# A Robust Adaptive Beamforming Algorithm using Neural Network against a Large Mismatch

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**Abstract:** Adaptive beamforming is mainly used for interference rejection and for resolution when the array steering vector is already known. And adaptive beamforming is signal processing system which combined a signal in a manner to increase the signal strength in a particular direction . Sometime there are some mismatches between the true value and assumed value,whichcausesdegradation in adaptive beamforming technique. In this paper, we characterize a novel neural network method to robust adaptive beamforming. In the proposed algorithm ,it depend on the class of diagonal loading styles which is three-layer RBFNN(radial basis function neural network) and in evident modeling of improbability in the required signal array response. In this algorithm, the list of the best weight vector is noticed as a mapping problem, which can be modeled with the help of RBFNN with input/output pairs.Here best performance under good conditions, provides the robustness against the signal steering vector whichreduce themismatches and output array SINR analogically near to the best one.Relative to other adaptive beamforming method simulation results improve the performance.This algorithm provides excellent robustness to mismatches, boosts the array system performance under non ideal situation.

**Keywords**: robust adaptive beamforming , RBFNN, steering vector mismatches, diagonal loading.

## Introduction

A one most usable technique is Adaptive Beamformingin which an array of antennas is broken in such a way to achieve maximum response or result in a particular lane by estimating the signal arrival from a preferred direction (in the presence of unwanted signals like noiseetc) while signals of the alike frequency from other directions are rejected or discarded. By increasing the weights of each of the sensors (antennas) used in the array this can beattained. Because of general purpose nature and fast convergence ratesNeural networks have found number of applications in the field of signal processing. Smart antenna is technology for higher user capacity mainly in wireless communication system. The heart of smart antenna is the adaptive beam- forming algorithms in antenna array because this technique can achieve maximum response in a particular direction by estimating the signal arrival from a desired direction.SMI, RLS, CMA arethe numerous Adaptive beamforming algorithmsvarying in difficulty based on different criteria for updating and computing the best possible weights.

Adaptive beamforming is identified to have resolution and interference rejection ability when the array steering vector is well-known, however the performance of adaptive beamforming may degrade severely due to mismatches. This problem can be controlled by neural network. Here the progress of a neural network- based robust adaptive beamforming algorithm, the problems are calculating the weights of an adaptive array antenna as a mapping problem.

When adaptive arrays are applied to practical troubles, the performance degradation of adaptive beam-forming techniques because some of underlying expectations on the environment, sources, or sensor array can be debased and this may cause a mismatch between the assumed and actual output signal. There are number of approaches which providebetter robustness against some types of mismatches. Out of all the most common is LCMV( linearly constrained minimum variance)beamformer , which is used to provide robustness against uncertainty in the signal. To account for the signal steering vector mismatches, additional linear controls can be used to improve the robustness of adaptive beamforming . Diagonal loading has been aacceptable approach to get better the robustness of adaptive beamforming algorithms. Here the serious drawback of this approach is that there is no trustworthy way to select the diagonal loading factor. From all of this we can see that these approaches can not be predictable to provide sufficient robustness improvements. Neural network, using addition, multiplication, division, and threshold operations, can be readily implemented in analog VLSI. Neural network methods have advantages as nonlinear property,general purpose nature, passive parallelism,generalization capability, adaptive learning capability and fast convergence rates. Neural network method have two phase: training phase and performance phase. Neural network is first trained with known input/output pattern pairs. It can be implemented off-line, although a large training pattern set is required for network training. After the training phase, it can be used directly to replace the difficult system dynamics. Motivated by these inherent neural networkadvantages, this paper represents the development of robust adaptive beamforming algorithm based on neuralnetwork , which treats the trouble of computing the weights of an adaptive array antenna as a mapping problem. In this paper, we propose a novel approach to robust adaptive beamforming and show clearly how to efficiently compute the weight vector by the neural network method to achive the better results. The proposed algorithm provides excellent robustness to signal mismatches, makes the mean output array SINR consistently close to the optimal one and enhances the array system performance innonideal conditions. The excellent performance of our proposed algorithm is proved via a number of simulation examples.

## The Radial Basis Function Neural Network (RBFNN)

The weight vector of the proposed algorithm is a nonlinear function of the sample covariance matrix, and is not suitable for real-time implementation. Therefore, it can be approximated using a suitable architecture such as RBFNN in this paper. The array outputs are preprocessed, and then applied to the RBFNN. The sample covariance matrix R is presented to the input layer of the RBFNN, and the vector RABw is produced at the output layer. As it is the case, with most neural network, the RBFNN is designed to perform an input-output mapping.

### The RBFNN Model

The RBFNN is a special three-layered feedforward network, which consists of the input layer, the output layer, and the hidden layer as shown in Fig. 1. In the hidden layer, the nonlinear functions which are performed in this transformation are usually taken to be Gaussian functions of suitably chosen means and variances. The weights from the hidden layer to the output layer are recognized by following a supervised learning system. Here we assume that J , L , P nodes are the input layer, the hidden layer, and the output layers correspondingly.

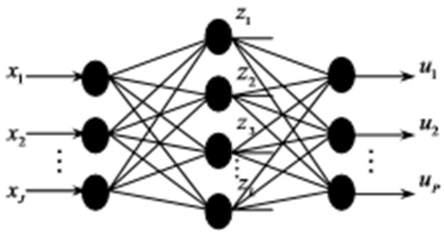


Fig 1: Structure of a three-layer RBFNN

### Training Phase of the RBFNN

The RBFNN is trained with a representative set of training input/output pairs, after training phase it is ready to function in the performance phase. In the performance phase, the RBFNN produces estimation of the weight vector that is W .

### Performance Phase of the RBFNN

In the performance phase after the training phase is complete, the RBFNN has established an approximation of the desired input-output mapping. In this phase, the neural network is expected to generalize, that is, answer to inputs that has never seen before, but drawn from the same distribution as the inputs used in the training set. In the performance phase, the RBFNN produces outputs to past unseen inputs by interpolating between the inputs used in the previous training phase.

a) Generate the rearranged covariance matrix z ;

b) Present the array output vector at the input layer of the trained RBFNN. The output layer of the trained RBFNN will produce the estimation of the weight vector for the array output.

Unlike the SMI, the least mean-square, or recursive least squares algorithms, where the optimization is carried out whenever the directions of the desired or interfering signals
change, in our algorithm, the weight vector of the trained network can be used to produce the optimum weight vector needed to steer the narrow beams of the adaptive array to the ways of the desired signal in real time.

## Simulation Results

To justify the performance here we present some simulations of the SMI, LSMI and robust adaptive beamforming.
We determined thatto prevent spatial aliasing the element spacing must be $d \leq \lambda / 2$. Here we relax this restriction and look at different element linear array and resulting array characteristics for various element spacing, namely, their beam-pattern.
Example 1: Array beampatterns of the algorithms .In the example, we assume that both the presumed and actual signal spatial signatures are plane waves impinging from the DOAs 0D and 2D, respectively. Fig. 2 displays the beampatterns of the

methods tested for the fixed SNR 10dB = for the no-mismatch case. The vertical line in the figure denotes the direction of arrival of the desired signal. From Fig. 2, we note that the proposed algorithm based on RBFNN can adapt the radiation pattern of the antenna to direct narrow beam to the desired signal and nulls interfering sources. Fig. 3 displays the beampatterns of the methods tested for the fixed SNR 10dB = for a 2D mismatch. The vertical line in the figure denotes the direction of arrival of the actual signal. From Fig. 3, we note that although the beampatterns of the proposed algorithm based on RBFNN do not have nulls at the DOAs of the interferences as deep as those of the SMI algorithm, the interferences are sufficiently suppressed by our algorithm.

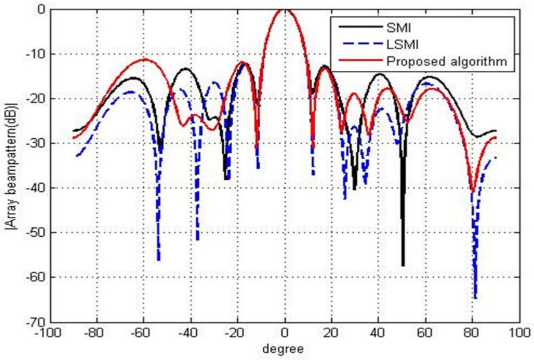


Fig 2 : Comparison of the beampatterns (no mismatch)

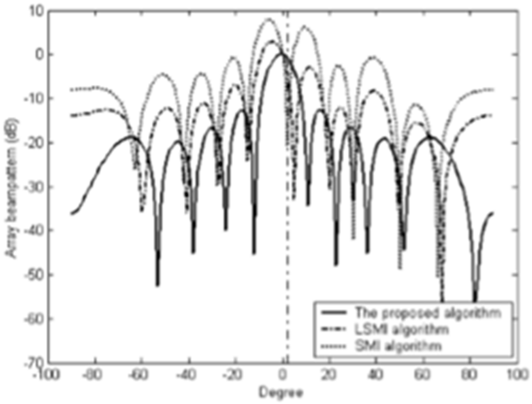


Fig 3: Comparison of the beampatterns (a $2^0$ mismatch)

SMI algorithm is very sensitive even to slight mismatches that can easily occur in practical situations and LSMI algorithm can improve the performance of the SMI algorithm. Obviously, the proposed algorithm based on RBFNN provides a significantly improved robustness against signal steering vector mismatches and makes the mean output array SINR close to the optimal one at all values of the SNR and N.

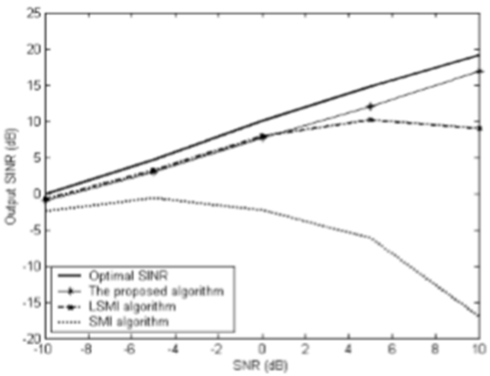


Fig 4: Output SINR versus SNR

## Conclusions

We have shown how to obtain robust adaptive beamforming based on the RBFNN, which is successful in tracking the desired signal while simultaneously nulling the interference sources. The proposed algorithm is much less sensitive to signal steering vector mismatches. Furthermore, the proposed algorithm based on RBFNN consistently enjoys excellent performance because it achieves the values of SINR that are close to the optimal one in a wide range of the SNR andN . A number of numerical examples clearly demonstrate that the proposed robust adaptive beamforming algorithm based on neural network consistently enjoys a considerably improved performance as compared to the other algorithms.

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## References

[1] H. El Zooghby, C. G. Christodoulou, and M. Georgiopoulos, “Performance of radia basis function networks for direction of arrival estimation with antenna arrays,” IEEE Trans. Antennas Propagat., vol. 45, pp. 1611-1617, Nov. 1997.
[2] L. Long and L. Y. Da, “Real-time computation of the noise subspace for the MUSIC algorithm,” Proc ICASSP 1993, vol. 1, pp. 485-488, Apr. 1993
[3] P. R. Chang, W. H. Yang and K. K. Chan, “A neural network approach to MVDR beamforming problem,” IEEE Trans. Antennas Propagat., vol. 40, pp. 313-322, 1992.
[4] L. E. Brennan, J. D. Mallet, and I. S. Reed, “Adaptive arrays in airborne MTI radar,” IEEE Trans. Antennas Propagat., vol. 24, pp. 607-615, Sept. 1976.
[5] J. L. Krolik, “The performance of matched-field beamformers with Mediterranean vertical array data,” IEEE Trans. Signal Processing, vol. 44, pp. 2605-2611, Oct. 1996.
[6] E. Y. Gorodetskaya, A. I. Malekhanov, A. G. Sazontov, and N. K. Vdovicheva, “Deep-water acoustic coherence at long ranges: Theoretical prediction and effects on large-array signal processing,” IEEE J. Ocean. Eng., vol. 24, pp. 156-171, Apr. 1999.
[7] L. C. Godara, “Application of antenna arrays to mobile communication, Part II: Beam-forming and direction-of-arrival considerations,” Proc. IEEE, vol. 85, pp. 1195-1245, Aug. 1997.
[8] T. S. Rapappport, Ed., Smart Antennas: Adaptive Arrays, Algorithms, and Wireless Position Location, Piscataway, NJ: IEEE, 1998.
[9] R. A. Monzingo and T. W. Miller, Introduction to adaptive arrays. New York: Wiley, 1980.
[10] K. M. Buckley and L. J. Griffiths, “An adaptive generalized sidelobe canceller with derivative constraints,” IEEE Trans. Antennas Propagat., vol. 34, pp. 311-319, Mar. 1986.
[11] S. Zhang and I. L. Thng, “Robust presteering derivative constraints for broadband antenna arrays,” IEEE Trans. Signal Processing, vol. 50, pp. 1-10, Jan. 2002.
[12] D. Carlson, “Covariance matrix estimation errors and diagonal loading in adaptive arrays,” IEEE Trans. Aerosp.Electron. Syst., vol. 24, pp. 397401, July 1988.
[13] A. B. Gershman, “Robust adaptive beamforming in sensor arrays,” Int. Journal Electron.Commun., vol. 53, pp. 305-314, Dec. 1999.
[14] S. Reed, J. D. Mallett and L. E. Brennan, “Rapid convergence rate in adaptive arrays,” IEEE Trans. Aerosp.Electron. Syst., vol. 10, pp. 853863, Nov. 1974.
[15] H. Cox, R. M. Zeskind, and M. H. Owen, “Robust adaptive beamforming,” IEEE Trans. Acoust., Speech, Signal Processing, vol. 35, pp. 1365-1376, Oct. 1987.
[16] Li, P. Stoica, and Z. Wang, “On robust Capon beamforming and diagonal loading,” IEEE Trans. Signal Processing, vol. 51, pp. 17021715, July 2003.
[17] Xin Song, Jinkuan Wang, and Yinghua Han, ―Robust Capon Beamforming in the Presence of Mismatches‖, Proceedings of ISCIT2005,pp.135-138, July2005.
[18] S. Zhang and I. L. Thng,―Robust presteering derivative constraints for broadband antenna arrays‖, IEEE Trans. Signal Processing, vol. 50, pp. 1-10, Jan. 2002.
[19] D. Carlson,―Covariance matrix estimation errors and diagonal loading in adaptive arrays‖, IEEE Trans. Aerosp. Electron. Syst., vol. 24, pp. 397-401, July 1988.
[20] H. Cox, R. M. Zeskind, and M. H. Owen, ―Robust adaptive beamforming‖, IEEE Trans. Acoust., Speech, Signal Processing, vol. 35, pp. 1365-1376, Oct. 1987.
[21] Li, P. Stoica, and Z. Wang, ―Doubly constrained robust Capon beamformer‖, IEEE Trans. Signal Processing, vol. 52, pp. 2407-2423, Sept. 2004.
[22] Xin Song Jinkuan Wang XuefenNiu, ―Robust Adaptive Beamforming Algorithm Based on Neural Network‖, Proceedings of the IEEE International Conference on Automation and Logistics, pp. 1844-1849, Sep. 2008.
[23] Simon Haykin, ―Neural Networks‖, Second edition, Pearson education asia, Fourth Indian reprint, 2004.