Detection of faults in antenna arrays using SVM

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Introduction

Antenna arrays are extremely useful in communication systems due to the flexibility and control that they allow over the radiation pattern of the antenna. Efficient and well-directed radiation patterns cause minimum interference and noise and are highly desirable. The simplest way to control the radiation pattern is by using antenna arrays which are just periodic arrangements of radiating elements since changing just the currents and the relative phase between the elements of the array results in a large change in the shape of the pattern and the direction of the beam. This is due to the so called array factor which quantifies the effect of combining radiating elements in an array without the element specific radiation pattern taken into account. The overall radiation pattern of an array is determined by this array factor combined with the radiation pattern of the antenna element.

Motivation

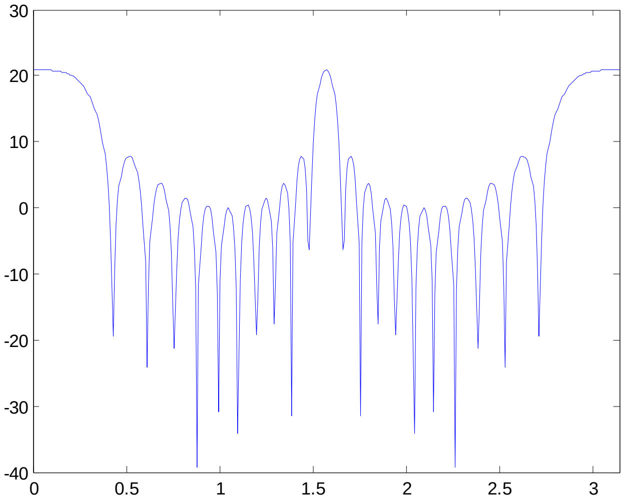
A common problem in antenna arrays is the failure of the elements due to wear and tear and detection of the faulty elements is a difficult problem if the size of the antenna is large. The most widely used techniques in the detection process are neural network algorithms [1][2] with radial basis functions in the decision nodes. But the disadvantage of using neural networks is that they require multiple layers and input nodes for training and these result in large amount of computations and hence large training time. Also the probability of ending up at a local minima is also not negligible. We therefore propose to use SVM based classification on this problem.

Problem Statement

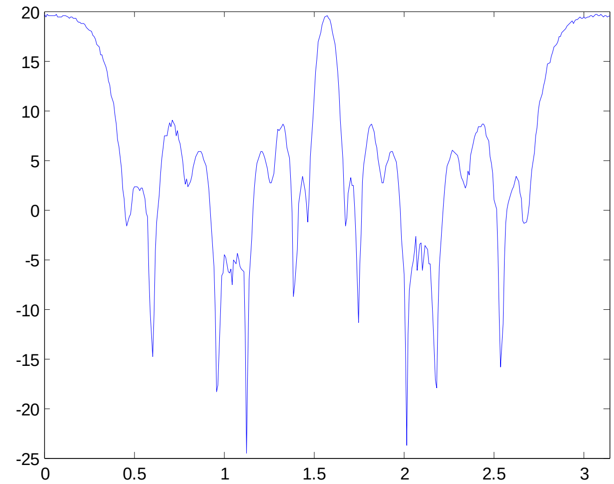
The training data for this problem is presently generated by simulating the radiation pattern of an 11 element linear array antenna. The radiation pattern is determined as a function of the distance from the radiating elements and the samples of the radiated power at different points constitute the training vectors. Thus our features are the samples of the radiated power. The different training vectors are generated by varying the current in the radiating elements and also the position of the faulty elements. Other parameters that can be varied are the separation between the elements and the wavelength of the transmitted signals. To the training vectors we added Gaussian noise and also uniformly distributed noise to simulate real world data. We collected a dataset of about 1332 training vectors for the linear antenna case. Each element in the antenna array is numbered and the decision vectors simply indicate the failed elements' indices.

This procedure was also applied to a planar antenna array which is just a 2-d version of the linear antennas comprising of 25 antenna elements in a 5*5 grid. The training set here is composed of measurements of radiation power as in the case of the linear array on a single plane. The decision vectors indicate the x and y indices of the failed elements in the planar array.

Radiation pattern of 11 element linear array antenna



Correct pattern of an antenna

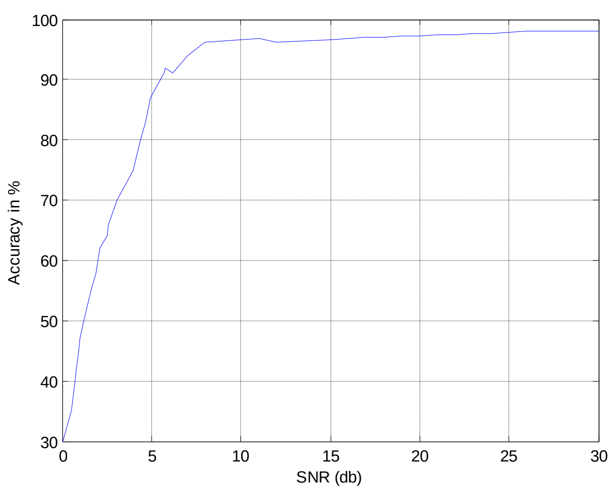


Distorted pattern of a faulty antenna

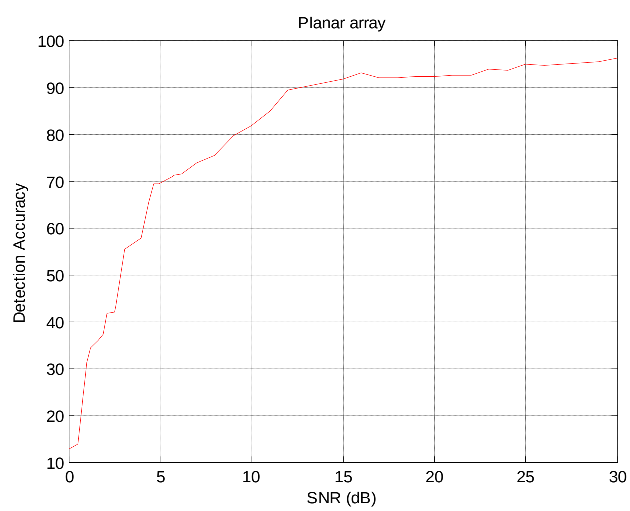
The radiation pattern changes as faults are introduced in the array of antennas. Noise is also added to the system when measurements of the radiated power are made due to interference and other factors. The above figure shows the degradation as the result of a single element of the array ‘failing’. As more elements fail the pattern gets degraded further.

Implementation of the training

LibSVM was used for SVM based classification and our initial training set consisted of 1332 sets of 361 training features each. The training vectors consisted of measured powers for different Signal to Noise ratios (SNR). A lower signal to noise ratio (less than 5 dB) resulted in a very less detection accuracy of around 30% while increasing the SNR to more than 10 dB increased the accuracy to more than 90%. As expected the accuracy improved with an increasing SNR. A similar pattern was also observed when tested with a planar array.

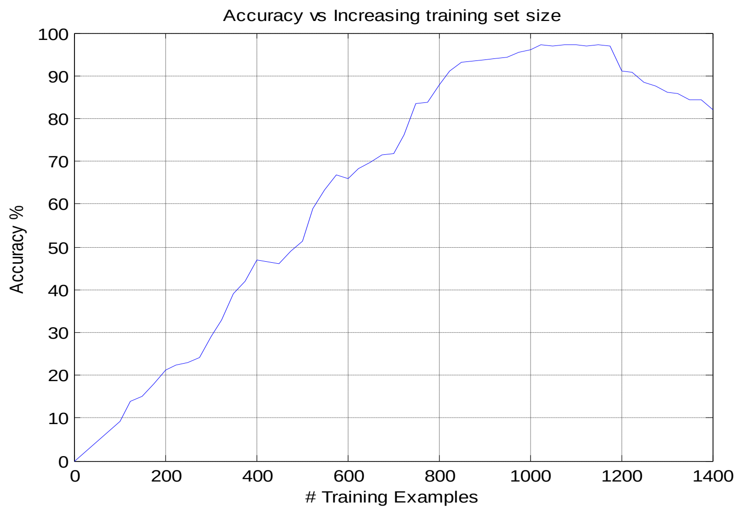


Accuracy vs SNR for a 11 element linear array



Accuracy vs SNR for a 5*5 planar array

The detection accuracy for both antennas remained constant as SNR was increased beyond 10 dB. While the testing error that we observed decreased with an increased size of training set, increasing it above 1200 resulted in more errors. This could be because of over-fitting and also because our increased training set consisted of training vectors that had more noise in the readings. These readings only distorted the data and also affected the accuracy of the classifier resulting in the decreased accuracy.



Effect of increasing training size on detection accuracy.

We also implemented the SVM classifier with different kernels, the polynomial, sigmoid, linear and the radial basis. The performance for the different kernels was almost the same. Only the sigmoid kernel performed poorly and had very low detection accuracy.

Redundancy of measured data:

The measured data from the antenna radiation patterns were vectors with 361 features. The inherent symmetry of the radiation pattern resulted in some redundancy in the training vectors. For this reason we used Principal Component Analysis, to reduce the dimension of the vectors. After performing PCA, we observed that the dimension of the data could be reduced to only 9 by taking only the most significant eigenvalues. Thus a large reduction in data size could be obtained.

Number of feature vectors	**Dimension of training vector**
1332	361
1332	9 (After PCA)

Conclusions

Over the course of the project we observed that SVM was a very good tool to identify faulty elements in an antenna array. Thus it could be the ideal replacement for the neural network based fault detection. We also observed that increasing the training examples, by adding training sets (with the elements having different excitation current), led to better results and lower testing error. But adding training sets with a high level of noise resulted in the accuracy dropping since these vectors actually distorted the training decision.

Future Work

1. The accuracy in predicting faulty elements for a planar array is not as good as that of the linear array. The feature set and the different training sets necessary should be optimized for better results.
2. Current work has taken into account only the radiation pattern. Scattering pattern can also be used to improve the performance of the predictor.
3. The symmetry of the antenna array can be used to further optimize the performance of the predictor.

References

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