Direction Finding Using GHA Neural Networks

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Abstract:-

This paper adapted the neural network for the estimating of the direction of arrival (DOA). It uses an unsupervised adaptive neural network with GHA algorithm to extract the principal components that in turn, are used by Capon method to estimate the DOA, where by the PCA neural network we take signal subspace only and use it in Capon (i.e. we will ignore the noise subspace, and take the signal subspace only).

Keywords: Direction of arrival (DOA), Generalized Hebbian Algorithm (GHA), Principal component analysis (PCA), Capon.

1.Introduction

Estimating the DOA of the source is a central problem in the array signal processing. Many methods for estimation the DOA have been proposed, including the Maximum Likelihood (ML) technique [1], the minimum variance method of Capon [2], and the MUSIC method of Schmidt [9]. The ML method has the best performance. Because of high computational load of the multivariate nonlinear maximization problem involved, the ML technique did not becomes popular. Suboptimal methods are more prevalent than the ML technique when the signal_to_noise ratio and number of samples are both not too small, because the suboptimal methods involve solving only a one-dimensional maximization problem and subspace (signal subspace or noise subspace).

This paper uses adaptive algorithm for extracting the subspace information based on the PCA neural network. Where we extract the principal component (i.e. the signal subspace only) by using of GHA algorithm with adaptive learning rate, which then used by a Capon to find the DOA.

The mapping of this paper is as follows: Section two provides some background information. Where the data model and the subspaces are present. In section three an expression for the Capon method is presented. In section four an expression for neural estimator is presented. In section five a computer simulation using matlab 6.0 is provided to support the theoretical observations.

2.General Consideration

Assume that plane waves emitted by D^1 narrow band sources impinged on a uniform circular array (UCA) consisting of

M sensors, and the DOAs of these sources (the azimuth angle is measured with respect to reference sensor, and elevation is measured with respect to z-axis as shown in figure (1) are $[(\theta_1, \Phi_1), (\theta_2, \Phi_2),\ldots, (\theta_D, \Phi_D)]$.The array output vector at the k_th snapshot can then be expressed as

$$x(k) = As(k)+n(k) \qquad (1)$$

Where $s(k)$ is the $D\times1$ vector of incident signals which are assumed to be zero mean stationary, complex and Gaussian random processes $n(k)$ is $M\times1$ vector of additive noises which assumed to be zero mean random processes that are uncorrelated with each other and with the signals, and A is the steering (or direction) matrix given by $A= [a(\theta_1,\Phi_1), a(\theta_2,\Phi_2),\ldots a(\theta_D,\Phi_D)]$.The steering vector corresponding to the i_th $DOA(\theta,\Phi)$ is given by

$$a(\theta i,\Phi i)=[\quad a_1(\theta_1,\Phi_1)e^{-j*w_0*\tau 1(\theta i,\Phi i)},.\quad .\quad .,$$
$$a_M(\theta_D,\Phi_D)\ e^{-j*w_0*\tau M(\theta i,\Phi i)}] \qquad (2)$$

Where $a_m (\theta i,\Phi i)$ denotes the complex gain response of m_th sensor to a wave front arriving from direction $(\theta i,\Phi i)$,w_0 denotes the center frequency of the signals ,and $\tau_m(\theta i,\Phi i)$ denote the

propagation delay between the sensors for a wave front impinging from direction $(\theta i,\Phi i)$ which is given by

$$\tau i=j2\Pi R/\lambda\sin\quad(\Phi i)\cos\quad(2\Pi m/M- \theta i) \qquad (3)$$

Where R is the radius of the circular array, and λ is the wavelength.

The covariance matrix of the array signal vector is given by

$$\mathbf{R} =E[x(k)x(k)^H]$$
$$=ASA^H+\mathring{o}_n^2 I$$
$$=\mathbf{R}s \qquad\qquad +\mathbf{R}n \qquad (4)$$

Where the superscript $"^H"$ denote the conjugate transpose $.S=E[s (k) \times s (k)^H]$ and $\mathring{o}_n^2$ is the variance of the additive noise, let $\lambda_1\geq \lambda_2\geq \ldots \lambda_D\geq \lambda_{D+1}= \ldots \lambda M= \mathring{o}_n^2$, denote the eigenvalues of $\mathbf{R}$ and $e_1, e_2. \ldots e_M$ denotes the corresponding eigenvectors. If the matrices Es and En are formed as

$$Es= [e_1, e_2,. \quad . \quad ., e_D] \qquad (5)$$

And $En=[e_{D+1}, e_{D+2} \quad . \quad . \quad .e_M]$
$$(6)$$

Then the linear span of Es, known as the signal space, is same as spanned by the columns of A. The linear span of En, known as the noise subspace, is the orthogonal component of the signal subspace, then $En^H\times a(\theta_k,\Phi_k)=0$,k=1,2,. . .,D.

3.The Capon Method

The Capon method tries to optimize the beamforming process according to the time varying covariance matrix .The spectrum is given by

$$P_{MV} (\theta, \Phi) =1/(a^H (\theta, \Phi)R^{-1} a (\theta, \Phi)) \qquad (7)$$

The method minimizes the power contributed by the noise and signals originating from other direction the current steering direction. Because R is consisting of a signal subspace and noise subspace, then we will take only the signal subspace R_S, which is equal to

$$E_S \qquad\qquad \Lambda_S \qquad\qquad E_S \qquad (8)$$

Where Λ_S is a diagonal matrix of the signal eigenvealues, and E_S is the corresponding eigenvectors as stated in (5).This feature of selection the signal subspace can be obtained by applying the Principal Component Analysis (PCA) Neural Network which extract the principal component i.e. $\lambda_1, \lambda_2,. . . , \lambda_D$ and its corresponding eigenvectors $e_1,e_2,. . . ,e_D$ as illustrated in the next section.

The number of sources is assumed known or we can find it by AIC, or MDL [10].

4.The Neural Estimator

In the last years several papers dealing with PCA neural networks [3],[4],[5],[6],[7],[8],[11]and [12] have discussed the advantages ,problems, and difficulties of such neural network (which is shown in figure 2) .In what follow we make use of an GHA algorithm with adaptive learning rate .

Our neural estimator can be summarized in the following steps:

1) The GHA Algorithms

FOR signal samples x(n): ferom n=1 To N

(i) set error signal $e_0(n)=x(n)$

FOR every neuron: FROM j=1 To D

(2) set $w_j(0)$ randomly

(3) set η_j in accordance with input variance

FOR input samples: FROM n=1 To N

(4) $y_j(n)=x(n)^H \times w_j(n-1)$

(5) $w_j(n)= w_j(n-1)+\eta_j y_j(n)[e_{j-1}(n)-w_j(n-1) \times y_j(n)]$

IF $\mid w_j(k)- w_j(k-1) \mid < Є$ (where Є is very small value)

THEN (6) $w_j=w_j(n)$; GO TO STABLE

(7) decrease η_j exponentially

STABLE:

FOR input samples: FROM n=1 TO N

(8) set $y_j(n)=x(n)^H \times w_j$

(9) set error $e_j(n)=e_{j-1}(n)-y_j(n)w_j$

2) $w_j \longrightarrow q_j$,and $y_j \longrightarrow \sqrt{v_j}$

Where q_j are the eigenvectors corresponding to eigenvalues v_j.

3) DOA estimator, we use the modified Capon method where we take the synaptic weight as the eigenvector of the signal-subspace and the output of the PCA neural network as the squire roots of the output [7].

Then DOA are obtained as the peak location of the function according to the equation

$P_{MCapon}(\theta, \Phi) =1/(a^H(\theta, \Phi)\check{R}_S^{-1} a(\theta, \Phi))$. (9)

Where $\check{R}_S^{-1}$=inverse of $\check{R}_S$, and $\check{R}_S=\sum_{i=1}^{D}(y_j)^2 w_i w_i^H$.

5.Simulation

In our simulation we will use a uniform circular array consisting of eight sensors of radius $5\lambda/\Pi$ as shown in figure 1. Assuming two noncoherent signals with the signal to noise ratio equal to one are impinging on the array and the first source have elevation angle $\theta_1=50$,and azimuth angle $\Phi_1=30$, while the second source have elevation angle $\theta_2=60$, and azimuth angle $\Phi_2=40$.Then by the use of the GHA algorithm we will find the signal subspace, that in turn are used by Capon method to find the DOA of impending sources as shown in figure 3,4, and 5,where figure 3 show the DOA($\theta i,\Phi i$),figure 4 , show the azimuth angle only, while figure 5 show the elevation angle only, where the angle will be corresponding to the peak locations in the

spectrum of the Capon as shown in previous figures.

6. Discussion and Conclusions

This paper described a simple ,but efficient methods based on PCA Neural Network to find the DOA ,where by use of the PCA neural network we don't need to compute the correlation matrix R rather the first D eigenvectors of R are computed by the algorithm directly from the input data .the resulting computational saving can been enormous especially if the number of element M in the input vector is very large ,and the required number of the eigenvectors associated with the D largest eigenvalues of the correlation matrix R is small fraction of M..Then the DOA is achieved by incorporating the neural network with Capon method, with use of signal subspace only. Thus by the use of PCA neural network we neglect part of the noise, due to the neglecting of the noise subspace.

7.Refereneces

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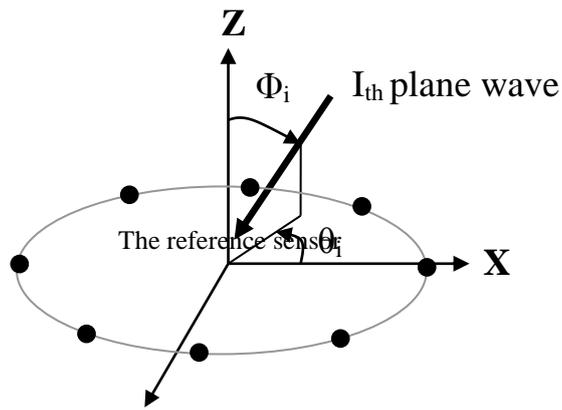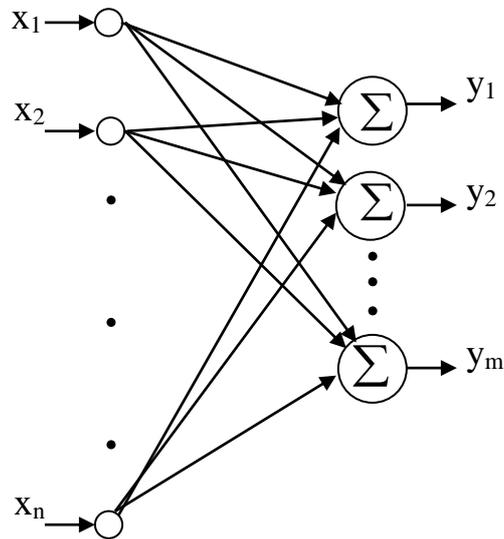
Figure 1: Uniform Circular Array
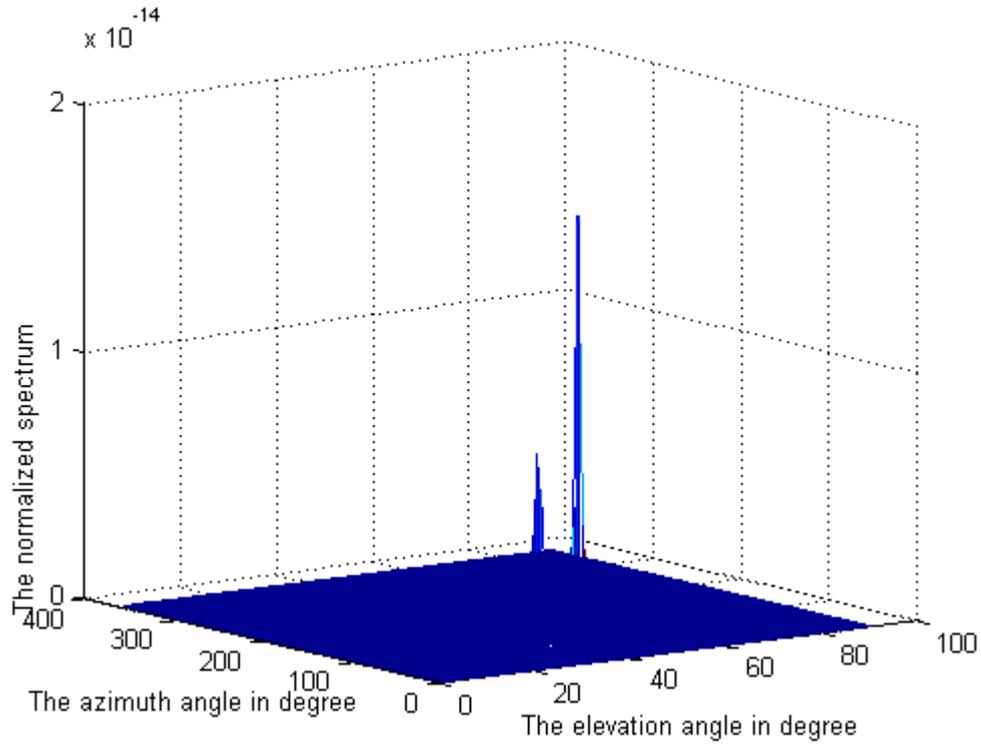

Figure 2: The PCA neural

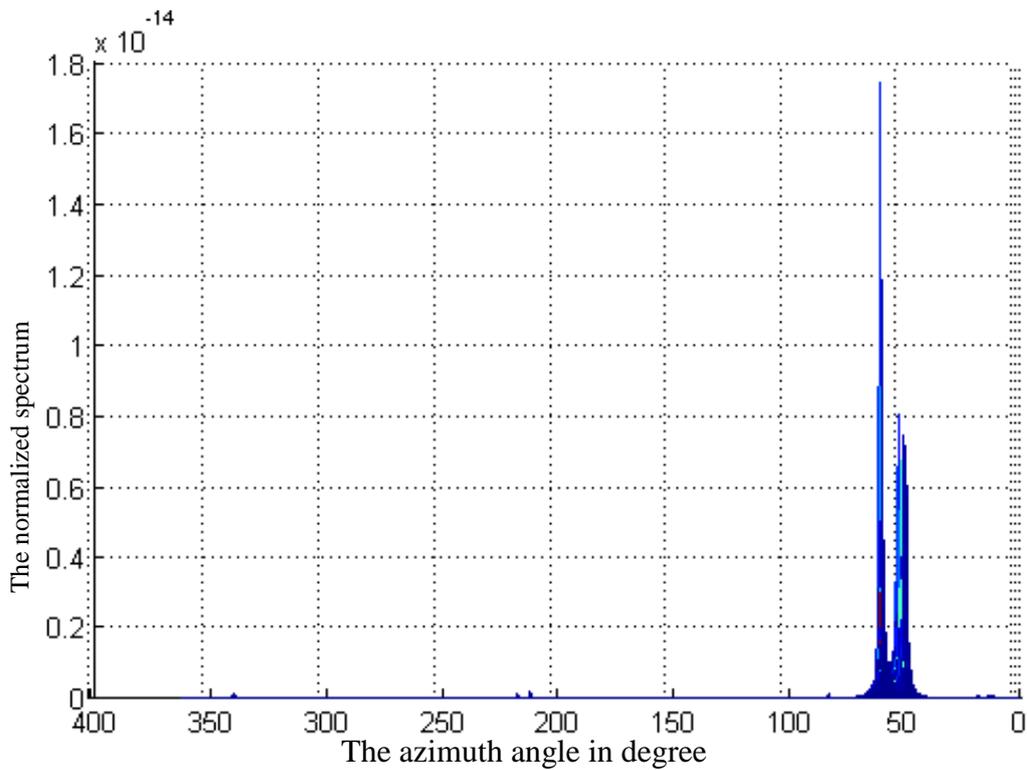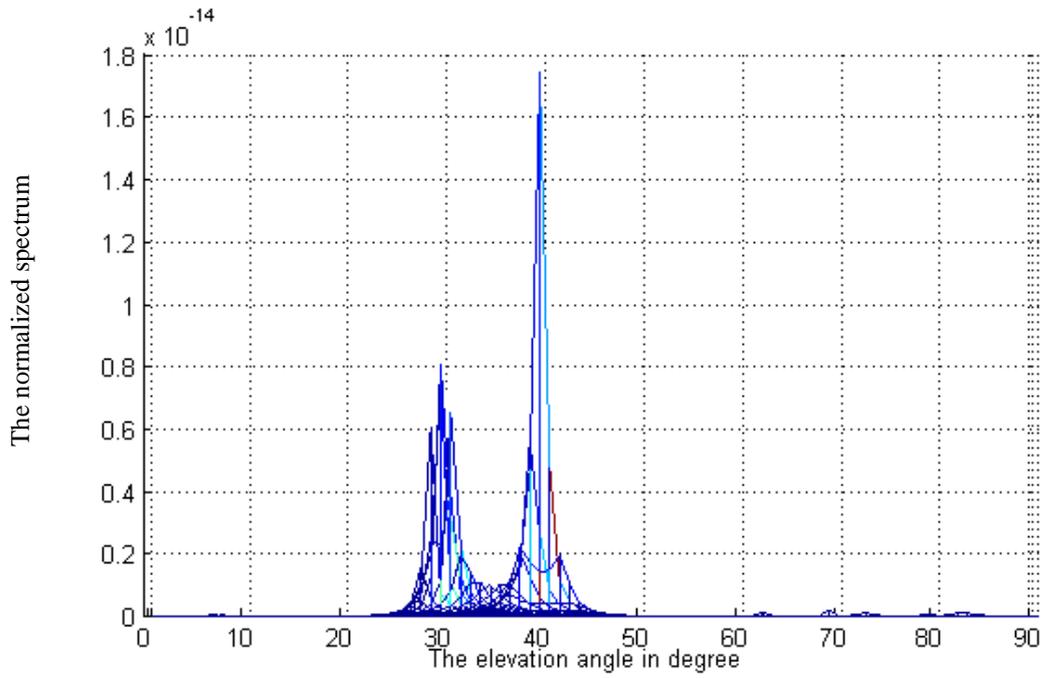**Figure 3: The DOA(θ,ϕ).**

Figure 4:The azimuth angle in degree

Figure 5:The elevation angle in degree

ايجاد الاتجاه باستخدام خوارزمية GHA مع الشبكات العصبية

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الخلاصة:
في هذا البحث تم تصميم شبكة عصبية لإيجاد زاوية الوصول . حيث استعملنا الشبكة العصبية ذات التعليم الذاتي مع خوارزمية
GHA لانتزاع المركبات الأساسية للإشارة المستلمة من قبل الهوائيات ذات الترتيب الدائري والتي بدورها تستخدم بطريقة كابون
لإيجاد زاوية الوصول . حيث ان الشبكة العصبية أل **PCA** تاخذ جزء من فضاء الاشارة (الذي بدوره يستخدم بطريقة كابون)
وتهمل فضاء الضوضاء.