SPARSE ARRAY ANTENNA - A NEURAL NETWORK APPROACH

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Abstract: A neural network based signal processing algorithm for the estimation of the angle of arrival is presented. The algorithm is designed for being employed in conjunction with massively thinned arrays, with arbitrarily deployed elementary radiators. It uses a radial-basis functions neural network mapping of the received signals onto the angle range. Sub-arrays are used as input for the neural network.

1. Introduction

Array antennas are presently widely used in the field of communication and radar technology. Filled arrays have their elements placed at each node of a uniform grid. In such arrays, the inter-element spacing is traditionally taken to be at most half of the wavelength at the operational frequency. This choice prevents the apparition of grating lobes in the visible domain.

When compared to full arrays, sparse arrays offer substantial reductions in cost, weight, power consumption, and heat dissipation, albeit with an accompanying reduction in antenna gain. Since in such arrays the inter-element spacing is inherently large (most notably, larger than half of the wavelength at the operational frequency) special techniques need to be designed for making the grating lobes invisible.

The design of the sparse arrays involves two distinctive aspects: the positioning of the individual radiators and the signal processing. As concerns the former aspect, several thinning strategies have been presented in the literature. A first class of such techniques employed a cut-and-try random placement [1,2]. This option retains some control over the side lobes through the deterministic placement of the elements. Later, dynamic programming and genetic search algorithms were proposed [3], providing superior performances. Recently, fractal structures were taken into consideration [4] showing good results for moderately thinned arrays. For massively thinned arrays originating from very large ones, the difference sets [5] provided the best results. Note that all those methods gave optimum positions for the elementary radiators in a thinned configuration.

As concerns the signal processing, the techniques enumerated above do not require any particular algorithm. Consequently, arrays designed in these manners are amenable to most of the antenna basic functions such as: scanning a narrow beam in transmission mode, shaping the antenna radiation pattern, synthetic aperture radar imaging (SAR) or direction of arrival estimation (DOA). In the case when the antennas are expected to work in receiving mode, only, non-linear signal processing algorithms can be considered, as well. For example, in [6] a thinned array is used for SAR processing. The antenna consists of two sub-arrays; a small size filed array and a large size sparse array. By positioning the nulls of the filled array on the grating lobes of the sparse array and by multiplying the patterns, a narrow beam pattern with low side lobes results.

The design strategies discussed thus far make no reference to any physical constraints in deploying the elementary radiators. However, experience demonstrates that in many practical situations (e.g. in aeronautic or automotive industries) hard constraints do occur. In such cases, the positioning of the elements in the sparse array is restricted to certain regions. It is then the task of the signal processing algorithm to ensure the desired antenna parameters.

This contribution describes a non-linear signal processing algorithm to be employed in conjunction with massively thinned arrays. The algorithm applies a neural network (NN) approach to

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the estimation of the angle of arrival (AOA). Furthermore, it also prevents the occurrence of false targets (that are the correspondents of the grating lobes in the case of the receiving mode operation).

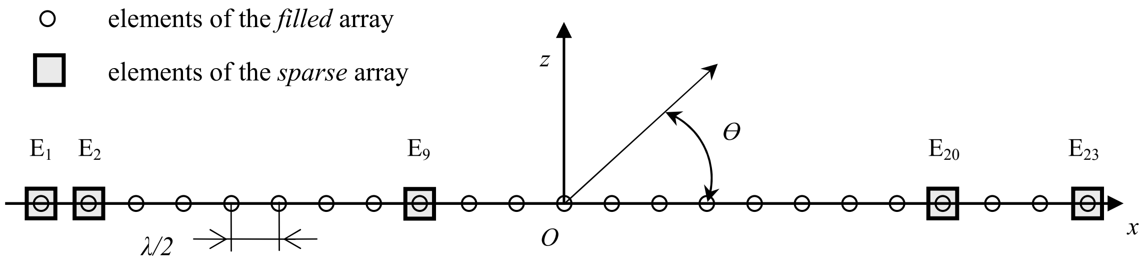


Figure 1. Geometry of the thinned array obtained from a linear uniform array with the inter-element spacing equal to half of the wavelength at the operational frequency.

2. Computational philosophy

The case of a linear (massively thinned) sparse array for tracking a single source in the positive horizontal half-plane is considered (see Fig. 1). These assumptions are made for the sake of intuitively introducing the new concepts and do not reduce the generality of the algorithm. Plane sparse arrays can be used at the cost of increasing the computation time whereas multiple sources can be tracked by training the NN with the corresponding number of sources [7].

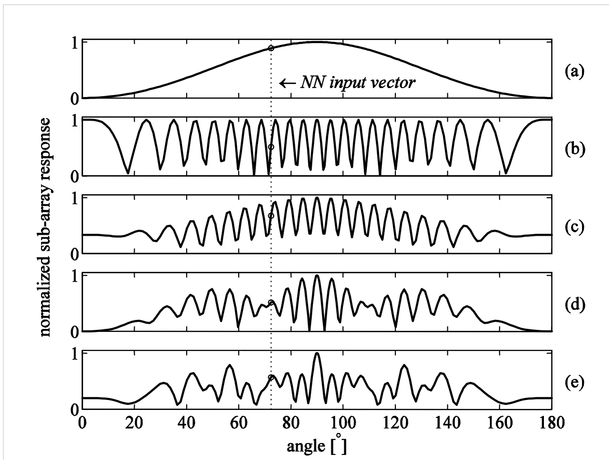


Figure 2. "Radiation patterns" corresponding to various sub-arrays. (a) Two elements at half wavelength (E_1+E_2*); (b) two elements at five wavelengths (*E_1+E_{23}*); (c) three elements (*$E_1+E_2+E_{23}$*); (d) four elements (*$E_1+E_2+E_{23}+E_{23}$*); (e) five elements.*

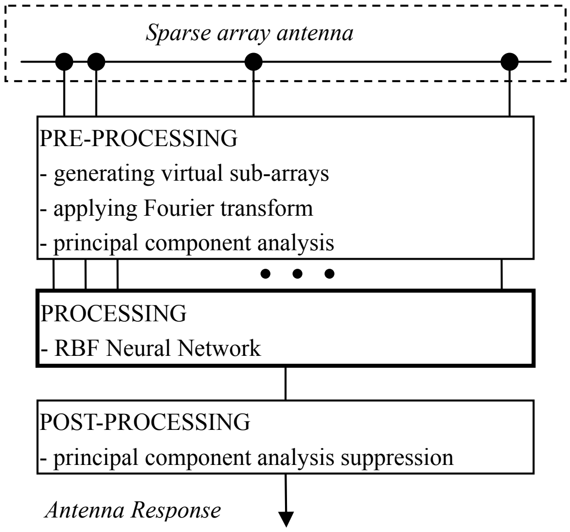


Figure 3. The block diagram of the RBFNN for the AOA estimation problem.

For solving the AOA problem, both the individual elementary receivers in the sparse array and the collections of elements are taken into account. The collections of elementary antennas (individual ones, included) are hereafter referred to as sub-arrays. Assuming that the array contains N primary antennas, the total number of sub-arrays that can be defined K equals the sum over all combinations of N choose k with k=1,…,N. Upon illuminating the considered sparse array with a plane wave, the samples measured by the N elementary arrays are recorded. Let "radiation patterns" denote the spatial Fourier transforms of the samples corresponding to each sub-array and let L be the number of spectral components (in this case, angles) where the "radiation patterns" are evaluated. Some examples of the spatial Fourier transforms are illustrated in Fig. 2. Note that the plots in Fig. 1, b, c, d, e clearly indicate that sub-arrays with inter-element spacing that exceeds half of the wavelength display undesired grating lobes.

These "radiation patterns" are fed into a radial-basis functions neural network (RBFNN) [7]. The choice for using a RBFNN is motivated by the fact that it is the most adequate neural network for curve fitting or interpolation problems in higher-dimensional spaces. The input vector for the RBFNN is constituted from the K spectral components corresponding to a specified angle in the "radiation pattern" of each sub-array (see Fig. 2). The RBFNN's output is 1 or 0 depending on whether or not the input vector fits the direction of the target.

3. Architecture of the neural network

In view of the neural network's input vector being multidimensional the mapping performed by RBFNN represents a hyper-surface S. Note that this mapping eliminates the ambiguities in the response of the sparse array. In the training phase, the input-output pairs are used by the NN to perform a fitting for the hyper-surface. During the test / generalisation phase, the NN interpolates the input data points through the learned approximation of S. The RBFNN considered in this paper has three layers, the input layer, a hidden layer and the output layer. The radial basis function is used to activate the neurons in the second layer, while the neurons in the output layer have a linear transfer function. When designing the network, the number of neurons in the input layer is derived from the size K of the input vector whereas the size of the output layer equals, in this case, 1. The number of input-output pairs L used during the training session gives the dimension of the hidden layer, for an exact design. Note that, since the input quantities (spatial Fourier transforms) require complex number arithmetic, the number of neurons in the input layers is, in fact, doubled.

The overall architecture of the AOA estimation system is presented in Fig. 3. The pre- and post-processing stages are used for converting the signals from the array elements into a proper input-vector for NN and for transforming the NN output into AOA information.

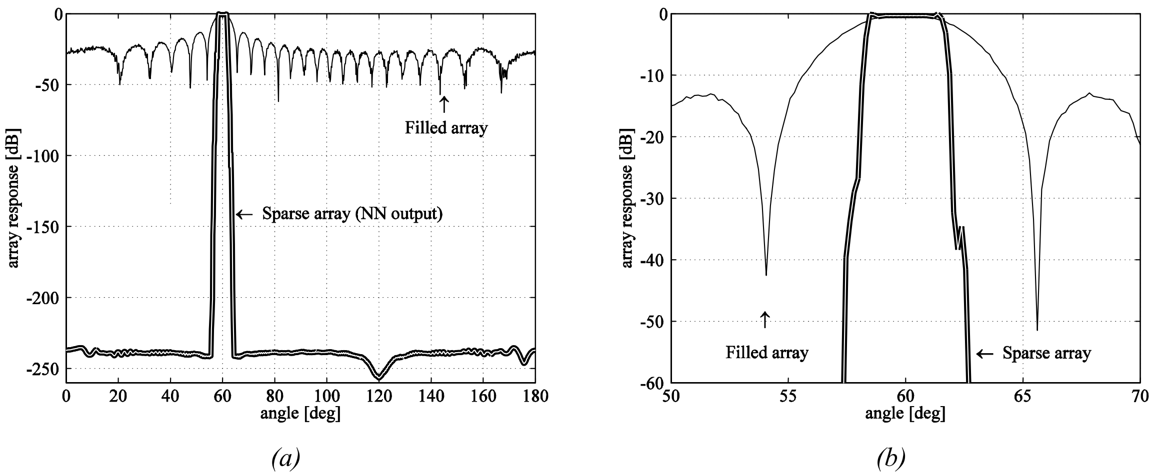
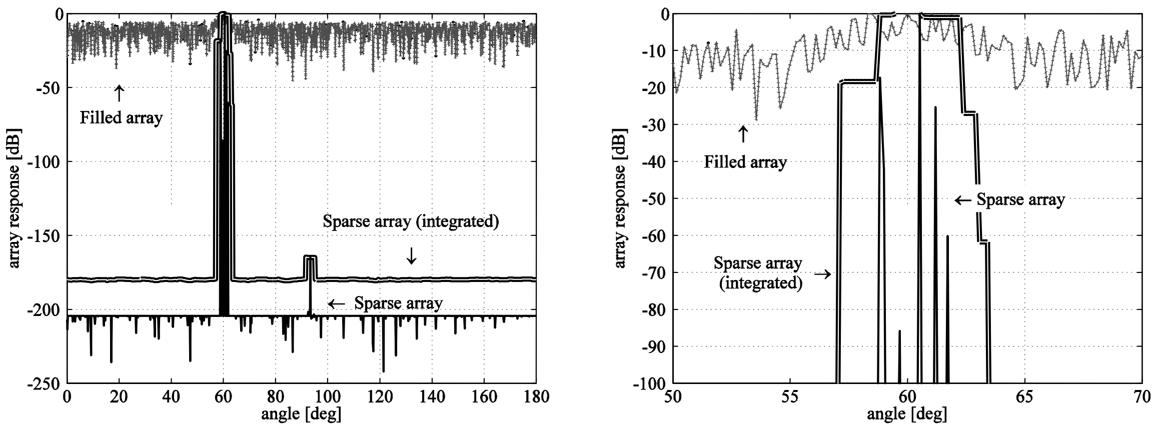


Figure 4. DOA estimation for a SNR=30dB. (a) Complete field of view; (b) detail depicting the main beam

4. Numerical results

In the simulations, an N=5 elements linear sparse array was used. The sparse array was obtained by thinning a uniform filled array with 23 elements E_i (i=1,…,23), the radiators E_1, E_2, E_9, E_{20} and E_{23} being kept, only. The inter-elements spacing in the full array is half of the wavelength at the operational frequency of 10 GHz. For the training stage, a plane wave at normal incidence was assumed. The five signals were recorded and used to evaluate the spatial spectrum for each possible sub-array. A number of 31 sub-arrays could be generated with the 5 radiators. The "radiation patterns" were evaluated at 180 non-uniformly distributed angles, ranging from 0º to 180º. The NN's output was an ideal spectrum with the maximum at the broadside (90º). By applying the principal component analysis to the complex input vector, its dimension was reduced from 62 to 25. Consequently, the exact designed RBFNN has the dimension (number of neurons per layer) 25/180/1. In the testing phase, the source was moved at 60º and the spectrums were computed at 1059 angles in the interval

0º,…,180º, yielding an angular resolution of 0.17º. Furthermore, the effect of noise was tested. In Fig. 4, the output of the NN for the case of a signal to noise ratio (SNR) of 30dB is depicted. The Fourier transform of the filled array is taken as a reference. It can be seen that AOA has been correctly estimated and that the accuracy is very good. In fact, the precision in estimating the angular position of the source is given by the beamwidth of the sub-array obtained with two of the farthest located



(a) *(b)*

Figure 5. DOA estimation for a SNR = 6dB. (a) Complete field of view; (b) detail depicting the main beam

elements in the sparse configuration. However, in the case of a low SNR (see Fig. 5), the output of the NN is spiky. Such behaviour of the DOA estimator must be avoided since it may result in missing the target. Another consequence of this noisy output of the NN is that it will introduce ambiguities in location of the source. In order to reduce this effect, an integration procedure was employed together with the estimation algorithm. In the case of Fig. 5, the output was integrated over a 3.4º angle. It is noted that the integration interval can be selected by considering the narrowest beamwidth of the sub-array radiation patterns and the statistical properties of the clutter.

5. Conclusions

A novel technique for estimating the AOA with sparse array antennas was proposed. The method is suitable for arrays with restrictions in elements deployment. For solving the DOA problem, a neural network approach is employed. Spatial spectrums of sub-arrays are used as input set for a RBFNN. The effect of noise on the computed results was also investigated. A smoothing technique was applied for improving the quality of the results in the case of highly noisy received signals.

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