SOURCE LOCALIZATION IN A MULTIPATH ENVIRONMENT VIA BEAMSPACE CUMULANT-BASED NEURAL PROCESSING *

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ABSTRACT

An application of the radial-basis function neural network (RBF NN) on the angle-of-arrival (AOA) estimation of a desired source in multipath environments is investigated. In conjunction with a set of judiciously constructed beamformers, the RBF NN are used to estimate the desired AOA within an angular sector of interest (ASOI). With a pilot signal emitted from each of the training AOA's within the ASOI, the RBF NN is trained with the higher-order statistics (HOS) estimated from the received array data. In principle, the RBF NN AOA estimator maps the complex HOS into the desired angle response as an function approximator. By matching the HOS to the center vectors associated with the hidden nodes and linearly combining the node values, an AOA estimate results. The efficacy of the proposed AOA estimator is confirmed by computer simulations.

1 INTRODUCTION

Source localization in a multipath scenario, such as low-angle radar tracking or user position estimation in urban mobile communications, has received much attention recently [1]. Conventional AOA estimation methods, such as MUSIC and ML, are of limited use in a practical multipath scenario due to the need of calibrating and storing the modified array manifold, as well as the heavy computational load incurred. The RBF NN approach was suggested as a potential solution to this problem [2]. The RBF NN is a three-layer network with a single hidden layer. Associated with each hidden node is typically a Gaussian function characterized by the center vectors and sensitivity factor. For source localization, the output node performs a linear combination of the hidden node value which yields an AOA estimate. With the center vectors judiciously chosen from the training set, the network performs a matching operation between the input data and a set of prescribed AOA related patterns.

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In this paper, the RBF NN is employed in conjunction with a set of judiciously constructed beamformers for localizing a source within a specified ASOI of an array receiver. By using beamformers with sufficiently low sidelobes, influence of out-of-sector interfering sources can be alleviated. The formation of the network is accomplished by first dividing the entire ASOI into sub-cells, each representing a particular multipath signal group, then training the network weights with a pilot source emitting signals at each of the sub-cells. The optimum weights, determined as the solution to a matching problem, are then used to obtain the mapping from some statistics of the beamformer output data into the source AOA estimate. The training procedure is non-iterative in nature, except that some efforts need be made in choosing the center vectors and sensitivity factor. Both data level [2] and correlation level [3] approaches were proposed for training the RBF NN in *element space* (ES). In this paper, the HOS, or cumulant [4] based approach is proposed for traininig the network in *beamspace* (BS). The motivation behind using the HOS is its inherent capability of suppressing Gaussian processes with unknown statistical properties. It is well known that for a Gaussian process, all cumulants of order higher than two equal zero. Therefore, a Gaussian noise source which contributes to the estimation error of the network under data or correlation level processing will be eliminated under HOS level processing. As a final remark, processing in BS domain greatly reduces the complexity of the network, as compared to the ES approaches.

2 SIGNAL MODEL AND BS PPOCESSING

Consider an M-element uniform linear array (ULA) with a half-wavelength interelement spacing. A non-Gaussian desired source and its associated multipaths are assumed to be in the ASOI of the array. The additive noise present at each sensor is assumed to be Gaussian with unknown covariance. At the kth sampling instant, the array receives an M-dimensional data vec-

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tor:

$$\mathbf{x}(k) = \sum_{l=1}^{L} \alpha_l \mathbf{a}(\theta_l) d(k) + \mathbf{n}(k) \quad (1)$$

where θ_l is the AOA of the lth path, and $\mathbf{a}(\theta_l)$ and α_l are the corresponding steering vector and complex attenuation coefficients, respectively. $d(t)$ is the desired signal received at the reference element, and $\mathbf{n}(k)$ is the noise vector. The composite steering vector [5] due to the L paths is defined as

$$\mathbf{a}_c(\theta_d) = \sum_{l=1}^{L} \alpha_l \mathbf{a}(\theta_l) \quad (2)$$

where θ_d is the true AOA of the desired source. In some extreme cases in which the direct path is completely blocked, θ_d does not belong to the set $\{\theta_l\}$.

Our goal here is to estimate θ_d based on $\{\mathbf{x}(k)\}$. From the viewpoint of data classification, some feature data associated with different source directions can be used to train the RBF NN into an AOA estimator. Training the RBF NN with the ES data directly is not preferred since interference from outside the ASOI may deteriorate the estimation accuracy. As a remedy, processing in the BS domain is suggested. The N-dimensional BS data is obtained from $\mathbf{x}(k)$ via a matrix transformation:

$$\mathbf{x}_b(k) = \mathbf{W}^H \mathbf{x}(k) = \mathbf{b}_c(\theta_d) d(k) + \mathbf{n}_b(k) \quad (3)$$

where $\mathbf{W}$ is the $M \times N$ beamforming matrix, $\mathbf{b}_c(\theta_d) = \mathbf{W}^H \mathbf{a}_c(\theta_d)$ is the BS composite steering vector and $\mathbf{n}_b(k) = \mathbf{W}^H \mathbf{n}(k)$ is the BS noise vector. By judiciously choosing the beamforming matrix, the unwanted interference can be suppressed. In addition, the computational complexity can be significantly reduced if $N \ll M$. Depending on the environment considered, the beamformers can be chosen to meet specific requirements such as low sidelobes or directional nulling. An example of $N = 4$ Chebyshev beamformers pointed at $-8°$, $-2.67°$, $2.67°$, $8°$ are shown in Figure 2.

3 FORMATION OF CUMULANTS

The HOS, or cumulants, are known to exhibit total suppression of Gaussian processes. Therefore, an RBF NN estimator based on cumulant data input will be free of the influence of Gaussian noise and interference. As suggested in [4], there are various types of cumulant structure for sensor array data. For the aforementioned BS data, a simple option for the $N \times N$ fourth-order cumulant matrix is given by

$$\mathbf{C}_b = Cum \left\{ \begin{bmatrix} x_{b,1}(k) x_{b,1}^*(k) x_{b,1}(k) \\ \vdots \\ x_{b,N}(k) x_{b,N}^*(k) x_{b,N}(k) \end{bmatrix} \cdot [x_{b,1}^*(k), \ldots, x_{b,N}^*(k)] \right\} \quad (4)$$

where $x_{b,i}(k)$ denotes the ith entry of $\mathbf{x}_b(k)$. It can be shown that $\mathbf{C}_b$ retains the structure of the BS correlation matrix [4]. In the following development, the entries of $\mathbf{C}_b$ are used as the input data to train the network and obtain the AOA estimate.

4 CUMULANT-BASED RBF NN AOA ESTIMATOR

The RBF NN consists of three layers: an input layer, a hidden layer and an output layer, as depicted in Figure 1. The input layer simply distributes the input data into the N_h hidden nodes. Each hidden node is characterized with a nonlinear, radially symmetric basis function. The choice of the basis function which we use for the ith hidden node is the Gaussian function performing the operation:

$$\Phi_i(\mathbf{y}, \mathbf{c}_i) = \exp\left\{ -\frac{||\mathbf{y} - \mathbf{c}_i||^2}{\sigma^2} \right\} \quad (5)$$

where $\mathbf{y}$ is an $N^2 \times 1$ data vector consisting of the entries of $\mathbf{C}_b$, $\mathbf{c}_i$ is the $N^2 \times 1$ center vector and σ is the sensitivity factor . If we take the feature cumulant vector from a certain AOA as the center vector $\mathbf{c}_i$, then $\Phi_i(\cdot)$ is the measure of the proximity of the source with the known AOA associated with $\mathbf{c}_i$. This in fact translates the problem of AOA estimation into one of data classification. By training the RBF NN with feature data from different AOA cells, the weights $\{w_i\}$ linking the hidden layer and output node can be determined. These weights then combine the hidden node values into an AOA estimate. There are various approaches to determining the center vectors, σ and linking weights [6]. Solutions for these parameters adopted in the simulation section are described in [7].

In summary, the network performs a mapping from the estimated input cumulant vector $\mathbf{y}$ into an AOA estimate through the linear combination:

$$\hat{\theta}_d = \sum_{i=1}^{N_h} w_i \Phi_i(\mathbf{y}, \mathbf{c}_i) \quad (6)$$

5 COMPUTER SIMULATIONS

The ULA employed was a vertical array composed of $M = 8$ elements. The multipath environment was as depicted in Figure 1. Specifically, for each source, a direct component and a symmetric specular component along with four weak scattering components spread within a sector of $6°$ were assumed. The specular path signal had a phase shift of $90°$ with respect to the direct path signal. The attenuation coefficients of the scattering path signals were assumed complex Gaussian distributed. The relative power levels of the three types of components were 1, 0.5 and 0.1, respectively. The desired source was a BPSK source at $\theta_d = 5°$ above the horizon. Spatially white Gaussian noise were also assumed present at the elements. The $N = 4$ Chebyshev beamformers as shown in Figure 2 were used to collect the BS data. The training AOA's for the network were $\{0°, 1°, \ldots, 15°\}$, and $N_h = 16$. The signal-to-noise ratio (SNR) was defined to be the ratio of the direct path power to the noise power. All cumulant and correlation data were calculated based on 1000 snapshots and all sample statistics in the following examples were obtained from 50 independent trials of the AOA estimator.

In the first set of simulations, the performance of the correlation- and cumulant-based RBF NN estimator was compared for the scenario involving a mainbeam Gaussian interference from 10° with the same power as the desired source. σ was chosen to be 0.1. The resulting sample root-mean-square errors (RMSE) versus SNR are shown in Figure 3. The results indicate that the Gaussian interference was successfully suppressed by cumulant processing. In the second set of simulations, we compared the proposed NN estimator with the cumulant-based BS MUSIC estimator [4]. No interference was involved in this case, and $\sigma = 0.03$. The RMSE versus SNR plotted in Figure 4 shows that the MUSIC estimator did not work well due to the large bias incurred with the multipaths, whereas the proposed estimator improved as the SNR increased. In the third set of simulations, the ES RBF NN estimator (which used ES cumulant input data) was compared with the proposed estimator. In this case, an interferer with the same power as the desired source arrived from 40°, which was outside the mainbeam region. σ was again chosen to be 0.1. The resulting RMSE values shown in Figure 5 confirms the effectiveness of the beamformers in suppressing sidelobe interference.

6 CONCLUSION

A beamspace cumulant-based RBF neural network approach to AOA estimation in a multipath environment has been presented. The network collects a set of cumulants formed with the outputs from a judiciously constructed beamformer bank whose spatial response encompasses a desired angular sector of interest. The training data for deriving the optimum weights of the network estimator are collected from sub-cells representing different AOA's in the given angular sector. The efficacy of the proposed scheme was confirmed by computer simulations, which show the effectiveness of beamspace transformation, high order statistics, and neural processing, respectively.

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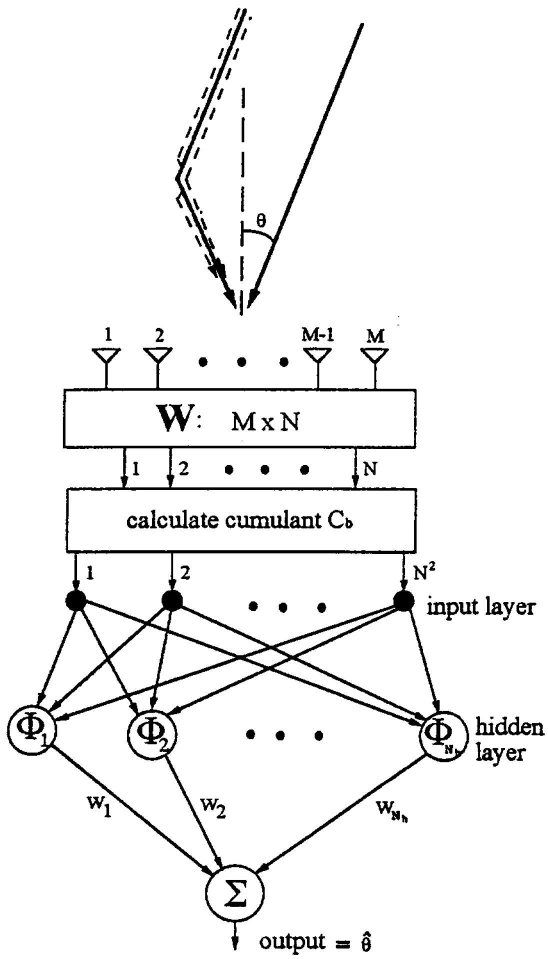

Figure 1: Array geometry and structure of the BS cumulant-based RBF NN AOA estimator.

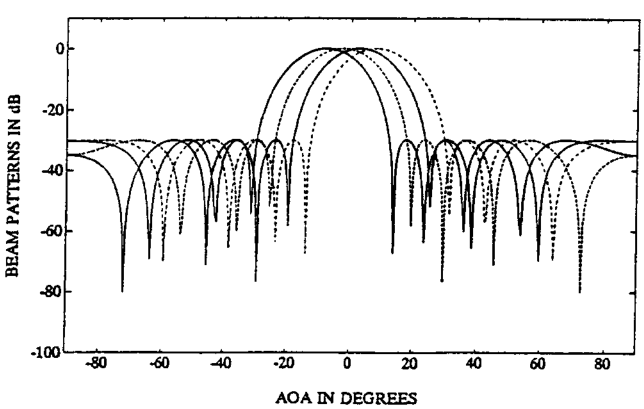

Figure 2: Four overlapping Chebyshev beampatterns with sidelobe level of −30 dB.

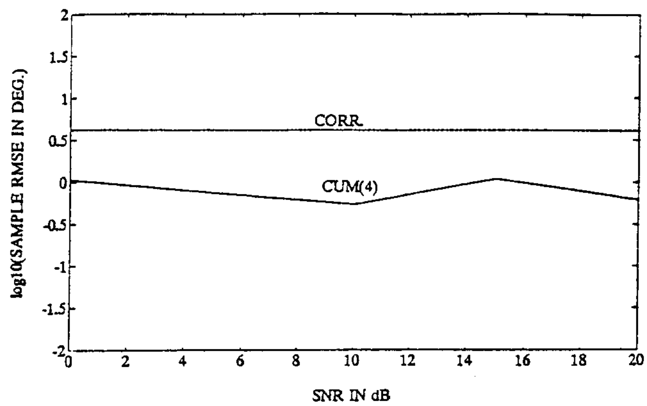

Figure 3: Performance comparison of the BS cumulant- and correlation-based RBF NN estimators.

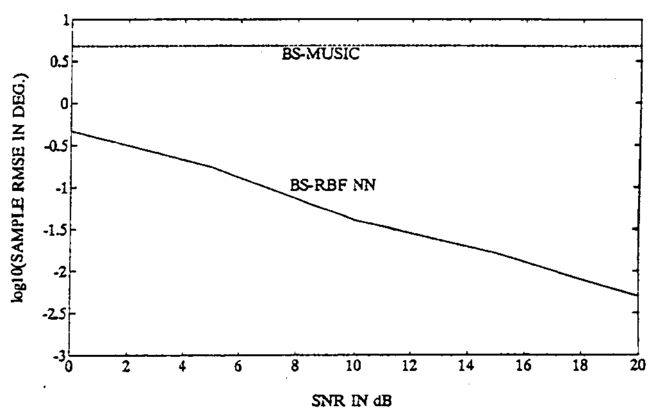

Figure 4: Performance comparison of the BS cumulant-based RBF NN and BS MUSIC estimators.

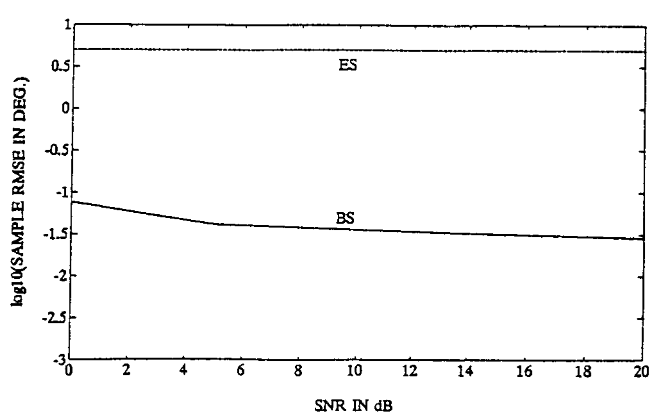

Figure 5: Performance comparison of the cumulant-based ES and BS RBF NN estimators.