Mean Square Error-Bounded Adaptive Beamforming for a Multiple-Input Multiple-Output (MIMO) Antenna Array

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Abstract: *Better localisation is achieved by using adaptive beam shaping on Uniform Linear Array (ULA) antennas using a Multikernel-based Bayesian learning technique. The Multikernel Sparse Bayesian Learning framework is used to pinpoint an unknown source's location. The challenge of beam formation is recast as an adaptive problem of source localisation in the presence of uncertainty. Adaptive properties of the manifold matrix allow for an increase in DOF with a fixed set of antennas. The Multikernel framework is used for the response model that iteratively modifies the manifold matrix in the Sparse Bayesian problem. The ULA's MATLAB-based implementation significantly outperforms the single-kernel model. By varying the Signal to Noise Ratio (SNR), we may measure how well the suggested implementation performs by calculating the Mean Square Error (MSE) and Root Mean Square Error (RMSE). The results gained are considered good, and they are on par with those of the most recent prior installation.*

Keywords: Direction of Arrival Estimation, Multikernel SparseRepresentation, Basis Pursuit Methods

I. INTRODUCTION

The necessity for sophisticated and more efficient algorithms is of vital importance in current communication frameworks due to the rising need for high-fidelity communication. There has to be more degrees of freedom (DOF) in order to determine the signal's Direction of Arrival (DOA). When a high number of antennas are employed, the degree of freedom (DOF) may be improved by positioning the antennas in a minimal redundancy manner [1].Beam formation is discussed in detail in [2-3], along with the historical context of today's beam forming methods.Multiple non-uniformly spaced antenna array configurations are investigated for their redundancy and lack thereof [4].Blind source localization techniques are described in several literatures as an alternative to improving DOF by increasing the number of antennas. The beam forming paradigm is laid forth, and specifics on subspace-based approaches are provided as well. Parameter estimation-based problem-solving techniques for processing signals from sensor arrays are presented [5]. The computational benefits of the covariance matching approach for channel estimation are compared to those of the maximum likelihood methods [6].We design a Bayesian learning framework for the sparse solution using fewer basis functions [7].

The inverse problem framework is used to construct a sparse regularization-based approach for source localisation [8].

It is discovered that using L1 and Lp regularization results in superior resolution, noise resistance, and source correlation [8]. In [9], the authors use a sparse Bayesian technique to handle the approximation issue when an extensive overcomplete vocabulary is at hand. When the number of antennas is smaller than the number of sources in the DOA paradigm, the Khatri Rao technique is evaluated using an antenna array [10]. To increase the DOF, [11] develops the strategy of layering several linear arrays. A new beam forming strategy is created and used to quasistationary data. Compressed sensing with Bayesian learning [12]: putting theory into practice during data collection. Fourth order cumulant and advanced approaches are used for parameter estimation of complex sinusoidal signals, linear chirp signals with additive and multiplicative noise [14]. Many Sparse-based beam formation techniques are implemented in [15-23]. This new study proposes employing a Multikernel-based manifold matrix to improve the robustness of the Bayesian Learning-based DOA estimation approach. Section II discusses the methodology used in the Multikernel Beam forming approach, and Section III analyzes the findings and discusses the implementation; this work is further arranged as a proposal.

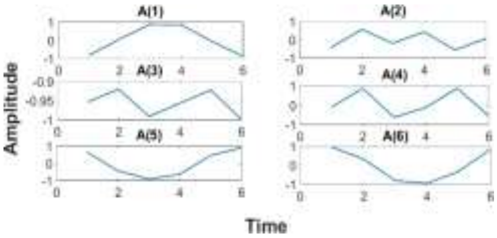
II. MULTIKERNEL BASED BAYESIAN LEARNING

Many strategies for prior and posterior distribution formulation and convergence are introduced in the previously described Dictionary Learning algorithms. In order to build the adaptive dictionary-based convergence technique for DOA estimation, this article takes use of the dictionary's inherent stochasticity. In this implementation, the Multikernel basis vectors are used in conjunction with the Sparse Bayesian Learning Algorithm described in [24]. The manifold matrix regulates the algorithm's sparseness. The major contribution of this study is an enhancement of the matrix's stochastic character. The concept of combining many kernels into a single, sparser kernel is created. The single-kernel version of the technique is improved upon with the Multi kernel variant detailed in [24].

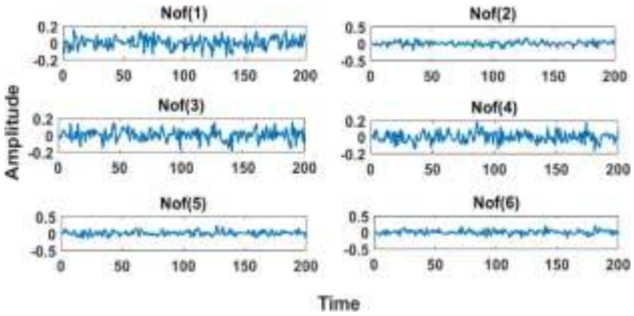
A. Multi kernel

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 toachieve near to zero of the signals its help dual kernel using this is kernel is Gaussian kernel using to finding manifold matrix.

$\Sigma_{i=1}^{\infty} \quad \phi^T(x)\phi(x')$………… (1) where $\phi(x)$ its manifold matrix



The Multikernel paradigm is included into the Sparse Bayesian Learning framework proposed in [24] to enhance the Gaussian Kernel utilized in constructing the manifold matrix. The more random character of the Multikernel framework aids in learning's convergence. The DOA is calculated by repeatedly iterating a two-dimensional manifold matrix based on the number of antennas and the quantity of incoming signals. The MultiKernel manifold improves upon the Gaussian Kernel by combining several Gaussian kernels to generate the manifold matrix. For convergence, the prior and posterior distributions are defined in [24]. Multikernel sparse representation based DOA estimation is converged using mean squared error and



root mean squared error. The multikernel manifold matrix is offered as a replacement for the traditional manifold matrix based on a single kernel. For Sparse Bayesian Learning DOA estimation, the weighted kernel sum is defined as follows.

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

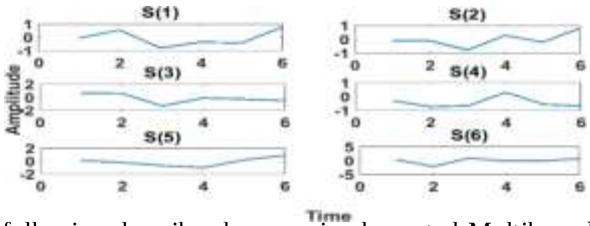
$k(x, y) = \Sigma$

$w_i \cdot k_i(x, y)$……….. (2)

Figure 2. Source Signal Input

Where(x, 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



The following describes how we implemented Multikernel Sparse Bayesian learning based DOA estimation in MATLAB. The MultiKernel's output vectors for directing. Figure1 depicts the correct combination. These steering vectors mix with the input signal to determine their relationship, so revealing the antenna's reception angle. The resulting signal looks like what's seen in Figure 2. The parameters used to calculate DOA are shown in Table 1.The chart reveals that a total of six antennas are put to use in the DOA estimate process. The DOA estimate results are verified by providing the measured angle of arrival.The nature of the steering vector is random. Due to the randomness of the steering vectors, the DOA may be estimated from a wide variety of 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.

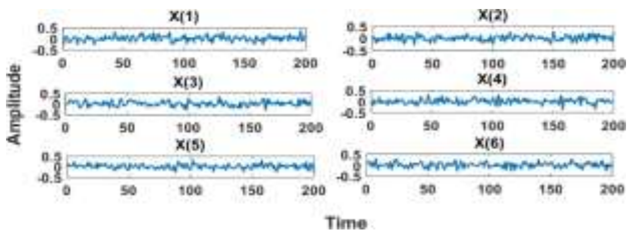


Figure4. Signal with Noise (received signal)

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].

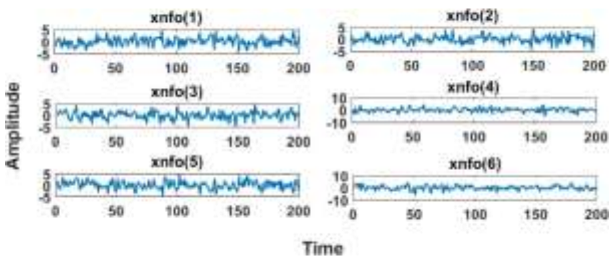


Figure 5. Signal with Manifold matrix

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.

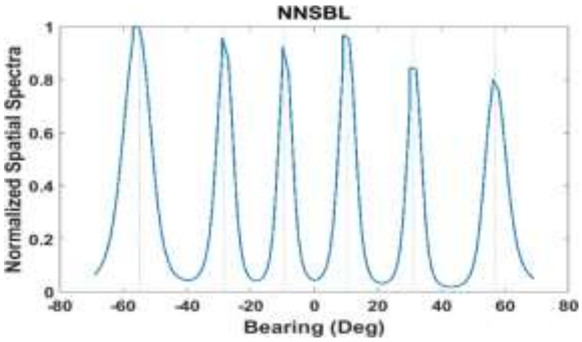


Figure 6. DOA estimated in NNSBL

Figure7. DOA estimated in Proposed MultikernelNNSBL

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.

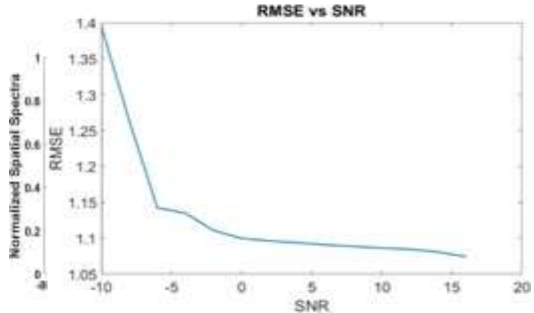


Figure 8. SNR vs RMSE for NNSBL

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.

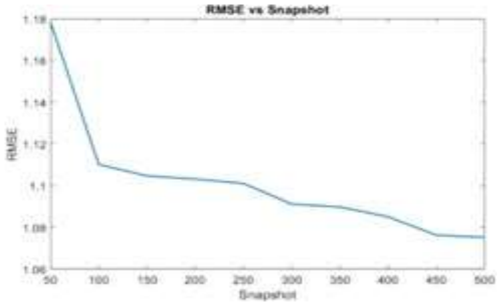


Figure 9. SNR vs RMSE for Multikernel NNSBL

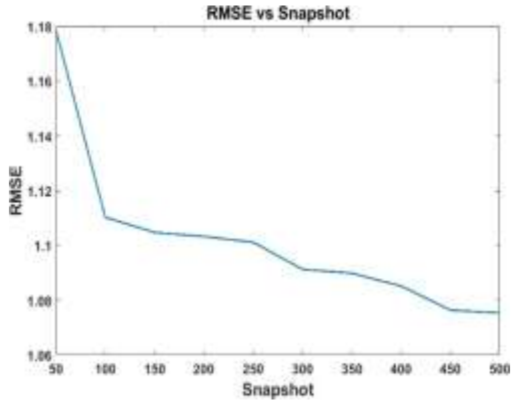


Figure 10. RMSE vs snapshot NNSBL

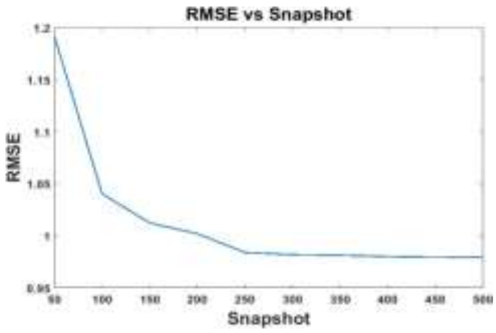


Figure11. RMSE vs snapshot multi-kernel NNSBL

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 snapshotsin 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 executiontime performance.

Table3. RMSE vs Snapshot NNSBL and MultikernelNNSBL

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

The Multikernel NNSBL technique for DOA estimation is simulated in MATLAB. The method employs Multikernel based Sparse Bayesian learning, which is an improvement over the NNSBL technique. Better DOA estimate was achieved with the Multikernel manifold matrix generation, and it also took less time to run. It is determined that the suggested approach is comparable to current literature. Overall, we're happy with the outcomes. When compared to the NNSBL used in the existing literature, the RMSE produced using the suggested technique is superior.

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