



Optimal Space-Time Transmit Signal Design For Multi-Static Radar



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Outline



- Motivation
- Approach
- Algorithm-1 (Collective Projection Algorithm)
- Algorithm-2 (Individual Projection Algorithm)
- Numerical Results
- Radar Model
- Results using the Radar Model
- Conclusions and Future Work



Objective



To develop Mathematical Algorithms that produce optimal space-time transmit signal, which would result in the responses from dissimilar targets to be as orthogonal as possible.



Motivation



- Why do we need the responses from dissimilar targets to be orthogonal to each other?
- REASON:
 - The response signal of a radar in vector-matrix form is given as,

$$\mathbf{r} = \sum_i \gamma_i \mathbf{H}_i \mathbf{s} + \mathbf{n} = \sum_i \gamma_i \boldsymbol{\rho}_i + \mathbf{n} = \mathbf{P}\boldsymbol{\gamma} + \mathbf{n}$$

Where, \mathbf{r} is the Measurement vector.

\mathbf{H}_i is the Propagation matrix.

γ_i is the scattering coefficient of target-i.

\mathbf{s} is the transmit signal.

$\boldsymbol{\rho}_i$ is the normalized response vector.

$$\boldsymbol{\rho}_i = \mathbf{H}_i \mathbf{s}$$



Estimators



- The response signal needs to be processed in order to estimate the scattering coefficients.

- Matched Filter

- Most common and simple estimator.
- The Scattering Estimate of a given target pixel using the Matched filter is given by,

$$\hat{\gamma}_i = \gamma_i + \sum_{i \neq j} \gamma_j \frac{\mathbf{\rho}'_i \mathbf{\rho}_j}{|\mathbf{\rho}_i|^2} + \frac{\mathbf{\rho}'_i \mathbf{n}}{|\mathbf{\rho}_i|^2}$$

- First term represents the desired estimate, second term is error due to clutter and the third term is error due to noise.
- Maximizes Signal to Noise Ratio (SNR), does nothing to suppress error due to clutter.
- A good estimate can be achieved if the responses from dissimilar target pixels are orthogonal to each other.

Hence in order to use the Matched filter and still get a good estimate we need,

$$\mathbf{\rho}'_i \mathbf{\rho}_j = 0 \quad \text{where } i \neq j$$



Approach



- AIM : To come up with a space-time transmit signal that produces the response signals from dissimilar targets to be as orthogonal as possible.
- MINIMAX SOLUTION :
 - Minimize the maximum correlation between two dissimilar targets.
 - Try to find the “worst code” corresponding to the highest correlation.
 - Find an orthogonal code to the worst code.
 - This code reduces the maximum correlation.
- Based on this Minimax solution, an Optimization criteria (χ) is designed that helps in selecting the worst transmit codes.



Optimization Criteria χ



- A criteria is needed to help us select the worst codes and to come up with the desired transmit signal.
- The Optimization Criteria,

$$\chi = \frac{(\mathbf{p}'_i \mathbf{p}_i + \mathbf{p}'_j \mathbf{p}_j + \mathbf{p}'_i \mathbf{p}_j + \mathbf{p}'_j \mathbf{p}_i)}{(\mathbf{p}'_i \mathbf{p}_i + \mathbf{p}'_j \mathbf{p}_j)}$$

- Range of χ values is given by, $0 \leq \chi \leq 2$

$\chi = 0$ or $2 \rightarrow \mathbf{p}_i$ and \mathbf{p}_j perfectly correlated.

$\chi = 1 \rightarrow \mathbf{p}_i$ and \mathbf{p}_j perfectly orthogonal to each other.



Analysis of χ



- The optimization criteria in terms of the propagation matrices (\mathbf{H}) is given as,

$$\chi = \frac{\mathbf{s}'(\mathbf{H}'_i \mathbf{H}_i + \mathbf{H}'_j \mathbf{H}_j + \mathbf{H}'_i \mathbf{H}_j + \mathbf{H}'_j \mathbf{H}_i)\mathbf{s}}{\mathbf{s}'(\mathbf{H}'_i \mathbf{H}_i + \mathbf{H}'_j \mathbf{H}_j)\mathbf{s}}$$

- Introducing two matrices \mathbf{A} and \mathbf{B} as,

$$\mathbf{A} = \mathbf{H}'_i \mathbf{H}_i + \mathbf{H}'_j \mathbf{H}_j + \mathbf{H}'_i \mathbf{H}_j + \mathbf{H}'_j \mathbf{H}_i$$

$$\mathbf{B} = \mathbf{H}'_i \mathbf{H}_i + \mathbf{H}'_j \mathbf{H}_j$$

- The optimization criteria can then be written as,

$$\chi = \frac{\mathbf{s}' \mathbf{A} \mathbf{s}}{\mathbf{s}' \mathbf{B} \mathbf{s}}$$



The C matrix



- Defining another matrix \mathbf{C} , we can write χ as,

$$\chi = \frac{\tilde{\mathbf{s}}' \mathbf{C} \tilde{\mathbf{s}}}{\tilde{\mathbf{s}}' \tilde{\mathbf{s}}}$$

Where, $\mathbf{C} = \mathbf{B}^{-1/2} \mathbf{A} \mathbf{B}^{-1/2}$ and $\tilde{\mathbf{s}} = \mathbf{B}^{1/2} \mathbf{s}$

- The \mathbf{C} matrix is a Positive-definite matrix, so Eigen analysis can be used.
- Representing \mathbf{C} in its eigen values and eigen vectors we have,

$$\mathbf{C} = \sum_{n=1}^N \lambda_n \hat{\mathbf{v}}_n \hat{\mathbf{v}}_n'$$

Where λ_n are the eigen values of the \mathbf{C} matrix.

$\hat{\mathbf{v}}_n$ are the eigen vectors of the \mathbf{C} matrix.

$$\chi = \lambda_n = \frac{\hat{\mathbf{v}}_n' (\mathbf{H}'_i \mathbf{H}_i + \mathbf{H}'_j \mathbf{H}_j + \mathbf{H}'_i \mathbf{H}_j + \mathbf{H}'_j \mathbf{H}_i) \hat{\mathbf{v}}_n}{\hat{\mathbf{v}}_n' (\mathbf{H}'_i \mathbf{H}_i + \mathbf{H}'_j \mathbf{H}_j) \hat{\mathbf{v}}_n} = \frac{\hat{\mathbf{v}}_n' \mathbf{C} \hat{\mathbf{v}}_n}{\hat{\mathbf{v}}_n' \hat{\mathbf{v}}_n}$$



Correlation Coefficient (ξ)



- The Correlation Coefficient gives us the measure of similarity between two response signals.

$$\xi = \frac{|\boldsymbol{\rho}_i' \boldsymbol{\rho}_j|}{\|\boldsymbol{\rho}_i\| \|\boldsymbol{\rho}_j\|}$$

Minimize $Max\{\xi\} \rightarrow 0$

- Relation between χ and ξ

$$\chi = 1 - \operatorname{Re} \left\{ \frac{\boldsymbol{\rho}_i' \boldsymbol{\rho}_j}{\|\boldsymbol{\rho}_i\| \|\boldsymbol{\rho}_j\|} \right\}$$

$$\chi = 1 - \xi \rightarrow \operatorname{Im}\{\boldsymbol{\rho}_i' \boldsymbol{\rho}_j\} = 0$$

$$\chi \rightarrow 1; \xi \rightarrow 0$$



Summary



- We intend to have $\boldsymbol{\rho}'_i \boldsymbol{\rho}_j = 0$ where $i \neq j$
- A solution \mathbf{s} , such that, $\mathbf{s}' \mathbf{H}'_i \mathbf{H}_j \mathbf{s} = 0$
- The Optimization Criteria, $\chi = \frac{\mathbf{s}'(\mathbf{H}'_i \mathbf{H}_i + \mathbf{H}'_j \mathbf{H}_j + \mathbf{H}'_i \mathbf{H}_j + \mathbf{H}'_j \mathbf{H}_i) \mathbf{s}}{\mathbf{s}'(\mathbf{H}'_i \mathbf{H}_i + \mathbf{H}'_j \mathbf{H}_j) \mathbf{s}}$

Such that $\chi = 0$ or $2 \rightarrow \boldsymbol{\rho}_i$ and $\boldsymbol{\rho}_j$ are perfectly correlated.

$\chi = 1 \rightarrow \boldsymbol{\rho}_i$ and $\boldsymbol{\rho}_j$ are perfectly orthogonal to each other.

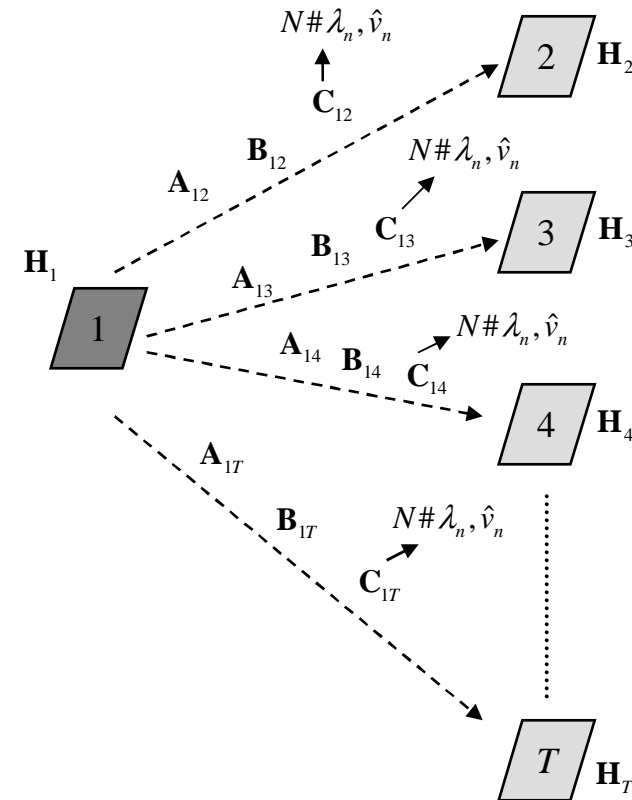
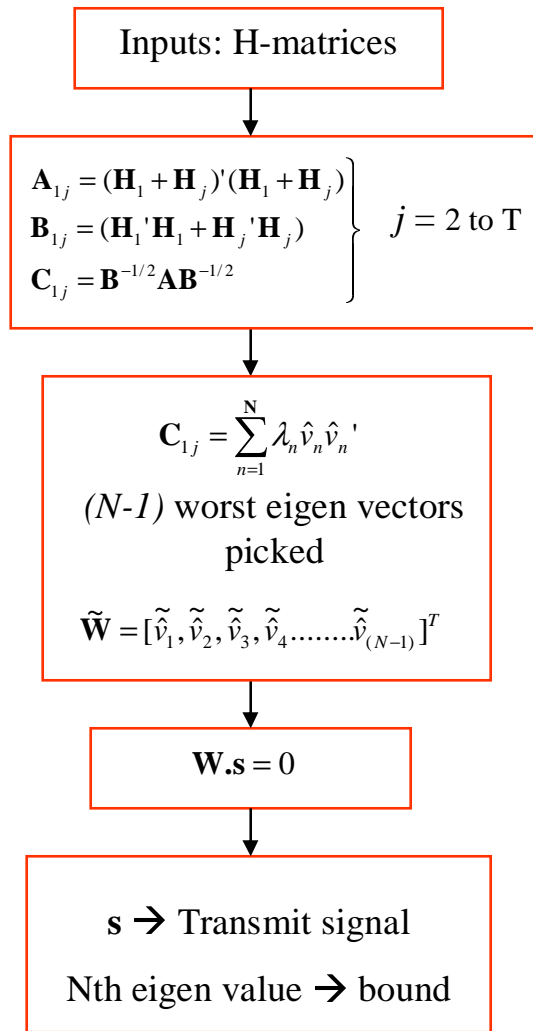
- Define \mathbf{C} matrix, $\chi = \frac{\tilde{\mathbf{s}}' \mathbf{C} \tilde{\mathbf{s}}}{\tilde{\mathbf{s}}' \tilde{\mathbf{s}}}$ and $\mathbf{C} = \sum_{n=1}^N \lambda_n \hat{\mathbf{v}}_n \hat{\mathbf{v}}_n'$

$$\chi = \lambda_n = \frac{\hat{\mathbf{v}}_n' \mathbf{C} \hat{\mathbf{v}}_n}{\hat{\mathbf{v}}_n' \hat{\mathbf{v}}_n}$$

- Correlation Coefficient, $\xi = \frac{|\boldsymbol{\rho}_i' \boldsymbol{\rho}_j|}{\|\boldsymbol{\rho}_i\| \|\boldsymbol{\rho}_j\|}$



Algorithm – 1 (Collective Projection Algorithm)



(T-1) # A,B,C matrices

$N*(T-1)$ # λ_n, \hat{v}_n

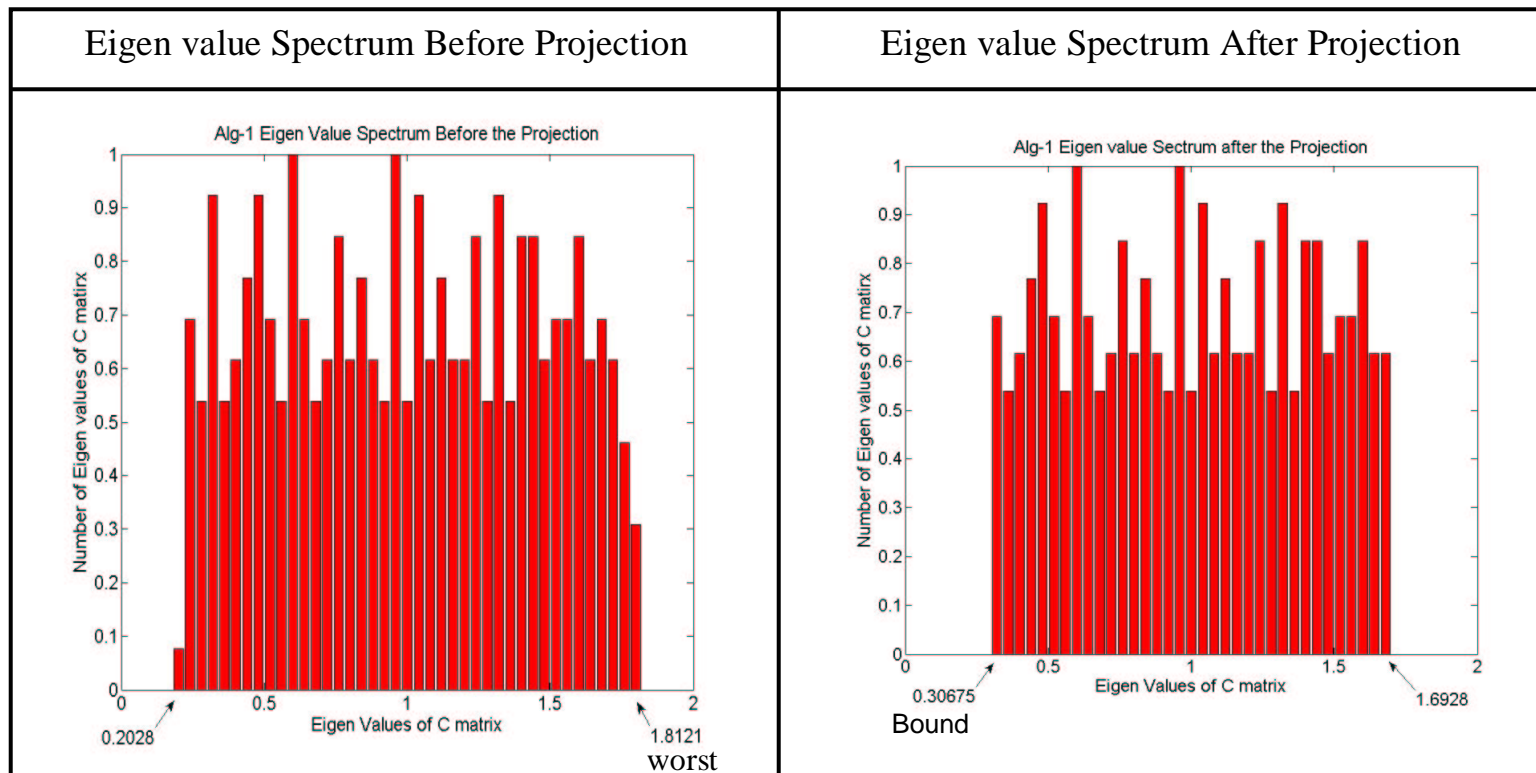




Numerical Analysis of Algorithm-1



- The Propagation matrices (H-matrices) generated Randomly from a Gaussian Distribution of 0 mean and variance 1.
- Total Number of Measurements (M) = 100
- Total Dimensions of the Tx signal (N) = 40
- Total Number of Targets (T) = 10
- $\mathbf{H} \rightarrow M \times N \times T$

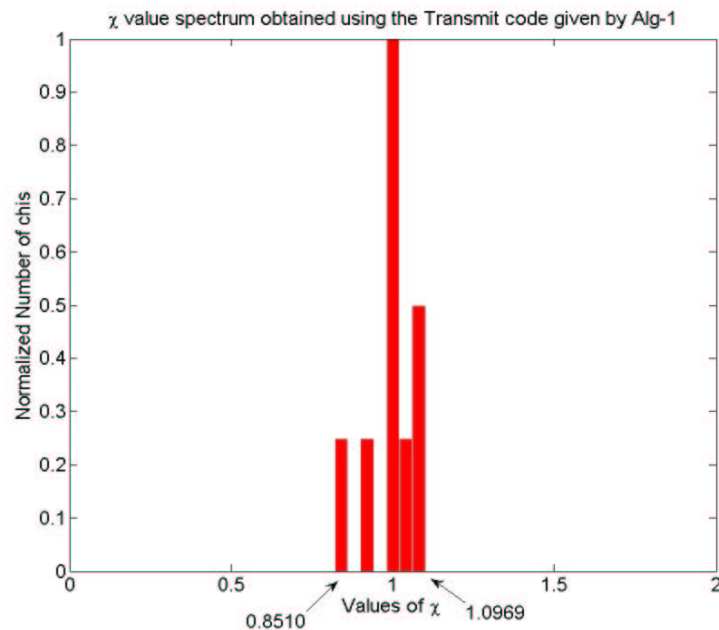




Conclusions from Algorithm-1



- \mathbf{s} is a vector orthogonal to $(N-1)$ vectors.



**Eigen Value spectrum obtained using
the \mathbf{s} vector**

- The χ values are well within the bound of 0.30675.

Conclusions:

- Tightened the χ -value bound from 1.8121 to 0.30675.

Problem :

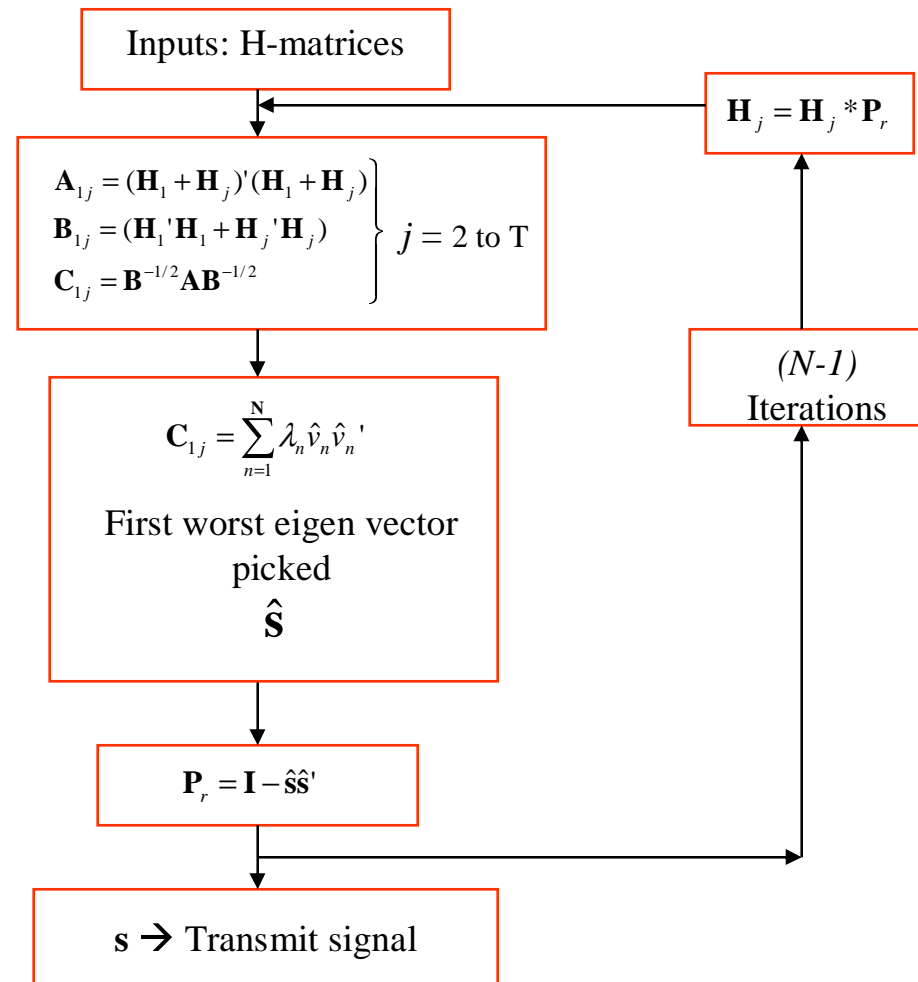
- Correlation among $(N-1)$ worst vectors.

Solution

- Algorithm-2



Algorithm-2 (Individual Projection Algorithm)





Numerical Analysis of Algorithm-2



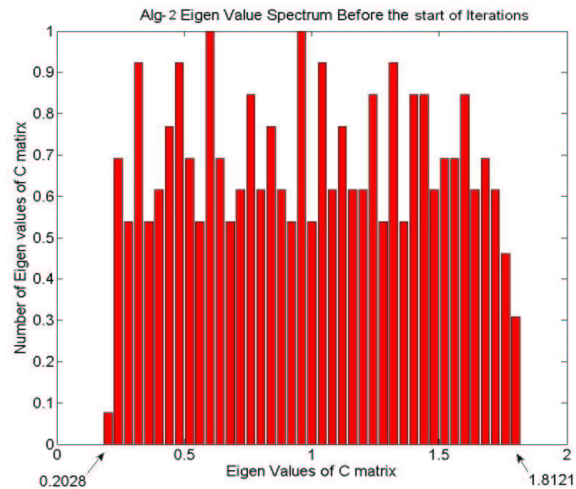
- The Propagation matrices (**H**-matrices) generated Randomly from a Gaussian Distribution of 0 mean and variance 1.
- Total Number of Measurements (M) = 100
- Total Dimensions of the Tx signal (N) = 40
- Total Number of Targets (T) = 10
- The propagation matrices are given as inputs to the Algorithm.



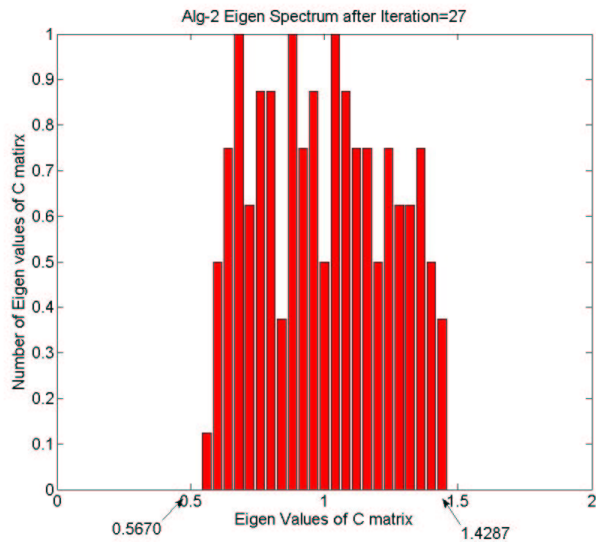
Numerical Analysis of Algorithm-2



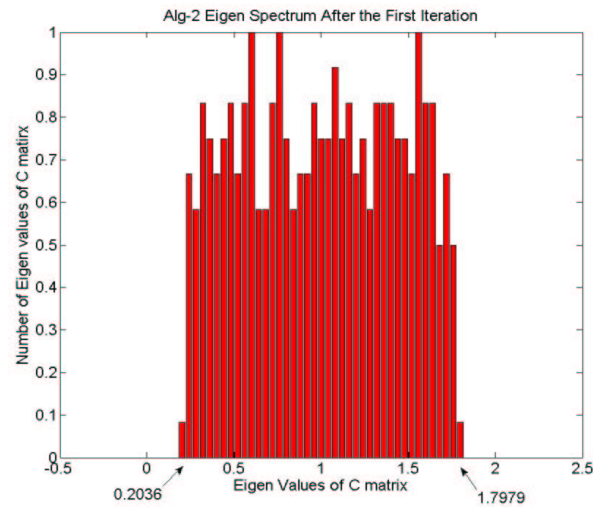
Before the start of the Iterations



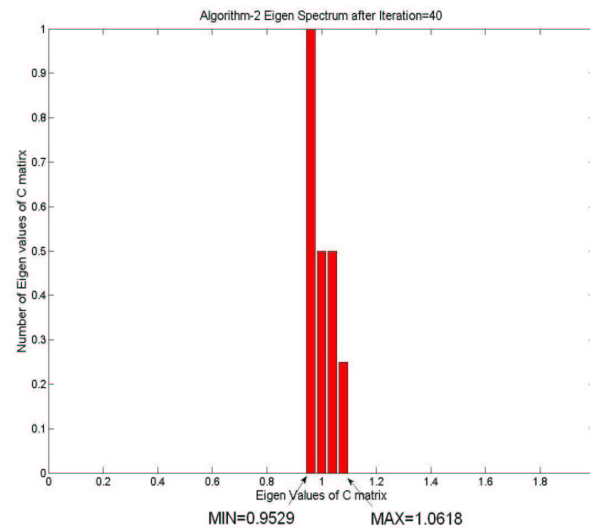
Iteration =27



Iteration =1



Iteration = 39 \rightarrow (N-1)



- Worst χ value has been improved from 1.8121 to 1.0167.
- No bound unlike Algorithm-1.



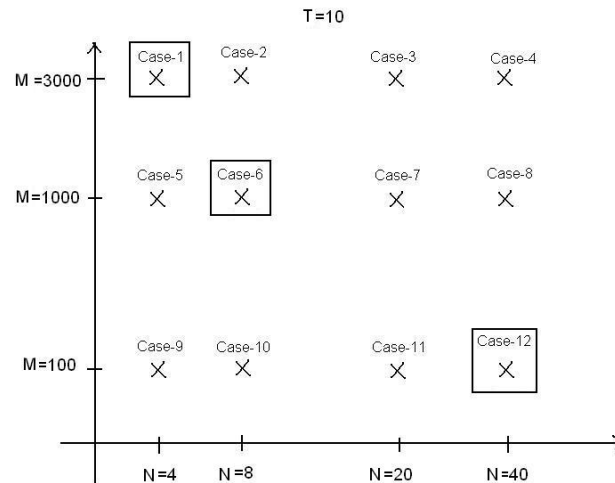
Comparison of Alg-1 and Alg-2



- Performances of Algorithm-1 (Collective Projection) and Algorithm-2 (Individual Projection) are compared.
- The Propagation Matrices (H-matrices) are generated randomly from 0 mean and variance 1 Gaussian Distribution.
- Monte Carlo Loop = 20
- The histograms of the χ values and Maximum Correlation Coefficient values are compared

$$\chi = \frac{\tilde{\mathbf{s}}' \mathbf{C} \tilde{\mathbf{s}}}{\tilde{\mathbf{s}}' \tilde{\mathbf{s}}} \quad \xi = \frac{|\boldsymbol{\rho}_i' \boldsymbol{\rho}_t|}{\|\boldsymbol{\rho}_i\| \|\boldsymbol{\rho}_t\|}$$

Different Cases for which the Algorithms have been compared

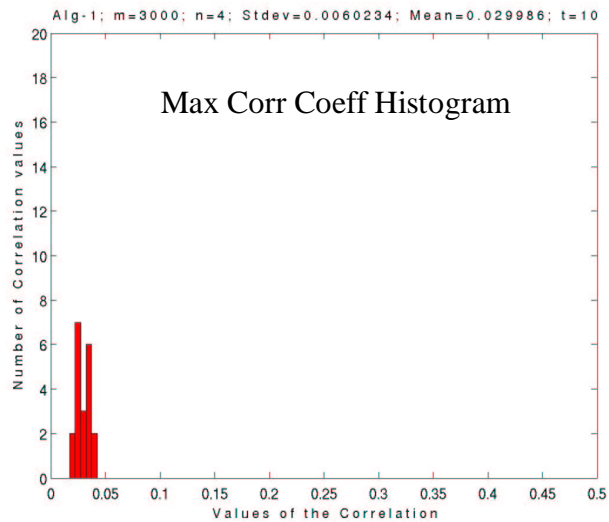
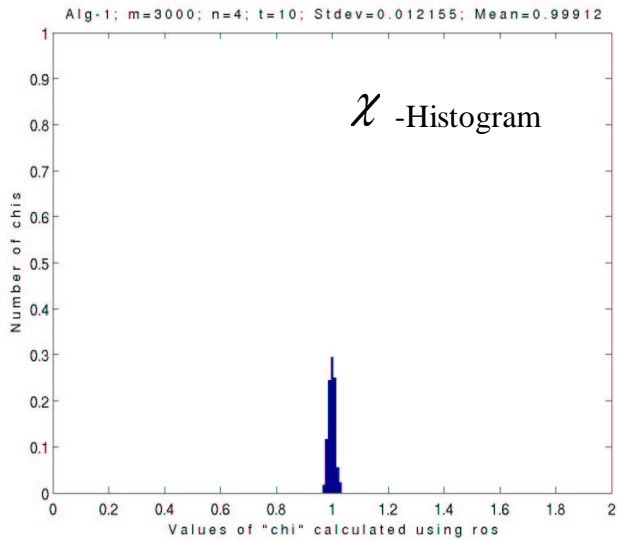




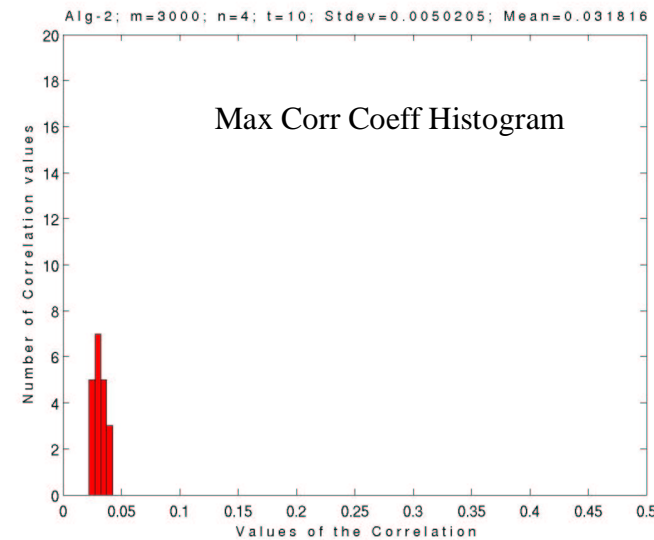
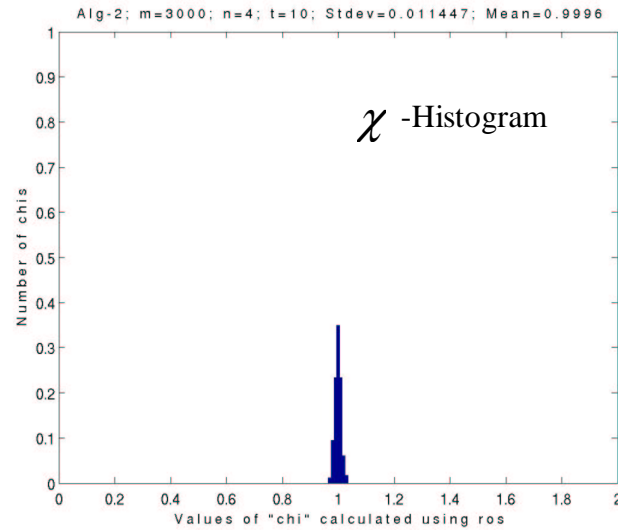
Case-1: M=3000; N=4; T=10



Algorithm-1



Algorithm-2



Ratio of χ Std
 Alg1 / Alg2 =
 1.06

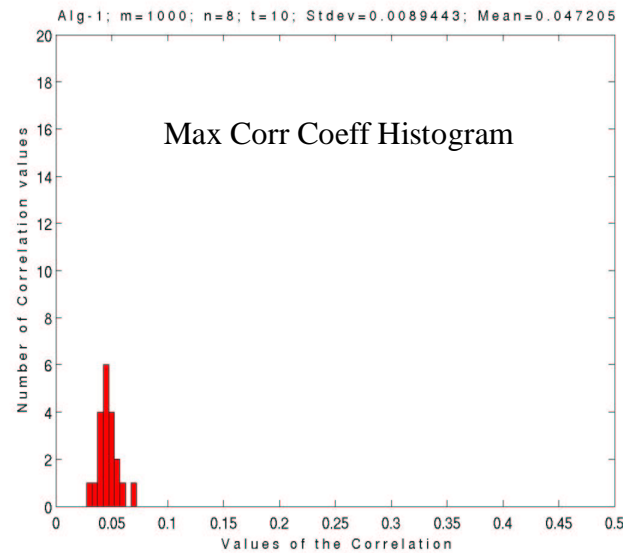
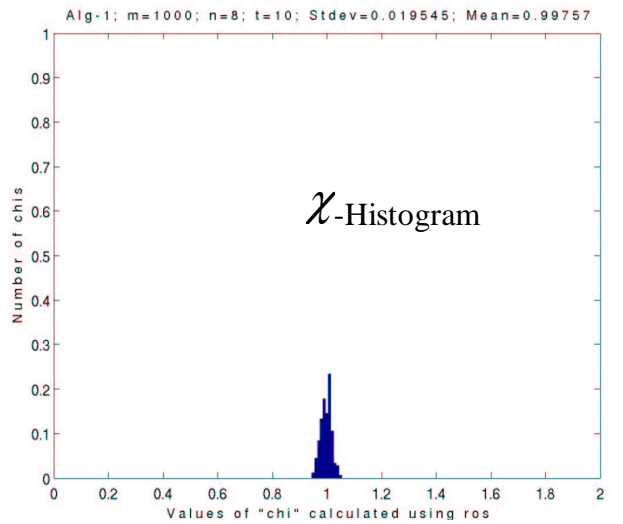
Ratio of Means of
 Max ξ Alg1/
 Alg2= 0.9424



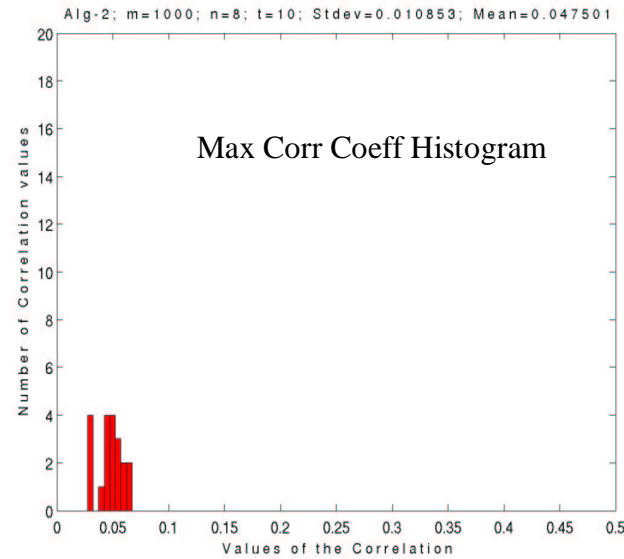
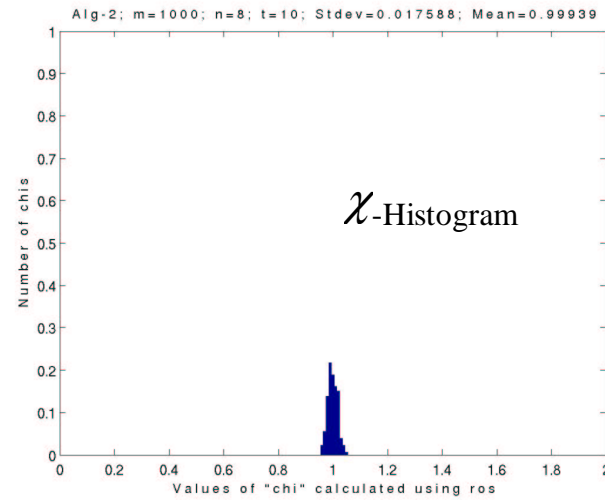
Case-6: M=1000; N=8; T=10



Algorithm-1



Algorithm-2



Ratio of χ Std
 Alg1 / Alg2=
 1.11

Ratio of Means of
 Max ξ Alg1 /
 Alg2= 0.99

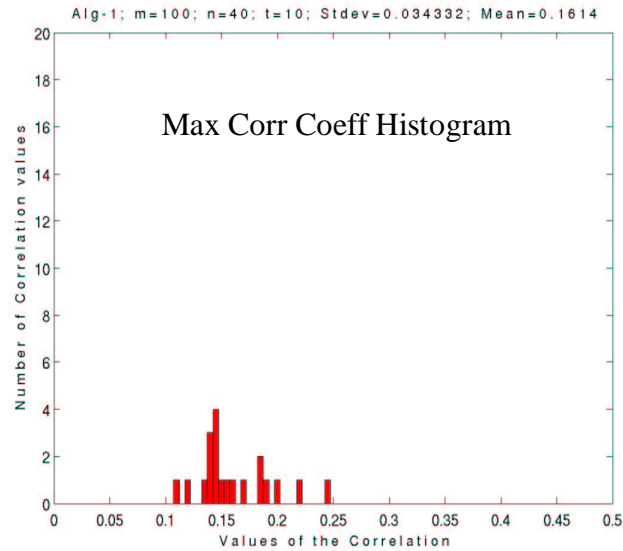
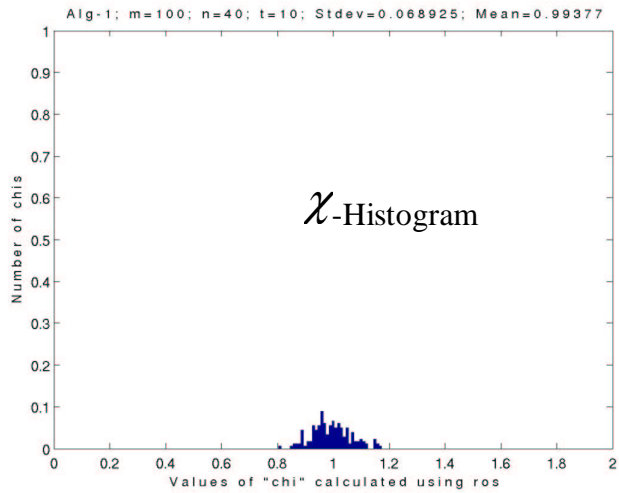




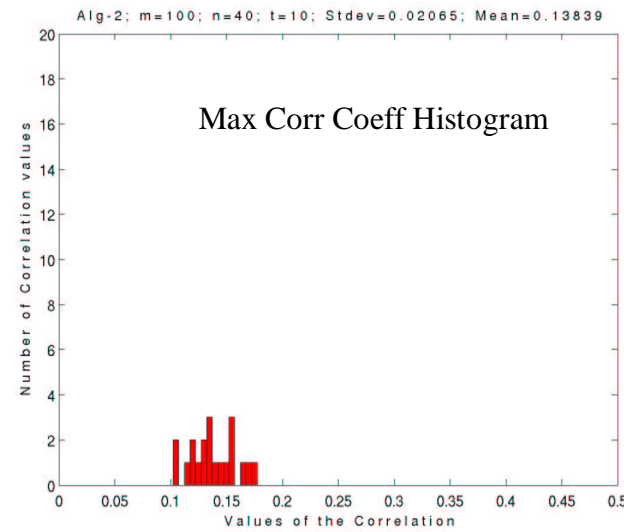
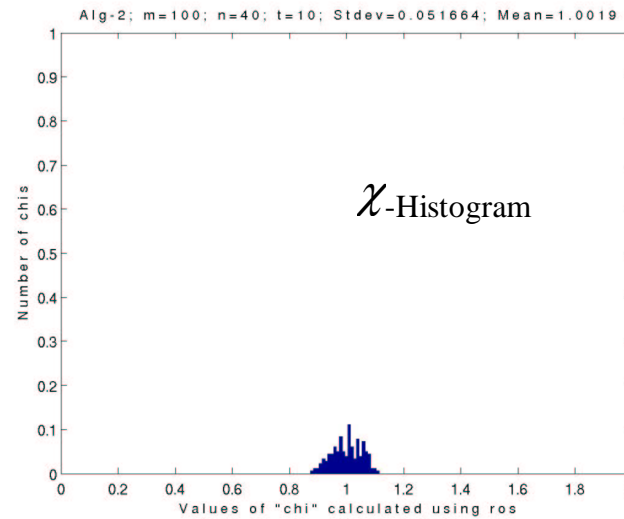
Case-16: M=100; N=40; T=10



Algorithm-1



Algorithm-2



Ratio of χ Std
 Alg1 / Alg2=
 1.33

Ratio of Means of
 Max ξ Alg1 /
 Alg2= 1.165



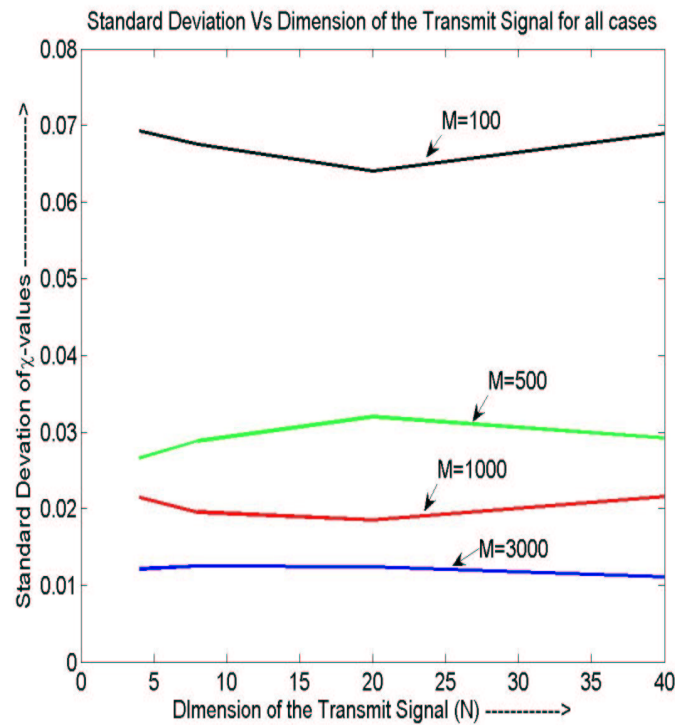


Summary of All the Cases

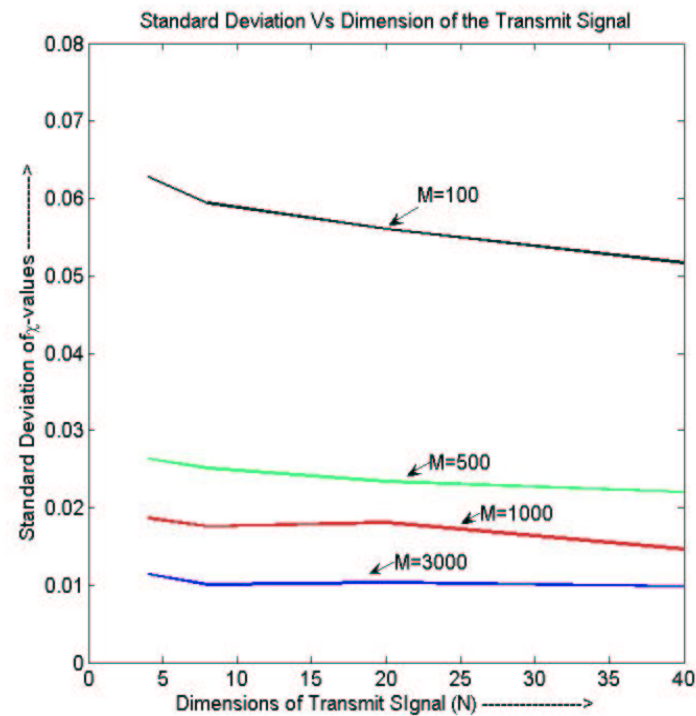


- Plots summarizing the standard deviation of χ values for all the cases.

Algorithm-1



Algorithm-2



- Not much improvement in performance of Alg-2 compared to Alg-1, when constant-H matrices are used.

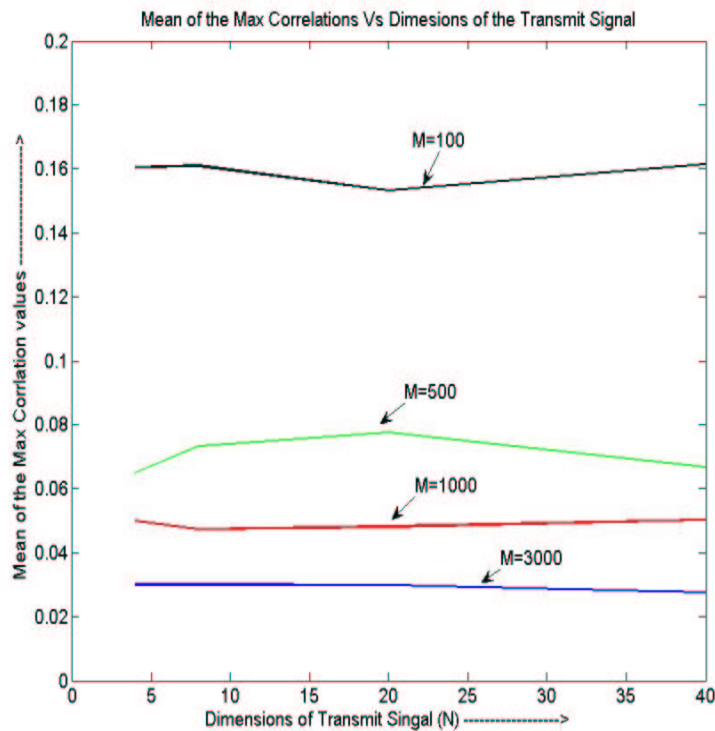


Summary of All the Cases

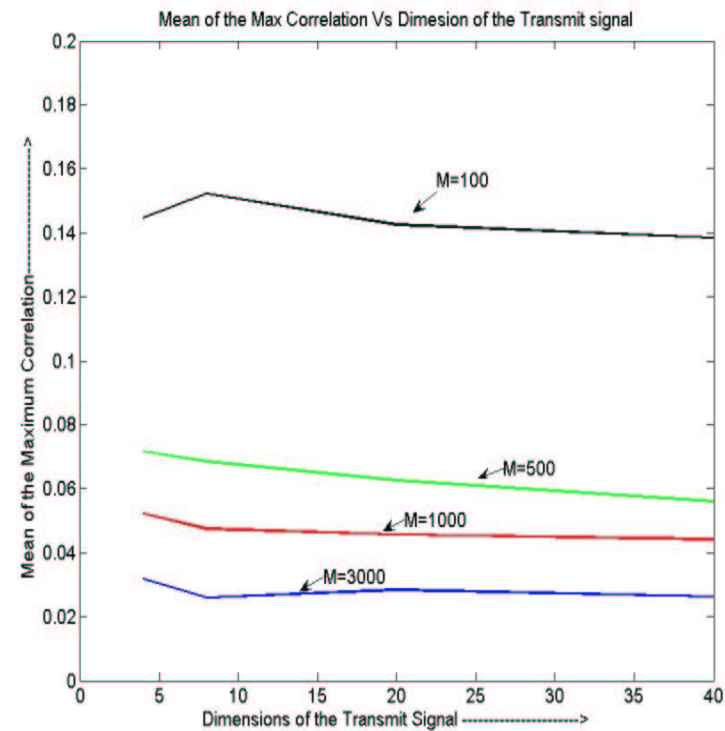


- Plots Summarizing the Means of Max Correlation Coefficient Values for all the cases.

Algorithm-1



Algorithm-2



- Not much improvement in performance of Alg-2 compared to Alg-1, when constant-H matrices are used.



Varying Propagation Matrices (**H**-matrices)



- **H**-matrices are generated from four different Gaussian distributions.

$$\mathbf{H} = \begin{bmatrix} M1 \times N1 & M1 \times N2 \\ M2 \times N1 & M2 \times N2 \end{bmatrix}_{M \times N}$$

mean = 0.5
stddev = 0.4

mean = 1
stddev = 0.7

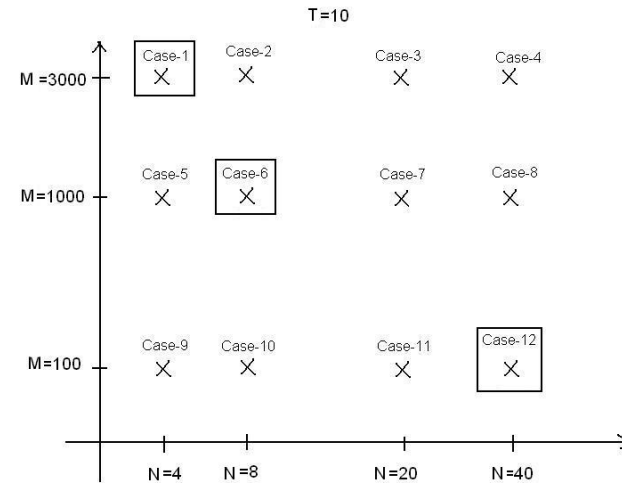
mean = 0.2
stddev = 0.1

mean = 0
stddev = 1

$$M = M1 + M2$$

$$N = N1 + N2$$

Composition of **H**-matrix



Different Cases of comparison

- These varying **H**-matrices are used as inputs to the Algorithms.
- Performance of the Algorithms are compared for the same cases as in previous slides.

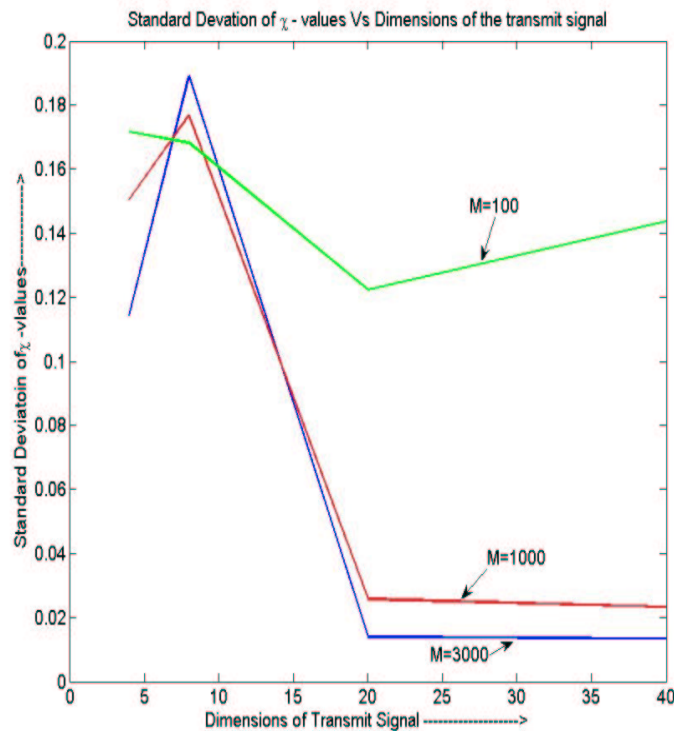


Summary of All the Cases

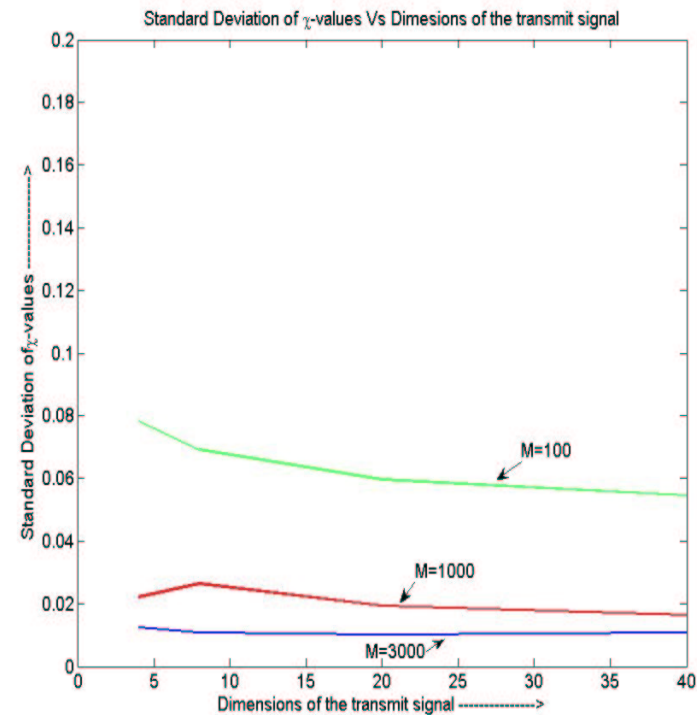


- Plots Summarizing the standard deviation of χ values for all the cases.

Algorithm-1



Algorithm-2



- Significant improvement in the performance of Algorithm-2 compared to Algorithm-1

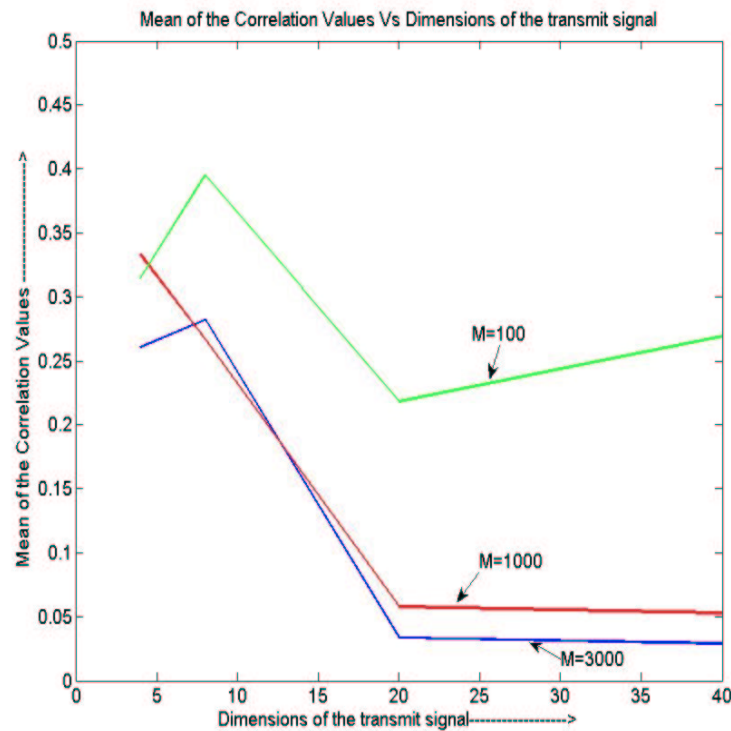


Summary of All the Cases

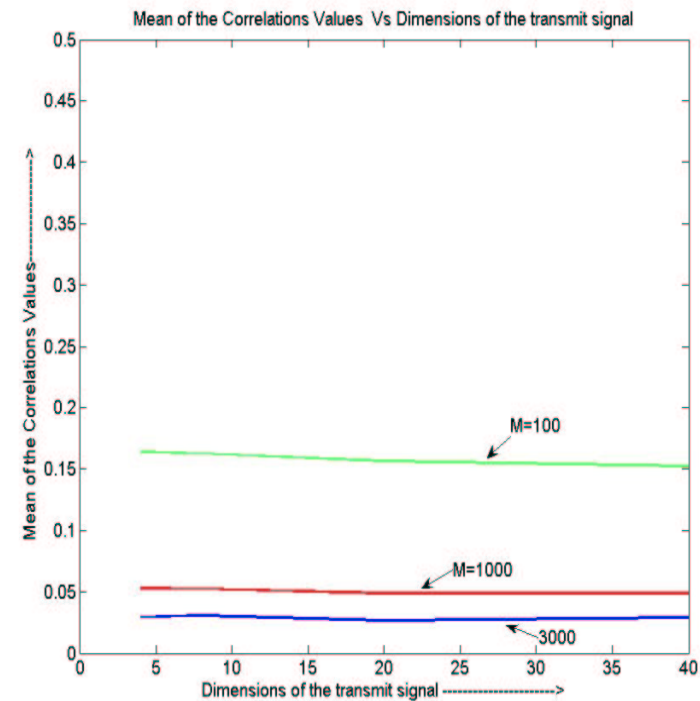


- Plots Summarizing the Means of Max Correlation Coefficient Values for all the cases.

Algorithm-1



Algorithm-2



- Significant improvement in the performance of Algorithm-2 compared to Algorithm-1



Conclusions from the Comparisons



- Higher the total number of measurements (M), and higher the total number of dimensions (N), better is the performance of both Algorithms.
- The performance of Algorithm-2 largely depends on the structure of \mathbf{H} -matrices.
- Hence, the performance of Algorithm-2 is either same or better than Algorithm-1.



Question : How good is the result given by
Algorithm-2 in general ??

Or

Is there a yardstick to measure the performance of the
Algorithm?

Answer : Compare the performance with *Random
code* and code given by *Genetic Algorithm*

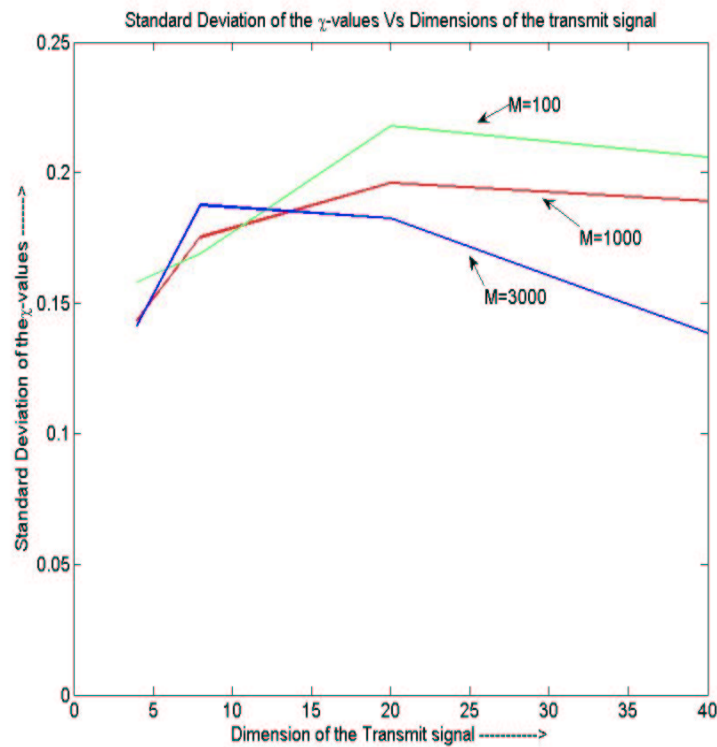


Comparison of Algorithm-2 with Random Code

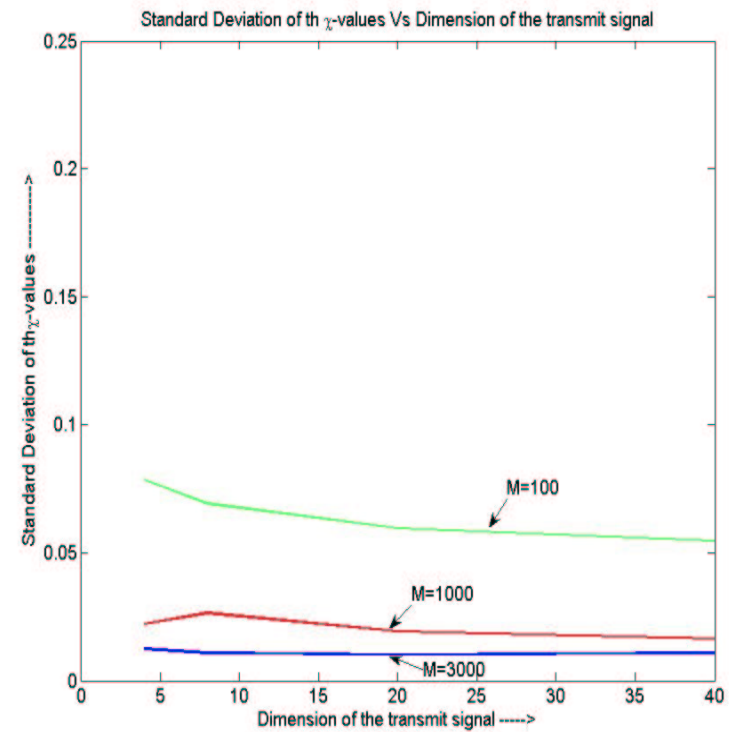


- Plots Summarizing the standard deviation of χ values for all the cases.

Random Code



Algorithm-2



- Algorithm-2 performs much better than a randomly chosen code.

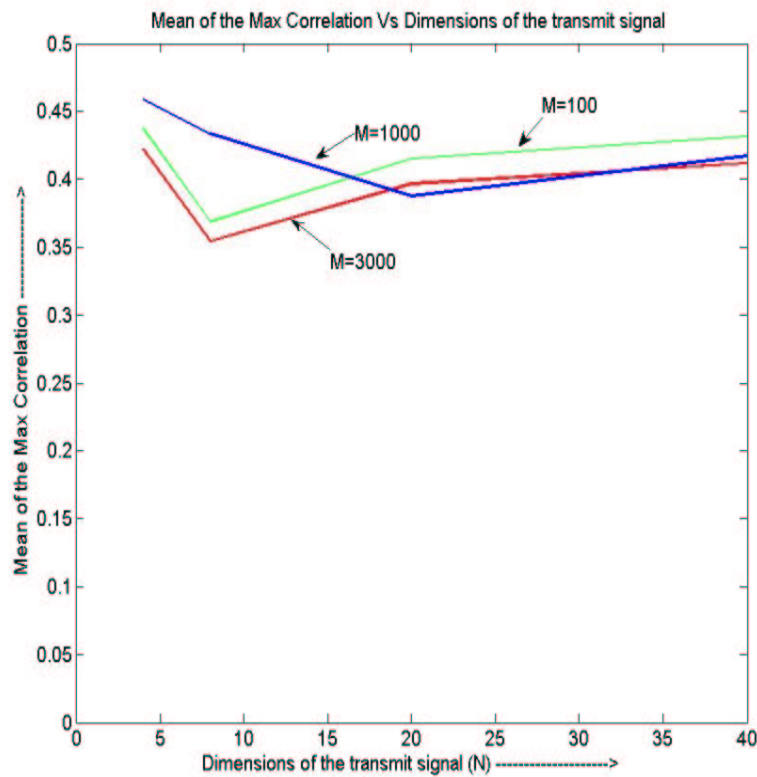


Comparison of Algorithm-2 with Random Code

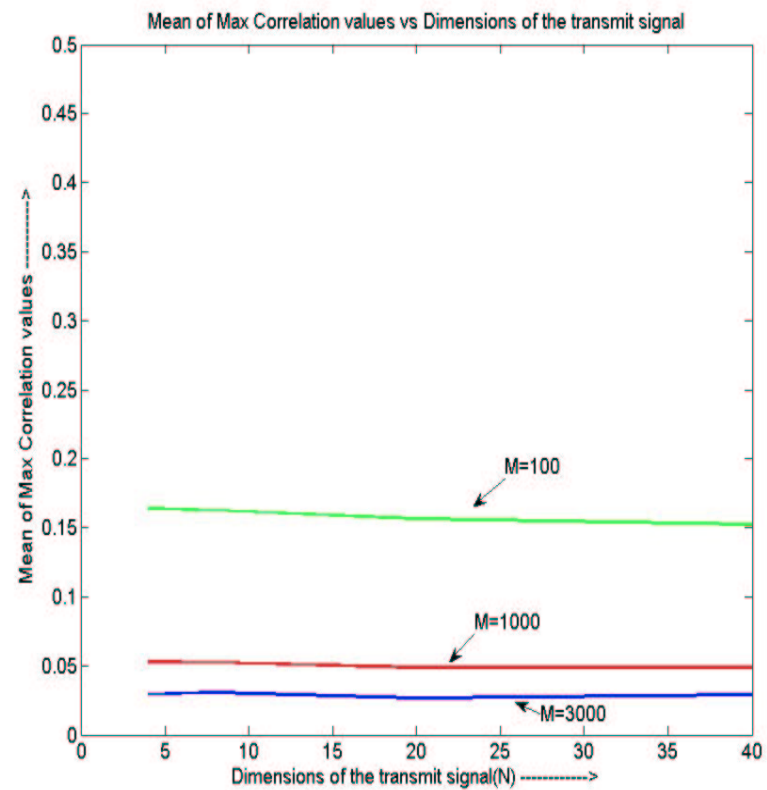


- Plots Summarizing the Means of Max Correlation Coefficient Values for all the cases.

Random Code



Algorithm-2



- Algorithm-2 performs much better than a randomly chosen code.



Comparison with Genetic Algorithm



- **Genetic Algorithm** (Master's Project by Fernando Soto)
 - A group of possible codes is considered.
 - A new group of fit solutions is selected out of the old group and are combined.
 - This process is continued till there is no improvement in the criteria.
- Varying- \mathbf{H} matrices were used with $M=100$; $N=8$; $T=10$
- Criteria given to the Genetic Algorithm
- \mathbf{s} – solution that minimizes the largest β_t value.

$$\beta_t = \frac{|\boldsymbol{\rho}_1' \boldsymbol{\rho}_t|^2}{|\boldsymbol{\rho}_1|^2 |\boldsymbol{\rho}_t|^2} = \frac{|\mathbf{s}' \mathbf{H}'_1 \mathbf{H}_t \mathbf{s}|^2}{|\mathbf{H}_1 \mathbf{s}|^2 |\mathbf{H}_t \mathbf{s}|^2} \quad \text{Where, } t \in \{2, 3, 4, \dots, T\}$$



Comparison with Genetic Algorithm



Genetic Algorithm

T	β_t		
Target-2	0.0001	Target-6	0.0002
Target-3	0.0000	Target-7	0.0002
Target-4	0.0002	Target-8	0.0002
Target-5	0.0011	Target-9	0.0000
		Target-10	0.0008

$$\text{Max } \beta_t = 0.0011 = -30\text{dB}$$

Algorithm-2

T	β_t		
Target-2	0.0162	Target-6	0.0003
Target-3	0.0021	Target-7	0.0175
Target-4	0.0092	Target-8	0.0019
Target-5	0.0041	Target-9	0.0057
		Target-10	0.0124

$$\text{Max } \beta_t = 0.0175 = -18\text{dB}$$

- Genetic Algorithm is better by 12 dB compared to Algorithm-2

Disadvantages of Genetic Algorithm

- No mathematical basis for the Algorithm.
- Takes huge amount of time compared to Algorithm-2.
- Cannot be used where processing time is an important factor.



Radar Model



Performance of the Algorithm using the Radar
Model.



Radar Model



- The Radar Model has been defined in three major parts.
 - Transmit signal.
 - Target set
 - Received Measurements.

- **Transmit Signal**

- Defined as a set of complex valued samples in a 5 dimensional space.

$$\bar{z}_{jk} = [x_j, y_j, z_j, t_k, \omega_k]^T$$

Where, $J \rightarrow$ total number of spatial samples (Total number of transmit elements).

$K \rightarrow$ total number of temporal samples.



Radar Model



- Further, the transmit signal is defined as, a superposition of wide timewidth and wide bandwidth orthonormal basis functions.
- Slow time functions (P) and Fast time functions (Q)
- Total # of orthonormal basis functions = PQ
- The response vector is transformed as,

$$\boldsymbol{\rho}_i = \mathbf{H}_i \mathbf{s} = \mathbf{H}'_i \mathbf{S}$$

- The \mathbf{H}'_i matrices which relate the received signal to the weights of the basis functions are used as inputs to the Algorithm.
- Algorithm works to find the best weight vector for the basis functions.



Radar Model



- **Target set**

- A total of N_t number of targets are considered.
- A grid of $N_x \times N_y$ is defined such that $N_t = N_x N_y$.
- The target position vector is defined in 4 dimensional subspace and is given as,

$$\bar{y}_t = [x_t, y_t, z_t, v_t]^T$$

- The spacing between the targets is set equal to the Doppler resolution and Range resolution in x and y directions respectively.



Radar Model



- **Received Measurements**

➤ Defined as a set of complex valued samples in a 5 dimensional space.

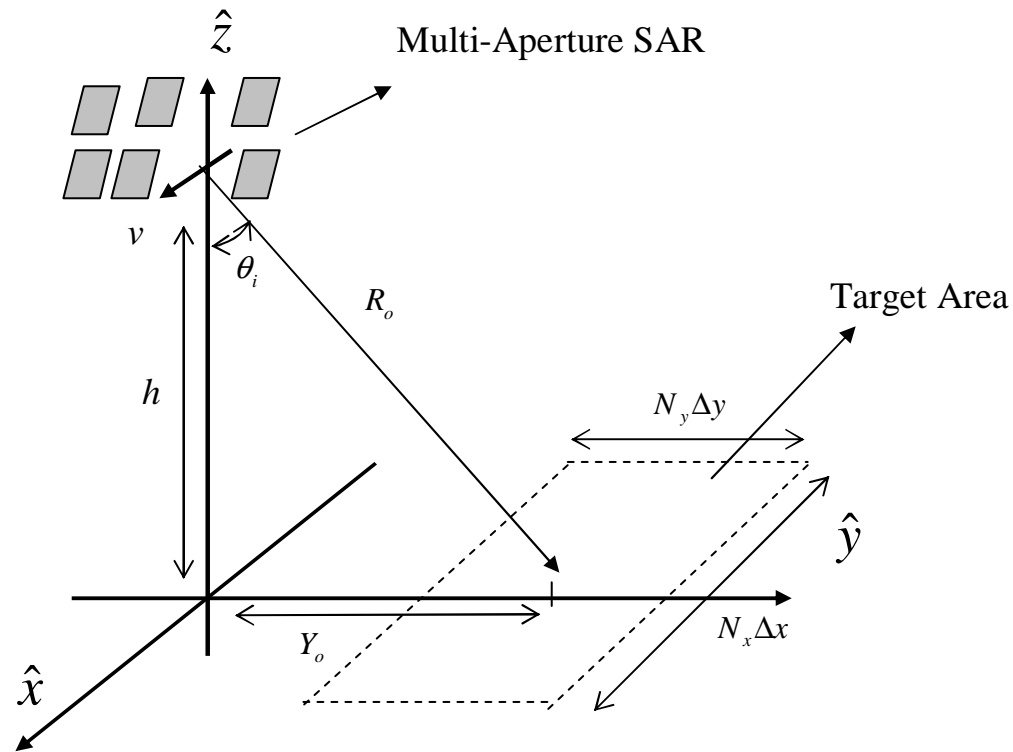
$$\bar{x}_{ik'} = [x_i, y_i, z_i, t_{k'}, \omega_{k'}]^T$$

Where, $I \rightarrow$ total number of spatial samples (Total number of Receive elements).

$K' \rightarrow$ total number of temporal samples.



Radar Model



The Radar Model setup

Assumed Default Values

$$c = 3 \times 10^8 \text{ m/s}$$

$$h = 183 \text{ km}$$

$$v = 7.8 \text{ km/s}$$

$$f_c = 10 \text{ GHz}$$

$$\theta_i = 45^\circ$$

- A target grid of 31 x 31 has been chosen based on the system memory and processing time.

$$N_x = 31; N_y = 31$$

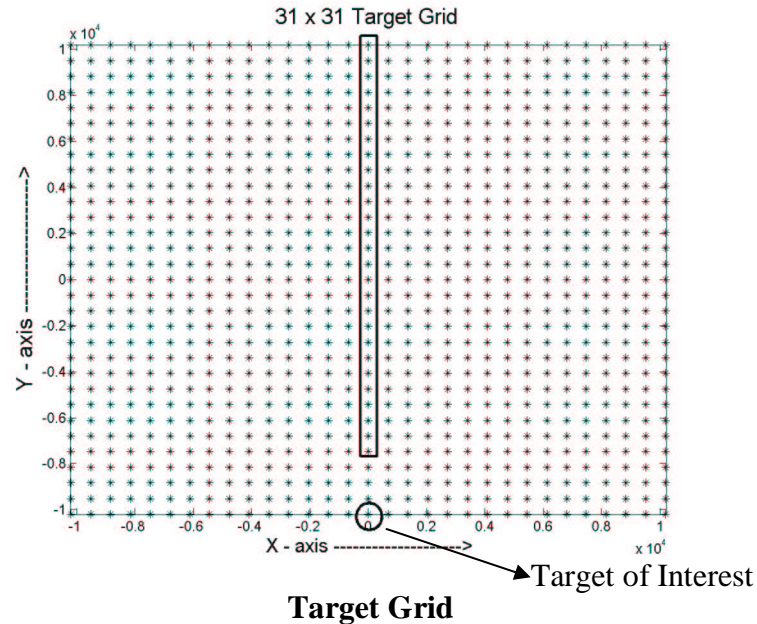
$$N_t = 961$$



Analysis of the Algorithm using the Model.



- H-matrices from the Model are used as Inputs.
- Total # of Transmit elements (J) = 1
- Total # of Receive elements (I) = 15
- Total number of slow-time functions (P) and Total number of fast-time functions (Q) - $P = 1$; $Q = 1$ to $P = 11$; $Q = 11$
- Performance of the Algorithm with varying number of basis functions.

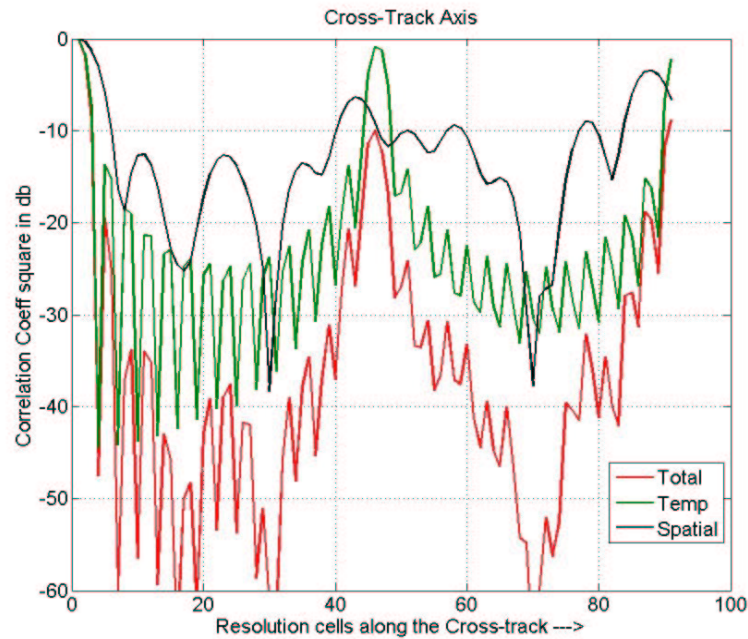




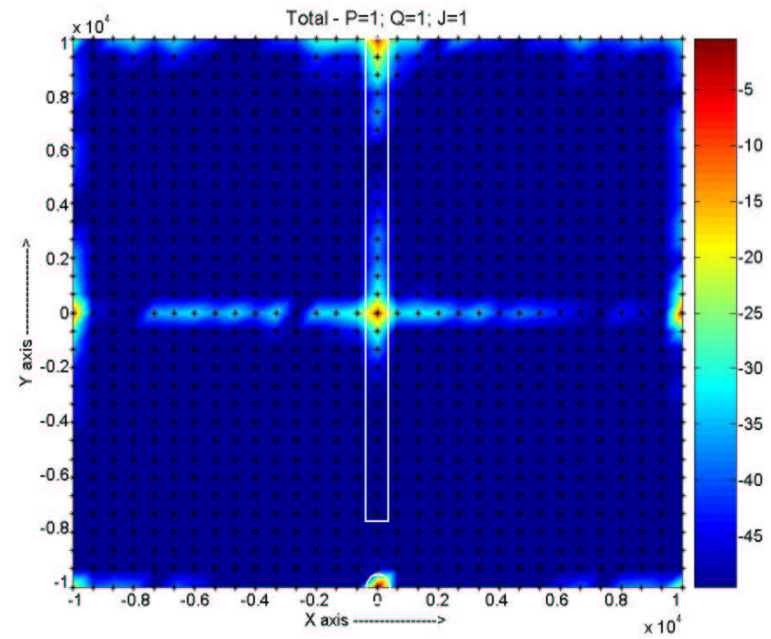
Tx element (J)=1; Slow-Time Fn (P)=1; Fast-Time Fn. (Q)=1



Correlation along the Range axis



Total Correlation of the entire grid



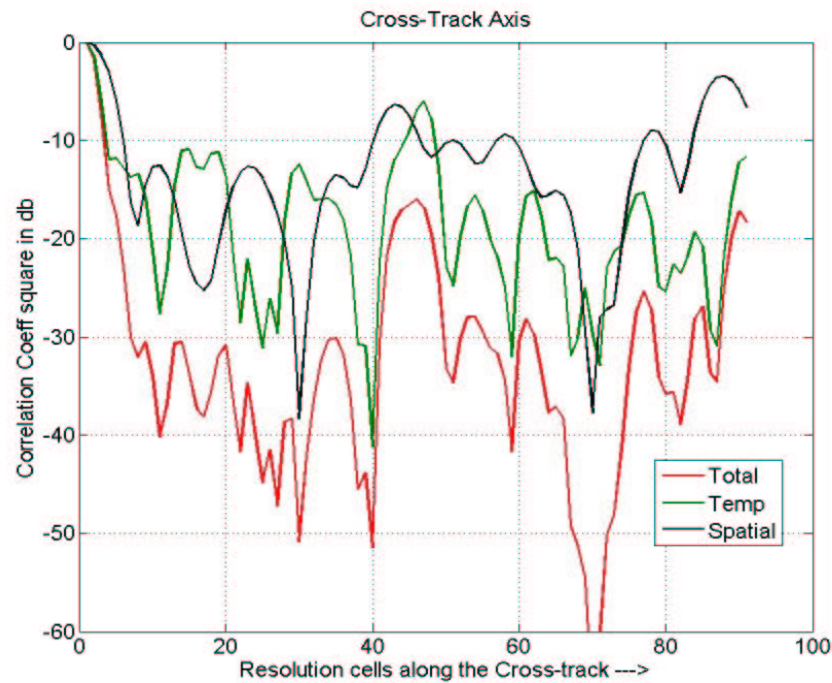
- Green \rightarrow Temporal; Black \rightarrow Spatial; Red \rightarrow Total
- Total Maximum Correlation = -9dB
- Not much freedom to the Algorithm.



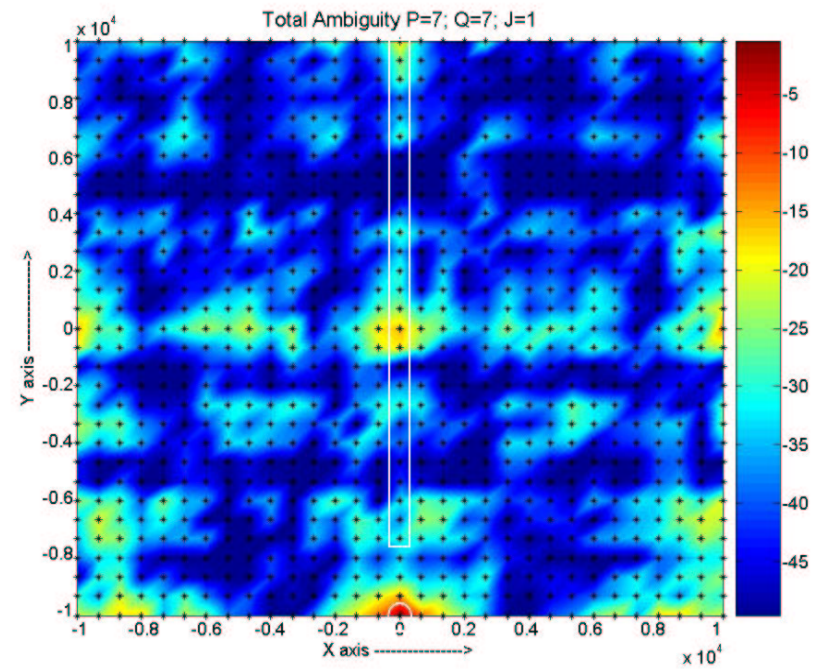
Tx element (J)=1; Slow-Time Fn (P)=7; Fast-Time Fn. (Q)=7



Correlation along the Range axis



Total Correlation of the entire grid



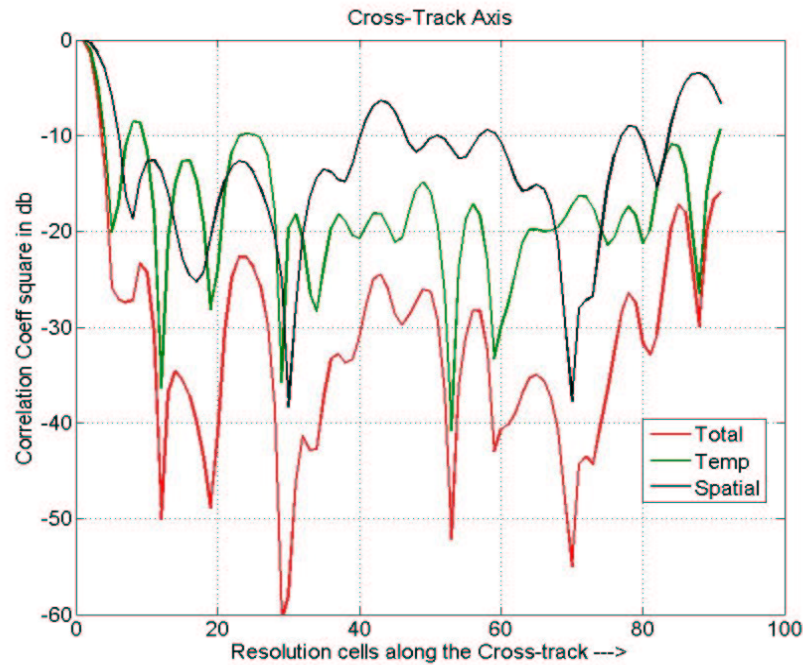
- Total Maximum Correlation = -16dB



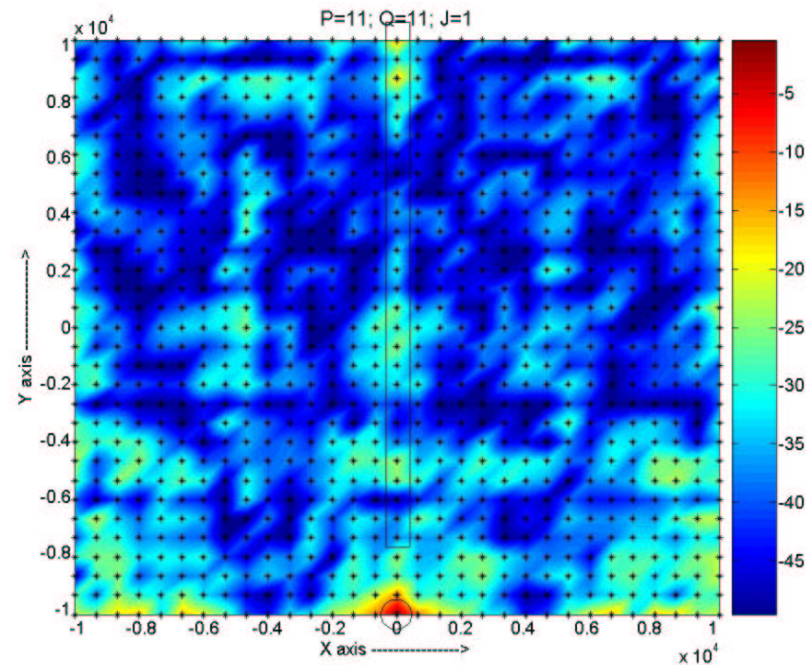
Tx element (J)=1; Slow-Time Fn (P)=11; Fast-Time Fn. (Q)=11



Correlation along the Range axis



Total Correlation of the entire grid



- Total Maximum Correlation = -16dB



Transmit Elements (J)



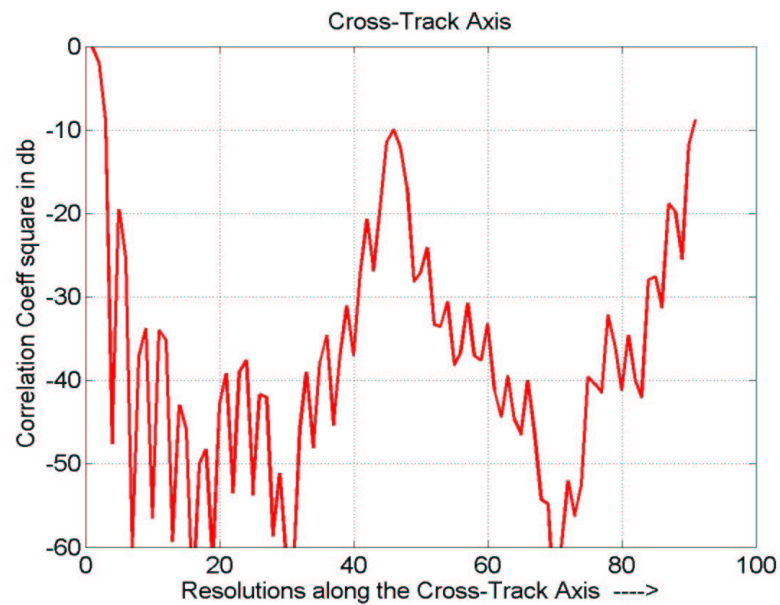
- The Number of Transmit Elements (J) are increased from 1 to 2.
- Algorithm analyzed by varying the total number of basis functions.



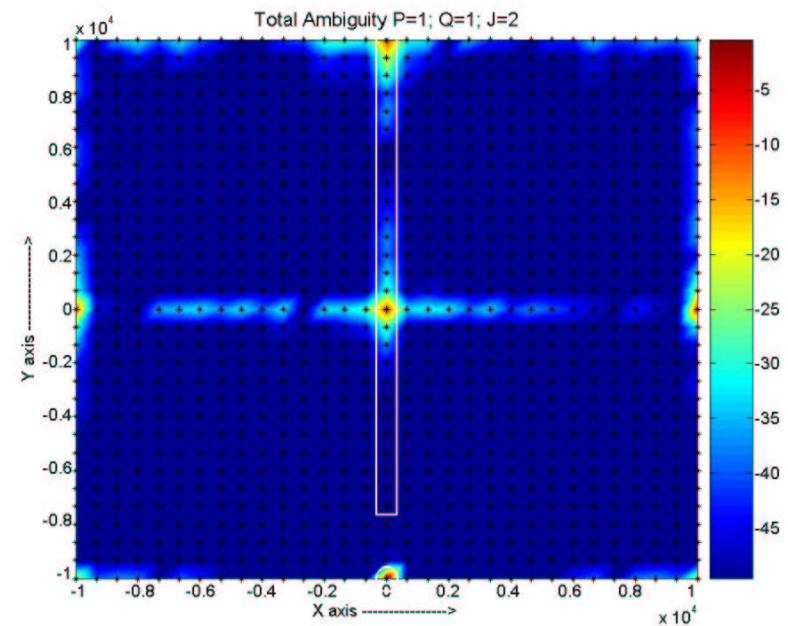
Tx element (J)=2; Slow-Time Fn (P)=1; Fast-Time Fn. (Q)=1



Correlation along the Range axis



Total Correlation of the entire grid



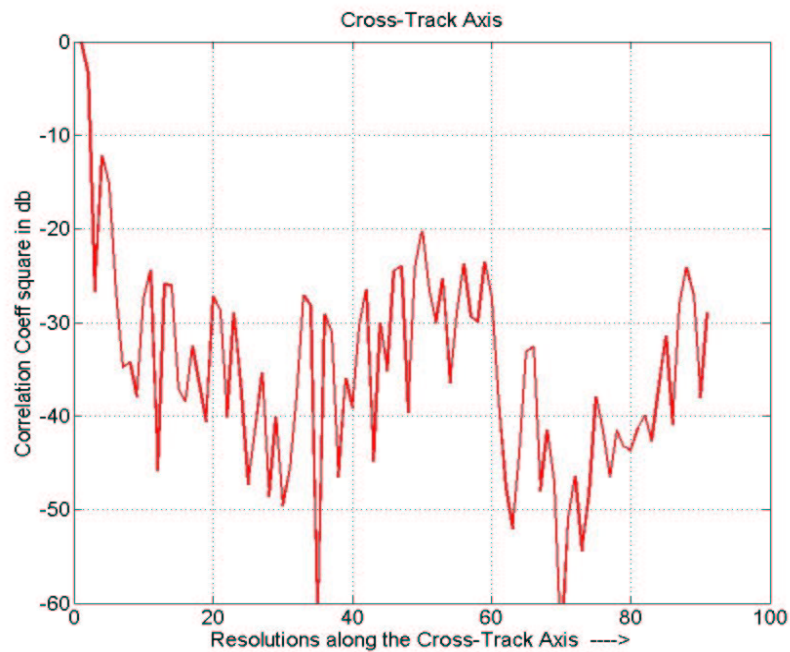
- Total Maximum Correlation = -9dB



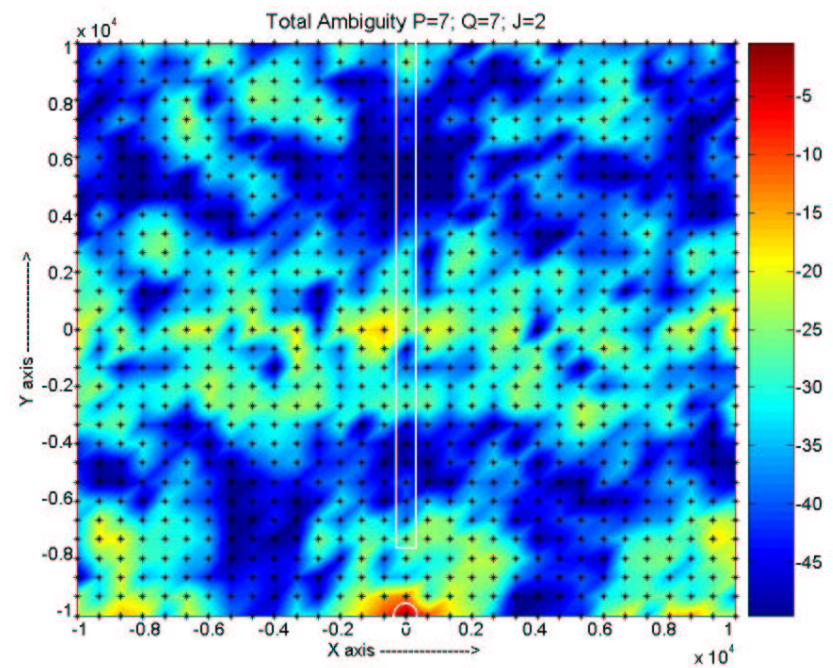
Tx element (J)=2; Slow-Time Fn (P)=7; Fast-Time Fn. (Q)=7



Correlation along the Range axis



Total Correlation of the entire grid



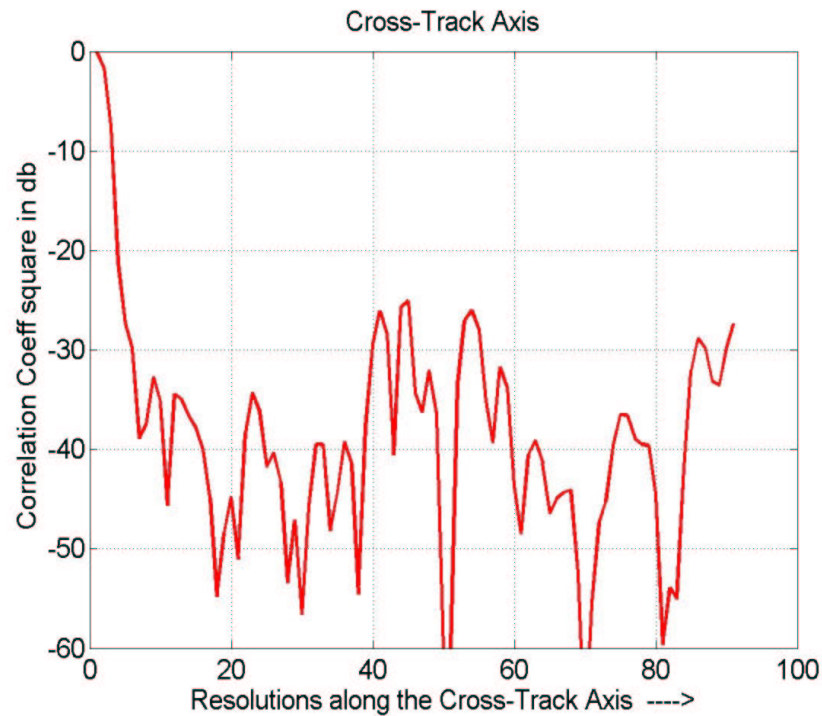
- Total Maximum Correlation = -24dB
- Improvement of 8dB compared to $J=1$; $P=7$; $Q=7$ case.



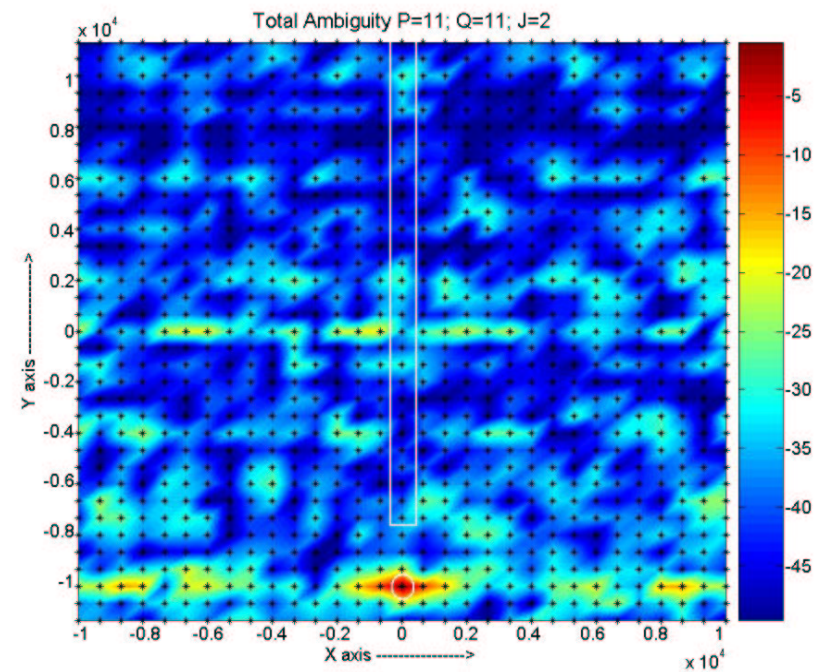
Tx element (J)=2; Slow-Time Fn (P)=11; Fast-Time Fn. (Q)=11



Correlation along the Range axis



Total Correlation of the entire grid



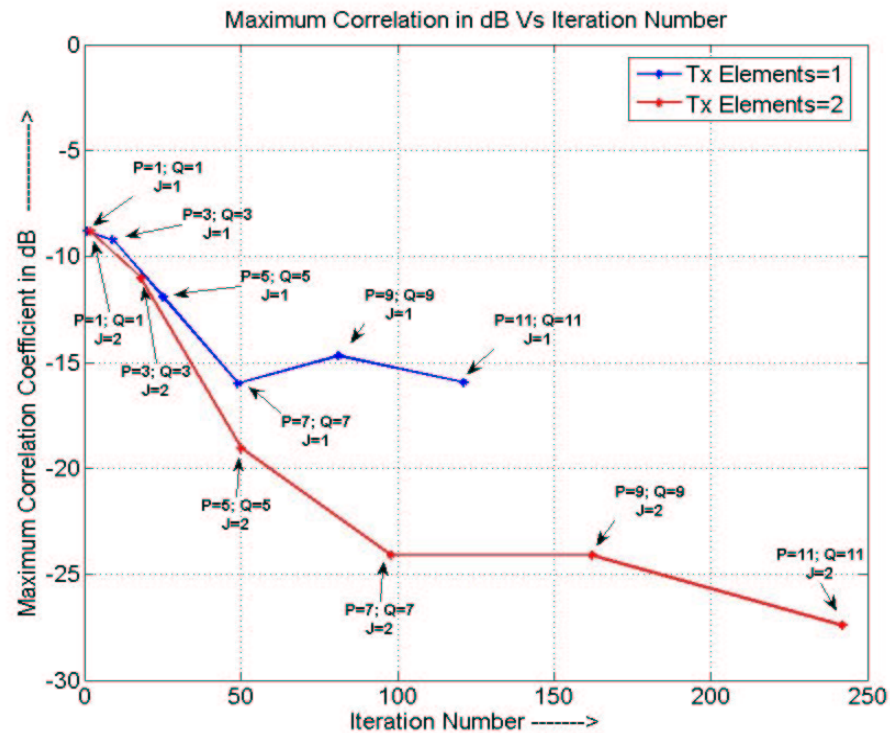
- Total Maximum Correlation = -28dB
- Improvement of 12dB compared to $J=1; P=11; Q=11$ case.



Summary of all the cases for $J=1$ and $J=2$



Maximum Correlation Vs Iteration Number



- Higher the total number of basis functions, more is the flexibility provided to the algorithm to come up with a better code



Efficacy of the best result.



Question: How good is the best result that is obtained?

Answer: Comparison with Standard code and Random Codes

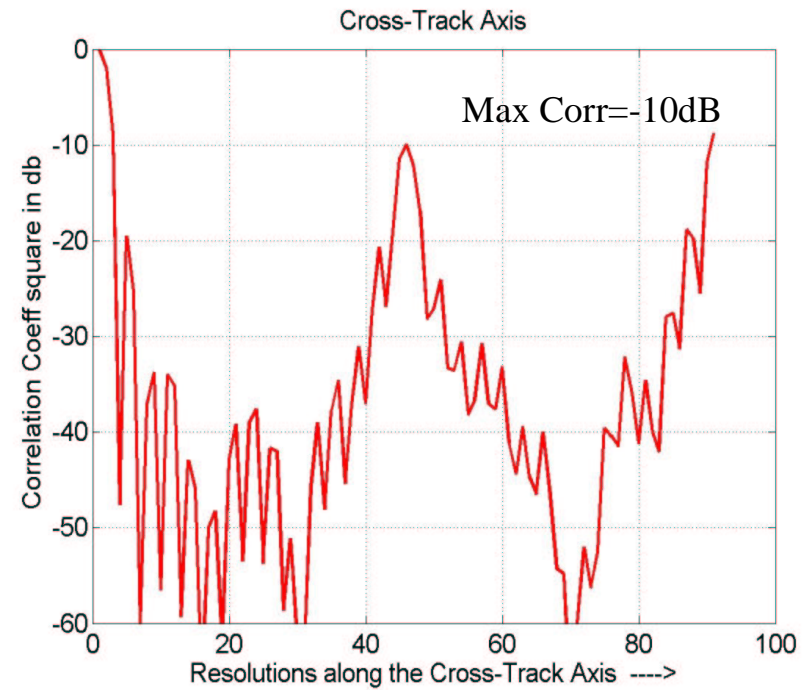
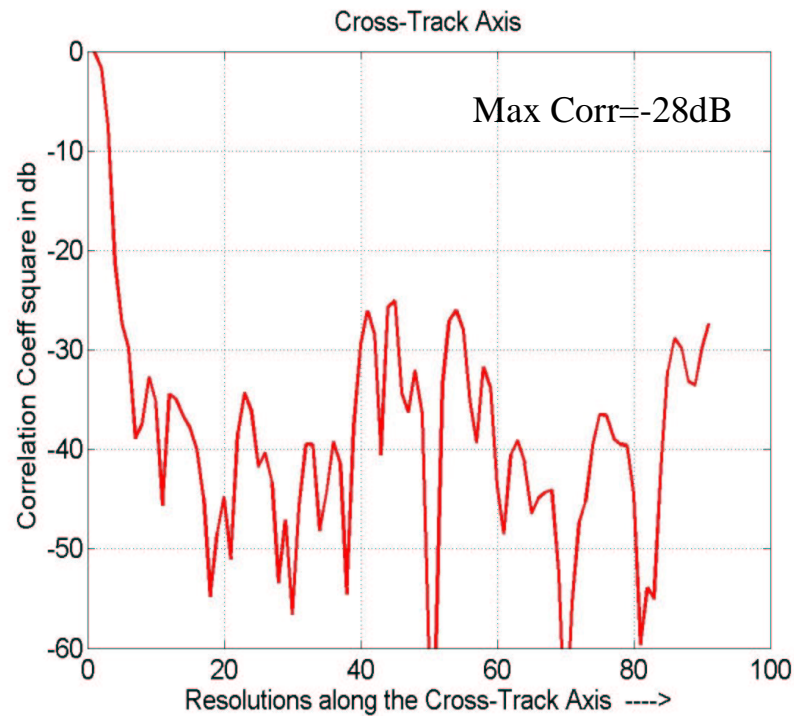


Comparison of the best result with Standard code



Best Code : J=2; P=11; Q=11

Standard Code : J=1; P=1; Q=1



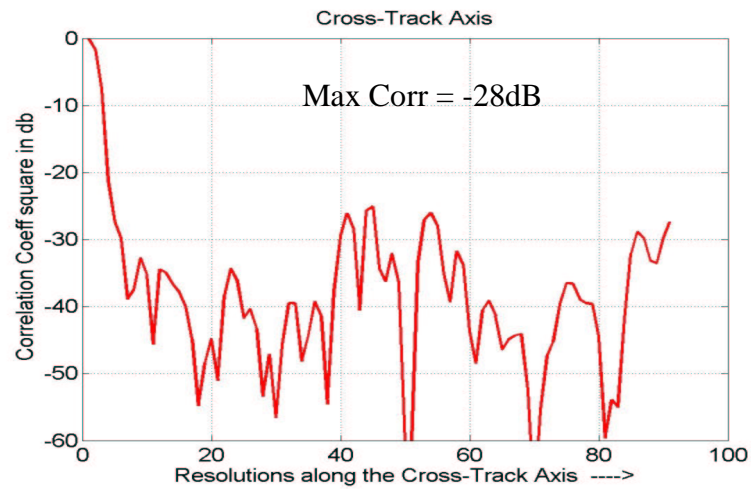
- Algorithm code is 18dB better than a standard code.



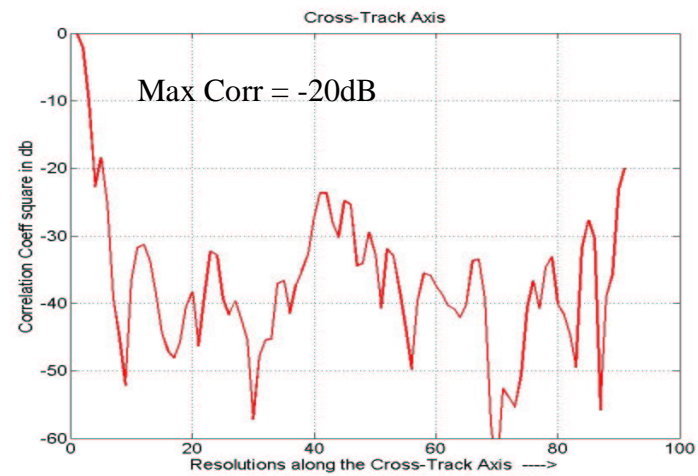
Comparison of the best result with Random codes



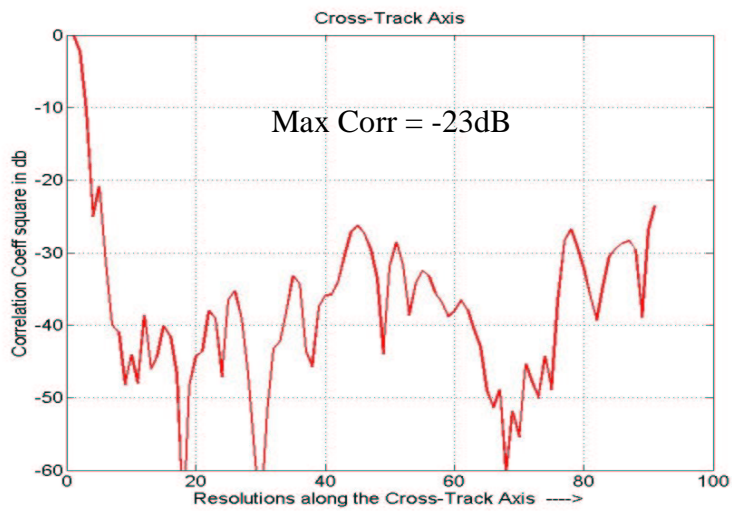
Algorithm Code



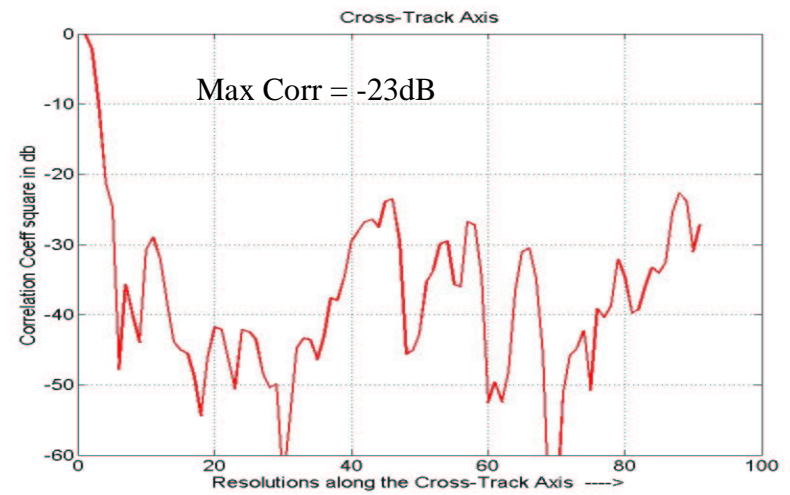
Random Code 1



Random Code 2



Random Code 3



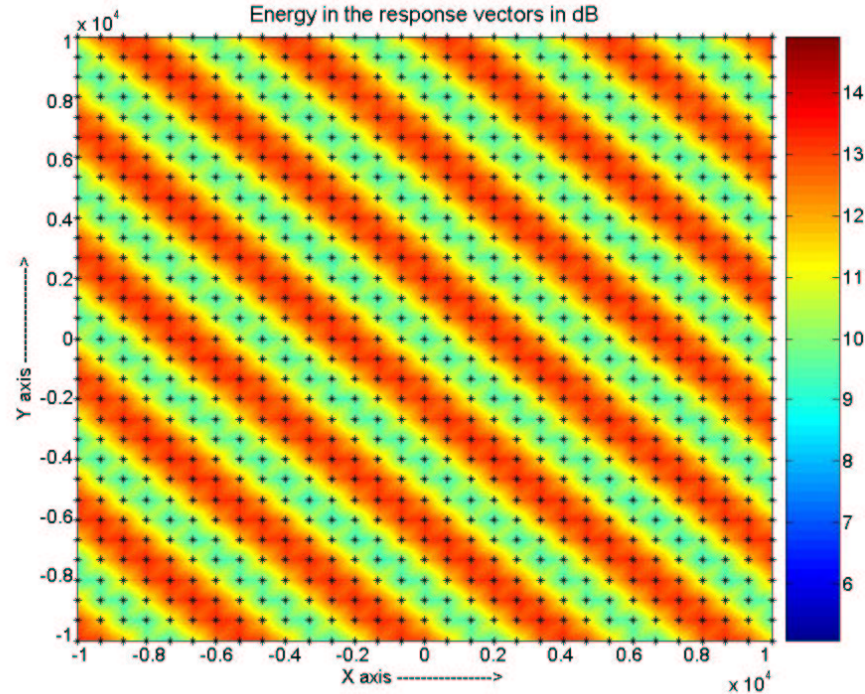


Energy in the Response vector



- The condition $\boldsymbol{\rho}'_i \boldsymbol{\rho}_j = 0$ can still be satisfied if,

Energy in $\boldsymbol{\rho}_i$ or $\boldsymbol{\rho}_j = 0 \rightarrow$ Not desired



Max Energy = 14 dB

Min Energy = 9 dB

Plot showing the energy in the response vectors for all the targets in dB.



Conclusions



- Proved that Space-Time transmit signal can be designed in order to reduce the maximum correlation.
- Higher the total number of measurements (M), higher the total number of dimensions of the transmit signal (N), better is the performance of the Algorithms.
- The performance also depends on the structure of the \mathbf{H} -matrices or, the radar scenario.
- As the total number of basis functions are increased, more flexibility is provided to the Algorithm to come up with the best code.
- As the total number of transmit elements are increased from 1 to 2, the maximum ambiguity is reduced to a great extent.



Future Work



- The performance needs to be evaluated in the Doppler direction.
- The ambiguity function is not invariant for $J=2$. Therefore a new algorithm needs to be developed to come up with a transmit code.
- The Algorithm needs to be modified accordingly when we use more than 2 transmit elements.



- Thank You !!
- Questions ??

