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Adaptive Beamforming Method for MIMO Antenna Array with Constrained Mean Square Error

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Abstract: The Adaptive beam forming with Multikernel based Bayesian learning method beam forming on Uniform Linear Array (ULA) antennas for better localization. Undetermined source localization problem is solved using the Multikernel Sparse Bayesian Learning framework. Beam forming problem is considered the undetermined source localization problem and solved using the adaptive method. The Degree of Freedom (DOF) is increased using the adaptive nature of the manifold matrix while maintaining the same number of antennas. The response model that adaptively adjusts the manifold matrix in the Sparse Bayesian problem uses the Multikernel framework. MATLAB based implementation thus carried out on the ULA clearly exhibits better results over the single kernel model. The Mean Square Error (MSE) and Root Mean Square Error (RMSE) with Signal to Noise Ratio (SNR) variation is obtained to evaluate the performance of the proposed implementation. The performance obtained is found to be satisfactory and is at par with the recent previous implementation.

Keywords: Direction of Arrival Estimation, Multikernel Sparse Representation, Basis Pursuit Methods

I. INTRODUCTION

The ever-increasing need for high-fidelity communication in the modern communication frameworks the need of advanced and more efficient algorithms is of utmost priority. The signal that is received must be found for its Direction of Arrival (DOA) which needs increase in Degree of Freedom (DOF). The DOF is increased by placing the antennas in a minimum redundancy form while large number of antennas are used [1].The concepts of beam forming and background of the modern beam forming algorithms are dealt in [2-3].Numerous non-uniformly spaced antenna array settings are analyzed with minimum redundancy and non-redundancy is considered [4].Instead of DOF increase by increasing the number of antennas the blind source localization methods are published in different literatures. Details on subspace-based methods are discussed along with the beam forming paradigm.

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Different sensor array signal processing with the parameter estimation-based problem-solving methods are discussed [5]. Covariance matching algorithm is developed for channel estimation algorithm and compared with maximum likelihood methods for its computational advantages [6].Bayesian learning framework for the sparse solution is developed with relatively lesser basis functions [7].

Sparse regularization-based source localization method is implemented using the inverse problem framework is investigated [8].

L1 and Lp regularization is utilized and found that it has the super resolution, robustness to noise and source correlation [8]. Sparse Bayesian approach for the approximation problem while there is a large over complete dictionary available is solved in [9]. The Khatri Rao approach is tested on the antenna array when the number of antennas is lesser than number of sources in the Direction of Arrival (DOA) paradigm [10]. The approach of nesting different linear arrays to improve the DOF is developed in [11]. This approach is applied on the quasistationary signals and a novel beam forming approach is developed. Implementation of the Bayesian learning framework in the compressed sensing framework while signal acquisition is carried out [12]. Parameter estimation of complex sinusoidal signals, linear chirp signal with additive and multiplicative noise is carried out using the fourth order cumulant and advanced methods [14]. Numerous Sparse based algorithms for beam forming implementations are carried out in [15-23]. This proposed work evolves the Bayesian Learning based DOA estimation method using the Multikernel based manifold matrix for higher robustness. Further the proposed work is organized with Section II discussing the Methodology involved in the Multikernel Beam forming method; Section III details the results and discussion of the implementation.

II. MULTIKERNEL BASED BAYESIAN LEARNING

The Dictionary Learning algorithms developed previously introduces numerous algorithms that are concentrating on the prior and posterior distribution formulation and convergence. This paper exploits the stochastic nature of the dictionary for implementing the adaptive dictionary-based convergence algorithm for DOA estimation. The Sparse Bayesian Learning Algorithm discussed in [24] is utilized in this implementation by introducing the Multikernel basis vectors. Sparseness of the algorithm is controlled by the manifold matrix. Improving the stochastic nature of the matrix is the main contribution of this paper.

Idea of multiple kernels cumulated to obtain sparser kernel is developed. With the implementation discussed in [24] the algorithm is enhanced by replacing the single kernel with the Multi kernel implementation.

A. Multi kernel

The MatrixΦ acts as the overcompletedictionary. This over complete matrix is generated using usually a Gaussian kernel. This kernel is advanced in the proposed algorithm to make it a multikernel implementation. In searching a or to generate manifold matrix processing time to using multi kernel using more than one kernel using is a multi-kernel .Using multi-kernel to finding manifold matrix it taking less time to achieve near to zero of the signals its help dual kernel using this is kernel is Gaussian kernel using to finding manifold matrix.

$$\Sigma_{i=1}^{\infty}\phi^{T}(x)\phi(x')\ldots\ldots\ldots\ldots (1)$$

where $\phi(x)$ its manifold matrix

The Gaussian Kernel used for developing the manifold matrix is improved by means of introducing the Multikernel paradigm in the Sparse Bayesian Learning framework developed in [24]. The convergence of the learning is improved by introducing the more stochastic nature of the Multikernel framework. The two-dimensional manifold matrix generated for the number of antennas and the number of incident signals is iterated for different angular variation to obtain the DOA. The Gaussian Kernel used for the manifold matrix is generation is upgraded by using the MultiKernel manifold using multiple Gaussian kernels. The prior and the posterior distribution for the convergence is as defined in [24]. The MSE and RMSE based convergence is carried out on the Multikernel Sparse representation based DOA estimation. The proposed method replaces the single kernel based manifold matrix with the multikernel manifold matrix. The summation of the weighted kernel to be used for the DOA estimation using Sparse Bayesian Learning is as defined below.

$$k(\vec{x},\vec{y}) = \sum_{i=1}^{K} w_i \cdot k_i(\vec{x},\vec{y})\ldots\ldots\ldots\ldots (2)$$

Where$k(\vec{x},\vec{y})$ is the term used for the generating the basis vector in the matrix. K is the number of kernels used for Multikernel basis vector.

III. RESULTS AND DISCUSSION

MATLAB based implementation of the Multikernel Sparse Bayesian learning based DOA estimation is developed and the results are arrived at as given below. The steering vectors generated from the MultiKernel. Combination is as given in Figure1. These steering vectors combine with the input signal to find the relation between them in order to know the angle with which the signal reaches the antenna. This combined signal is as shown in Figure 2. The following Table 1 defines the parameter chosen for the DOA estimation .From the table in can be observed that the total number of antennas that are used for DOA estimation is six. And the actual angle of arrival also is provided to validate the output that is achieved after DOA estimation .Steering vectors are of stochastic in nature. This stochastic nature of the steering vectors is used to estimate the DOA from any undetermined input signal.

Table1. Parameters Chosen for DOA estimation

Details	Configuration
Number of Antennas	6
Antenna Array type	Non-uniform
Angle Range	$-\frac{\pi}{3}$ to $\frac{\pi}{3}$
Min to Max degrees	-70 to 70
Carrier frequency	200Hz
Propagation velocity	340
Interval of angle Searching	1
Angles of source signals	-54.8, -28.6 -9.2, 10.5 31.4, 56.7

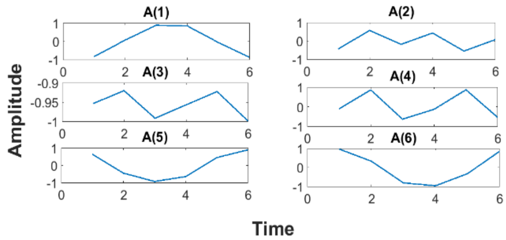

Figure 1. Steering Vectors of the Manifold matrix

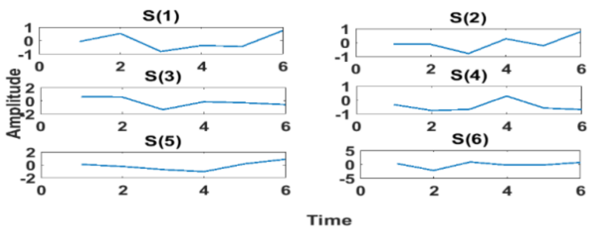

Figure 2. Source Signal Input

The Additive White Gaussian Noise (AWGN) that is introduced in the incoming wave is as given in the Figure 3.

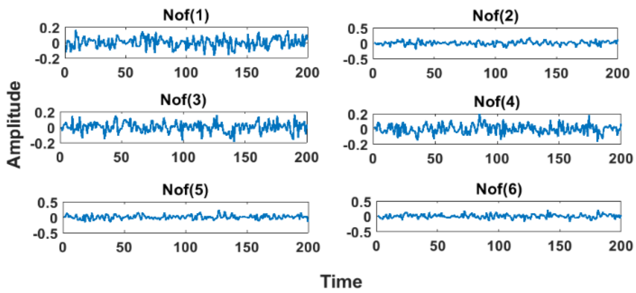

Figure 3.Noise signal

The complete wave that is received by the antenna after adding the signal with the AWGN is as given in the Figure 4. This received signal with the noise is stochastically checked for different angle of arrival.

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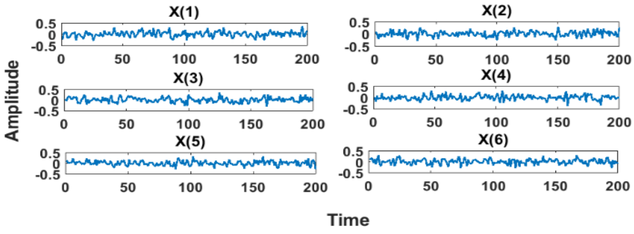

Figure4. Signal with Noise (received signal)

The stochastic nature us furthered using the Multikernel manifold matrix generation in order to be able to acquire the source signal DOA. Manifold matrix with the convergence condition as in [24].

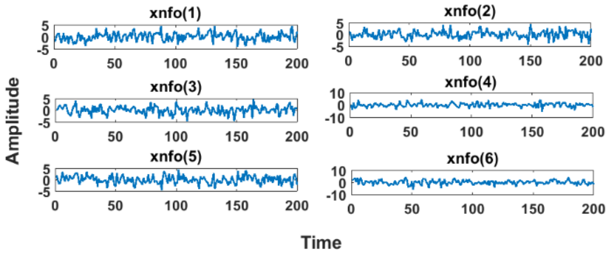

Figure 5. Signal with Manifold matrix

The signal with the manifold matrix is as shown in Figure 5.The condition for the convergence being the MSE and RMSE it is tested with different Signal to Noise Ratio (SNR) of the AWGN and results are obtained.

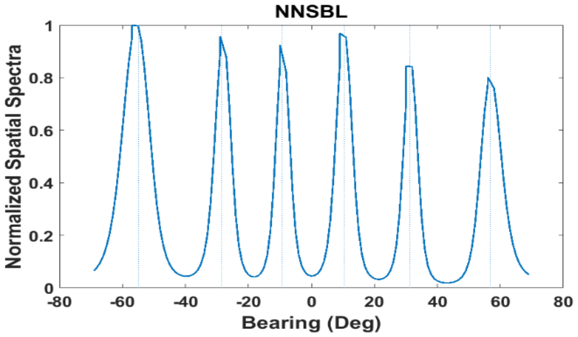

Figure 6. DOA estimated in NNSBL

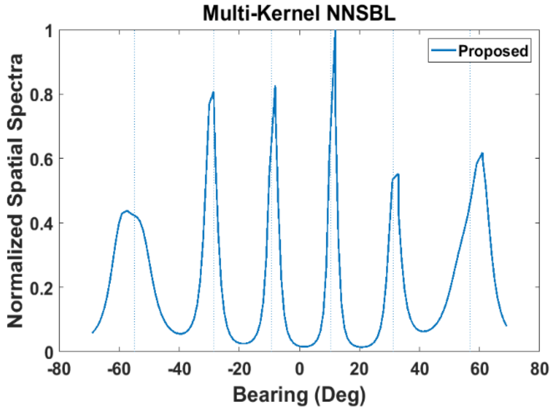

Figure7. DOA estimated in Proposed Multikernel NNSBL

The DOA estimated using both the NNSBL and the proposed Multikernel NNSBL is as shown in Figure 6 and 7 respectively. The total execution time for both the NNSBL and the proposed
Multikernel NNSBL is given in Table 2.

Table2. Execution Time for DOA estimation

Comparison between Multi-kernel NNSBL and NNSBL		
Sl.No	Algorithm type	Compilation time
1	NNSBL[24]	0.305865 seconds
2	Multi-kernel NNSBL[proposed]	0.293121 seconds

The RMSE vs SNR graph for the proposed method and the Non-Negative Sparse Bayesian Learning (NNSBL) discussed in [24] method is in the following Figures 8 and Figure 9 respectively. The execution time for the proposed method is also lesser than the previous method that is advantageous. This little improvement in time is significant while it is implemented on the real time scenario.

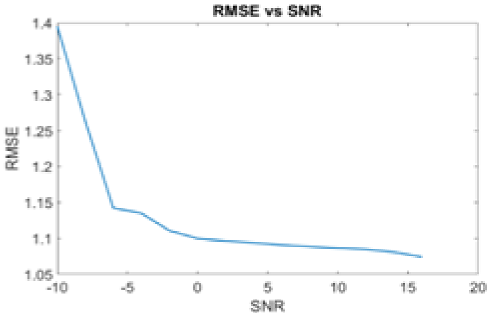

Figure 8. SNR vs RMSE for NNSBL

Observing Figure 8 and Figure 9 it can be observed that the RMSE obtained while implementing Multikernel NNSBL is reduced compared to that of the RMSE obtained from NNSBL implementation.

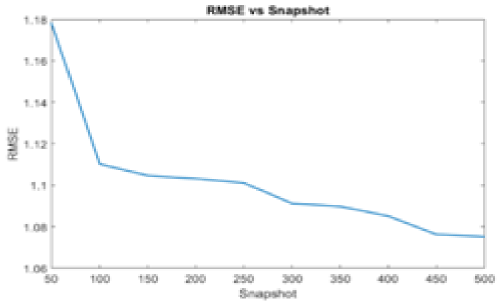

Figure 9. SNR vs RMSE for Multikernel NNSBL

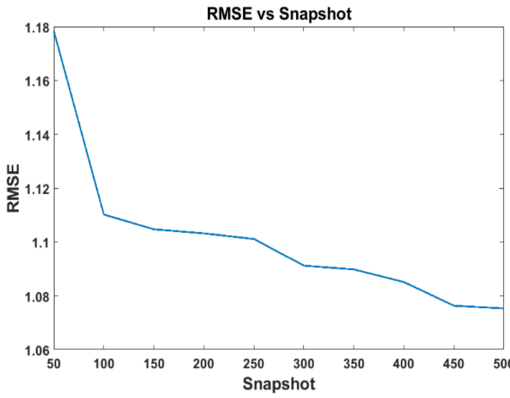

Figure 10. RMSE vs snapshot NNSBL

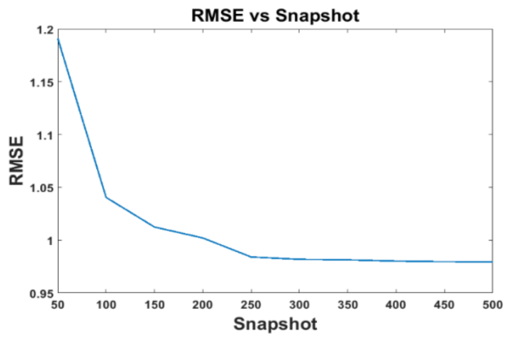

Figure11. RMSE vs snapshot multi-kernel NNSBL

The RMSE and snapshot-based graph is obtained by using NNSBL and Multikernel NNSBL in Figure 9 and Figure 11.It can be observed from the Figure 10 and 11.The Table 3 discusses the RMSE obtained for different range of snapshots in the signal. The objective of any new algorithm is to improve the performance of the application. This algorithm Multikernel NNSBL has improved the RMSE and execution time performance.

Table3. RMSE vs Snapshot NNSBL and Multikernel NNSBL

RMSE vs snapshot multi-kernel NNSBL[24] and NNSBL			
Sl.N0	Snapshot	RMSE_NNSBL	RMSE_MK_ NNSBL[Proposed]
1	50	1.1784	1.1911
2	100	1.0851	1.0405
3	150	1.0912	1.0124
4	200	1.0898	0.9795
5	250	1.1102	1.0021
6	300	1.0753	0.9841
7	350	1.1011	0.9814
8	400	1.0763	0.9796
9	450	1.1047	0.9802
10	500	1.1032	0.9818

From Table 3 RMSE vs snapshot although don't show much variation between the NNSBL and the Multikernel methods the reduction in RMSE in the Multikernel NNSBL shows a clear performance improvement. It can be observed that there is an improvement in the execution time of the proposed method.

IV. CONCLUSION

MATLAB based simulation is carried out on the DOA estimation using the Multikernel NNSBL method. The approach improves the NNSBL method by using the Multikernel based Sparse Bayesian learning. The Multikernel manifold matrix generation yielded better DOA estimation along with the lesser execution time. The proposed method is found to be at par with the recent publications. The results are found to be satisfactory. The RMSE obtained from the proposed algorithm is better than the NNSBL applied in the previous literature.

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