A Novel Approach to the Recovery of Aperture Distribution of Phased Arrays with Single RF Channel using Neural Networks

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***Abstract* — A novel approach to the problem of the recovery of complex aperture distribution of the phased array antenna with singe RF channel is presented in this paper. The computation of the amplitude and phase of each array element is developed as a mapping problem which can be modeled using a three-layer radial basis function neural network (RBFNN) trained with input/output pairs. RBFNN was used because it is characteristic of accurate approximation and good generalization, as well as robustness against interference and noise. The proposed approach has near optimal performance under various noise environments in terms of the error in amplitude and phase of recovered signals relative to other recovery methods.**

Index Terms — Array signal processing, neural networks, phased arrays.

I. Introduction

Conventional digital beamforming (DBF) in phased-arrays is based on element-space information meaning that an individual complex response from each array element is detected and digitized at the element level. Consequently, each array element is followed by a separate RF channel including low-noise amplifiers (LNAs) and mixers. Therefore, the phased-array system becomes very complex by having high power consumption and cost. On the other hand, single RF channel, which is based on beam-space estimation, offers N-fold reduction in hardware, power dissipation, and circuit size.

Several attempts have been made in order to reduce the number of RF channels to a single RF channel. In [1], antenna array elements are spatially and sequentially sampled and then multiplexed into a single channel. In this scheme, the channel receives $1/N$ of the incoming signal power by the uniform sampling of N array elements. So, the subsequent LNA gain requirement is increased by $10 \log_{10} N$ which represents a problem especially in large arrays.

In [2], the authors have proposed a DBF antenna array with a single RF channel. In this array, each element is followed by a $0/\pi$ phase shifter to realize the time sequence phase weighting (TSPW) technique in which N different phase weightings are generated to recover each element signal. However, due to the imperfection of phase shifters including insertion losses and phase errors, large error is introduced to the reconstructed aperture distribution of the array in both amplitude and phase. In attempt to correct the errors from phase shifters, the same authors proposed a correction method in [3] that needs $3N/2$ phase weightings to correct the entire aperture distribution instead of the N weightings generated in the conventional TSPW technique; thus, consuming more processing time.

In [4], the authors introduced a new approach for the reconstruction of the aperture distribution of the phased array antenna. The approach stems from the non-uniform spatial sampling (NUSS) of array elements and then multiplexed into a single RF channel in the regular fashion. In NUSS technique, the “on” times of individual elements are overlapped so that two or more elements can be simultaneously on. This technique is different from the conventional uniform sampling technique introduced in [1] in which only one element is on at a time while the other elements are off. Consequently, the NUSS method passes more power, on average, to the single RF channel. In this way, the gain requirement of LNA of the channel is lessened. Additionally, as a result from not using phase shifters, this method does not suffer from the errors in recovered signal amplitude and phase information emanating from the imperfections of phase shifters. However, the problem in NUSS is that the single channel receives different power level at a time thus requiring a LNA of high dynamic range.

Neural networks [5] are gaining momentum in the field of signal processing [6], mainly because of their general purpose nature, nonlinear property, massive parallelism, adaptive learning capability, generalization capability, fast convergence rates, insensitivity to uncertainty, and new VLSI implementations. The neural method is typically used in two steps: training and recalling. The network is first trained with known input-output pattern pairs. Although a large training pattern set is required for network training, it can be implemented offline. After training, it can be used directly to replace the complex system dynamics.

Motivated by these inherent advantages of the neural network, this paper presents the development of a radial basis function neural network (RBFNN)-based approach to recover the complex aperture distribution (amplitude and phase) of the phased-array with single RF channel. The novel approach treats the problem of finding the amplitude and phase of each array element as a mapping problem. The proposed algorithm provides an excellent robustness to noise, enhances the recovery process under non-ideal conditions, and makes the recovered aperture distribution consistently close to the optimal one. The excellent recovery performance of our proposed approach is demonstrated via a number of simulation examples of different signal-to-noise ratio (SNR) and interference scenarios.

II. RBFNN-Based Approach for Phased-Array Data Recovery

The functional block diagram for the phased-array data recovery using RBFNN is shown in Fig. 1. With the received signal x_k by the kth element, the complex amplitude distribution on the array forms a column vector $\mathbf{X} = [x_1, x_2, \ldots, x_k, \ldots x_N]^T$, where N is the number of array elements. Then the sum of array signals X is applied to the RBFNN as a single input. The vector $\hat{\mathbf{X}}$ is produced at the output layer of the RBFNN as an estimate of the vector of the array signals $\mathbf{X}$.

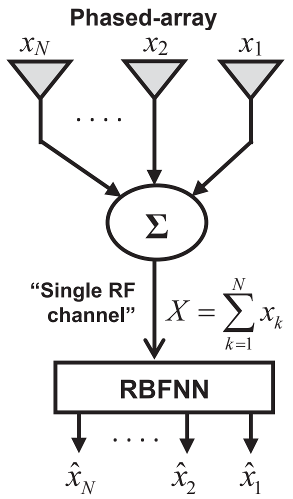

Fig. 1. Block diagram for phased-array data recovery using RBFNN.

A. RBFNN Training

As it is the case with most neural networks, the RBFNN is designed to perform an input/output mapping trained with examples (X^l; $\mathbf{X}^l$); $l = 1,2,\ldots,N_T$, where N_T stands for the number of examples contained in the training set. The training data is generated by assuming a plane wave impinging on the array with an incident angle θ ranging from −90° to +90° to span the field of view of antenna. The angular separation is taken as 1°, so we have 181 training example. Once the RBFNN is trained with a representative set of training input/output pairs, it is ready to function in the recalling phase or the real-time operating mode.

B. RBFNN Recalling

After the training phase is complete, the RBFNN has established an approximation of the desired input/output mapping. In the recalling phase, the neural network is expected to generalize, that is, respond to inputs that have never been seen before, but are drawn from the same distribution as the inputs used in the training set. Once the training phase of the RBFNN is completed offline, the neural network is ready for online processing of the array data in real time using the following simple steps:

1) Generate the sum of the array signals X.
2) Present the array sum at the input layer of the trained RBFNN. The output layer of the trained RBFNN will produce as an output the estimates of the array signals (i.e., $\hat{\mathbf{X}}$).

III. Simulation Results

The recovery of complex aperture distribution of a single-channel uniform linear array (ULA) antenna with eight elements is simulated using the RBFNN technique. The space between two adjacent elements is $0.5\lambda_0$, where λ_0 is the wavelength in free space. The RBFNN is trained by the Matlab training function *newrb* in which a hidden node is added each epoch (iteration) until a target MSE is reached. In all following simulations, the final number of hidden nodes (or epochs) is 169 for a target MSE of 0.01. The training time is about 20 seconds. The spread parameter for the basis functions is fixed at 0.01.

In the first simulation example, the RBFNN is tested (recalled) by assuming that there is a plane wave impinging on the array with incident angle $\theta = 3°$. In this case, the elements theoretically have outputs of uniform amplitude and linear progressive phase distribution. As shown in Fig. 2, with no noise, the recovered amplitude and phase distributions conform exactly to the theoretical ones. However, with an additive white Gaussian noise, some very small errors will be introduced to the recovered distributions as shown for SNRs of 20 and 5 dB.

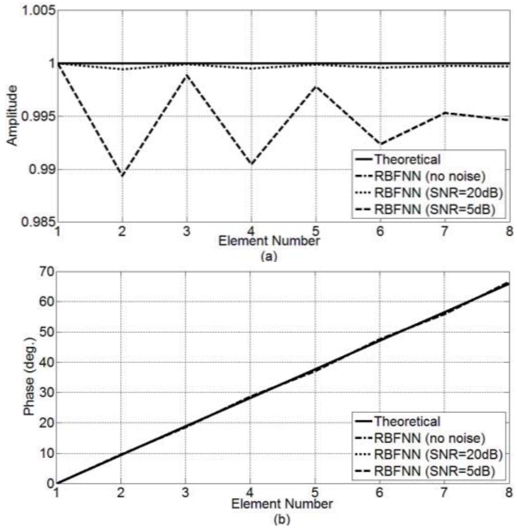

Fig. 2. The theoretical and RBFNN aperture distributions of a plane wave at $\theta = 3°$: (a) the amplitude distribution and (b) the phase distribution.

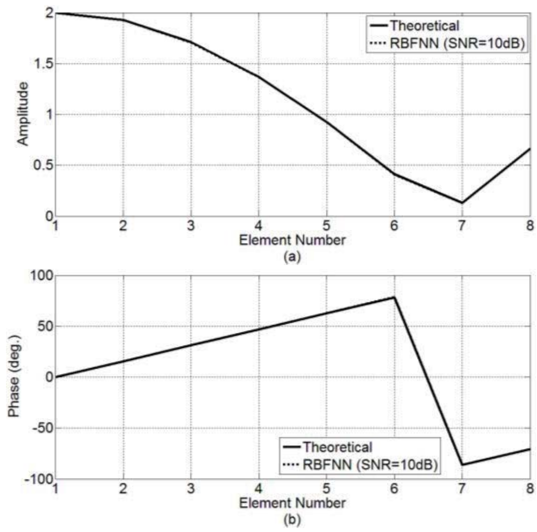

Fig. 3. The aperture distributions of a desired source at $\theta = 0°$ and an interferer at $\theta = 10°$: (a) the amplitude distribution and (b) the phase distribution.

The RBFNN method is compared with NUSS method in [4] and the TSPW method in [3]. The comparison is made in terms of the maximum error in recovered amplitude and phase distributions under the same conditions of antenna array configuration, incident angle of plane wave, and noise. The comparison results are summarized in Table I. We can see that the RBFNN method has an extremely small error in both amplitude and phase distributions compared to the NUSS and TSPW methods.

In the second Simulation example, the RBFNN is tested with a desired source at $\theta = 0°$ and an interferer at $\theta = 10°$. The SNR is 10 dB. Fig. 3 illustrates the recovery results showing a maximum error of 0.5% in amplitude and 0.3° in phase.

TABLE I
COMPARISON BETWEEN THE RBFNN, NUSS, AND TSPW METHODS

Maximum Error	SNR = 20 dB		
	RBFNN	NUSS	TSPW
Amplitude	0.05%	7.7%	9.2%
Phase	0.02°	3.4°	6.3°
	SNR = 5 dB		
Amplitude	1.1%	29.8%	40%
Phase	0.57°	24.6°	30°

IV. CONCLUSION

We have shown how to recover the aperture distribution of the phased array antenna with single RF channel based on the RBFNN, which is of good approximation, rapid processing, and high accuracy. The proposed algorithm consistently has an excellent performance because it achieves a recovered aperture that is very close to the ideal one even at very low SNRs. Also it was demonstrated, through a number of simulation examples, that the neural network is able to generalize using data sets derived from different signal conditions mainly with the effect of noise and interference added to the data used for testing.

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