Convolutional Neural Network based models to perform RF Source detection

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Detection of the number of received signals is an important problem in antenna array processing. This is a preprocessing step in most Direction of Arrival estimation algorithms like MuSiC and ESPRIT. The most popular methods to perform Source detection are Minimum Description Length (MDL) and Akaikes Information Criterion (AIC). However, the performance of such techniques suffers in the presence of low SNR and small sample sizes.

Machine learning based solutions have recently found success in solving many array processing problems to overcome these challenges[1]. Another advantage such approaches offer is that they can be trained on actual data to learn the general pattern and apply it to perform well even in low SNRs. A neural network based approach has been used to estimate the number of RF sources[2]. However, this method performs Eigen Vector decomposition and thus can be computationally expensive, especially if we consider large number of elements. In this paper we propose an alternate model which considers only the upper triangular elements of the autocorrelation matrix and separates out the real and imaginary values and considers them as the input features. This preprocessing step can reduce the complexity of the model and can be used to perform source detection with a high accuracy at less computation time. In our experiments, we simulate synthetic data by controlling the number of sources in the sampled waveform which forms our ground truth. The model considered is a Convolutional Neural Network(CNN), which makes use of filters to extract abstract features from the processed data. Regularization is done in the form of batch normalization and max pooling after each layer to prevent overfitting. These filters are locally made to perform convolutional operations and cover the entire input data. The final output layer will have only a fully connected layer which predicts the labels. The number of sources are one hot encoded, and this thus forms a multi label multi class classification problem. The success and popularity of CNN comes from the availability of large amounts of data. In our case, we are able to create datasets of differing SNRs for sampled waveforms with the number of sources varied from 1-6 for an antenna array of 10 elements. In addition to this, we can also consider correlated signal sources which follow multi path fading. To resolve such a scenario, we perform Forward Backward Spatial smoothing on the autocorrelation matrix before performing the preprocessing[3].

Once the network is trained, we gauge the accuracy of the model by using the test data. We also assess the sensitivity and specificity of each class by evaluating a confusion matrix for the predictions of the test data.

References

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