Simulation Results

Conclusion

- Design of cost functions using MED is discussed
- Two algorithms named β-CMA and β-MMA are proposed for APSK and QAM constellations respectively
- Superior performance of proposed schemes is shown with the help of SINR comparison with conventional schemes

Questions

Thank you!