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An Integrated Kernel PCA Neural Network and EGM for Number of Sources Estimation in Wireless Communication

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Abstract—The present work argues estimating number of sources in communication system using an integrated model of Principal Component Analysis (PCA) neural network and kernel method to produce Eigenvalue Grads Method (EGM). The essential advantage of this new suggested model is that, PCA neural is used to determine the covariance matrix instead of the traditional computation process which is time consuming. Simulation outcomes of this adopted model demonstrate wonderful responses through effectiveness, fast converge speed for (PCA) neural network, as well as achieving correct number of sources.

Keywords- Principal Component Analysis Neural Network, kernel Method, Eigenvalue Grads Method.

I. INTRODUCTION

Estimation number of sources is a widely attention issue in wireless communication system, Eigenvalue Grads Method (EGM) represents a universal method for estimating number of sources [1,2]. On the other hand, principal component analysis (PCA) neural network play a vital role in linear dimensionality reduction and feature extraction, and approve its effectiveness in many applications including mobile and communications system [3]. Noticeably, Researchers cannot approve that linear PCA will always able to detect all structures in a given data set. Furthermore, using suitable nonlinear features lead to extract more information. In this context, Kernel method with PCA is a magnificent new technique to extract the interested nonlinear structures of data [4,5]. Recently, integrating Kernel method with PCA neural network is an active research field to gain their full benefits. Consequently, this paper adopts an integrated Kernel and PCA neural network method to detect the number of sources in communication systems based on EGM. More specifically, this system can estimate sources number devoid of covariance matrix computing.

II. PCA NEURAL NETWORKS

Principal component analysis (PCA) can be considered as an appropriate numerically scheme for diminishing the dimensions of a measurements set in linear form even though holding information [6,7]. Figure 1 shows PCA neural networks consist of M input node and single output layer containing N neurons. PCA extraction can perform a linear transform from an M-dimension input vector

$$X = [x_1,\ \ x_{2,}\ \ x_{3,}\ \ \dots\ \ x_M]^T, \qquad (1)$$

to N -dimension (N < M) output vector can be obtained via

$$Y = [y_1,\ \ y_{2,}\ \ y_{3,}\ \ \dots\ \ y_N]^T, \qquad (2)$$

Corresponding to

$$Y = W^T X, \qquad (3)$$

In which W represents an *MxN* matrix.

Furthermore, the updating statutes for W_i *(i=1,2,3,…..,N)* can be obtained via [8]:

$$W_i(n+1) = W_i(n) + \mu y_i(n).\left[X(n) - y_i(n)W_i(n) - \sum_{j<i} y_j(n)W_j(n)\right], \quad (4)$$

In which n represents the re-iteration factor and μ represents the factor of learning rate

$$y_i(n) = W_i^T(n)\, X(n), \quad (5)$$

Up until reaching the convergence state for all neurons, subsequently, PCA contains vectors W_i which reflect the leading N eigenvectors of the input covariance matrix $R_{xx} = E[XX^H]$ and the output vector (y) components are un-correlated and contain variance equals to R_{xx} eigenvaules.

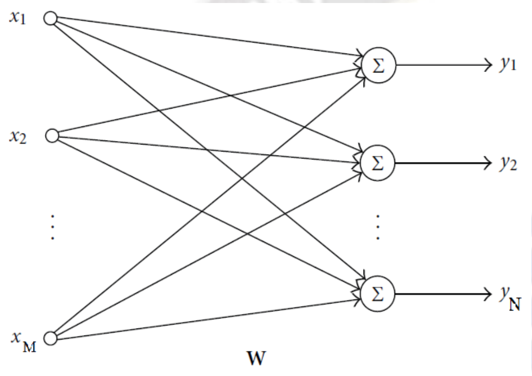

Figure 1. PCA neural networks.

III. KERNEL METHOD

In few past decades, kernel method has been anticipated and applied to solve signal processing problems and machine learning fields efficiently [9,10]. The essential concept of the kernel technique is the transformation of data S_i from an input space into vectors $\emptyset(S_i)$ of high dimension feature space. In which, the internal product could be calculated via a positive definitely kernel function that satisfy Mercer's conditions [11,12]:

$$k(S_i, S_j) = \langle \emptyset(S_i), \emptyset(S_j) \rangle. \quad (6)$$

This clear process leads to get nonlinear version for any other linear algorithm that can be defined through internal products even with no deliberating of the precise mapping $\emptyset$.

Moreover, a predominantly characteristic of the obtained feature space is its RKHS. In more particular; the distance of function $\{k(.,S) : S \in S\}$ expresses its Hilbert space function. The reproducing property of kernel algorithm represents the critical property of these steps

$$f(S) = \langle k(.\,,S),\, f\rangle,\ \forall f \in F. \quad (7)$$

More specifically, a non-linear mapping from an input space into the RKHS could be expressed as $\emptyset(S) = k(.,S)$, in which [13,14]

$$\langle \emptyset(s), \emptyset(y)\rangle = \langle k(.,s), K(.,y)\rangle = K(s,y), \quad (8)$$

and hence $\emptyset(S) = k(.,S)$ represents the kernel Hilbert space, which could be agreed as the non-linear transformation from an input into feature space.

IV. EIGENVALUE GRADS METHOD

The array model considers has q antennas, every antenna received L samples from *p* sources. The paces of this method to estimation number of sources can be summarized as follows [2]:

1: Determining auto-correlation matrix for output data y(t) through:

$$\hat{R} = \frac{1}{L}\sum_{t=1}^{L} Y(t)Y(t)^T \quad (9)$$

2: Determining eigen-decomposition for $\hat{R}$, afterwards, organizing eigenvalues through order minimizing,

$$\hat{R} = \sum_{i=1}^{q} \hat{\lambda}_i e_i e_i^T, \quad (10)$$

$\hat{\lambda}_1 \geq \hat{\lambda}_2 \geq \hat{\lambda}_3 \geq \ldots. \geq \hat{\lambda}_p \geq \hat{\lambda}_{p+1} \geq \ldots. \geq \hat{\lambda}_q$ where e_i is the corresponding eigen-vector for eigenvalue $\hat{\lambda}_i$

3: Determining average grads of all eigenvalues via

$$\Delta\bar{\lambda} = (\hat{\lambda}_1 - \hat{\lambda}_q)/(q-1) \quad (11)$$

and each grads according to

$$\Delta\lambda_j = \hat{\lambda}_1 - \hat{\lambda}_{j+1}, j = 1, \ldots., q+1, \quad (12)$$

4**:** Detecting all *j* satisfying $\Delta\lambda_j \geq \Delta\bar{\lambda}$ in order to structure the set $\{j_k\} = \{j | \Delta\lambda_j \geq \Delta\bar{\lambda}\}$,

5: Taking j_0 which represents the initial former continuous block of *j* in set $\{j_k\}$ to estimate source number $\hat{p} = j_0$-1

V. PROPOSED MODEL

More details regarding the working stages of the proposed model of estimating the number of signals in light of PCA neural network, Kernel and EGM are illustrated in Figure (2) and described as follows:

Stage 1. At this stage, data signal $(X(n))$ are received by antennas.

Stage 2. The signal $(X(n))$ is transformed into a high dimensional feature space F as $\emptyset(X(n))$.

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Stage 3. At this stage, the PCA (y) output is calculated using the equation:

$$y_i(n) = W_i^T(n)\,\emptyset(X(n)),\ \ i = 1,2,3,\dots,q \qquad (13)$$

In which q represents neurons' number and W represents weight coefficients for PCA network.

Stage 4. In this stage, the updates of the PCA neural network weights are computed in the kernel feature space according to following equations:

$$W_i(n+1) = W_i(n) + \Delta W_i(n),\ \ i = 1,2,3,\dots,q \qquad (14)$$

$$\Delta W_i(n) = \mu y_i(n).\left[\,\emptyset(X(n)) - y_i(n)W_i(n) - \sum_{j<i} y_j(n)W_j(n)\right], i = 1,2,3,\dots,q \qquad (15)$$

Stage 5. At this stage, the covariance matrix eigenvalues are determined thru multiplication to get the PCA neural network output corresponding to:

$$\hat{\lambda}_i = y_i y_i^H,\ \ i = 1,2,3,\dots,q \qquad (16)$$

In which $\hat{\lambda}$ represents the data covariance matrix eigenvalues and y represents PCA neural networks output.

Stage 6. The essential process of this stage is executing EGM process in order to estimate sources number.

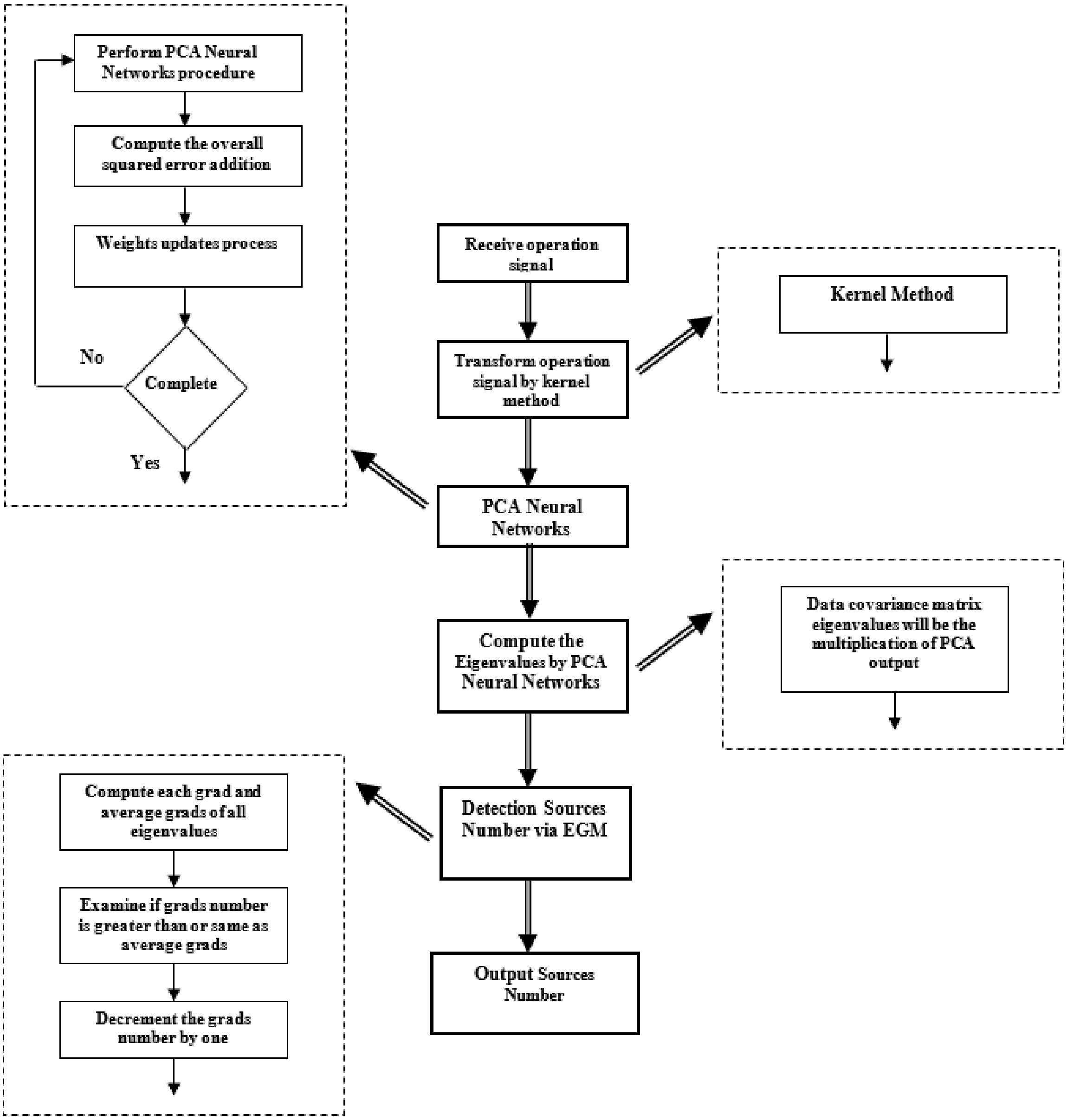

Figure 2. Proposed model block diagram

VI. SIMULATION AND RESULY EYALUTION

Computer simulation has been carried out via MATLAB 13 in order to examine the effectiveness of adopted model (sources estimation by means of an integrated kernel with PCA neural networks for EGM Method (kernel-PCA-EGM)) as compared to the traditional model (sources estimation by means of PCA neural networks for Eigenvalue Grads Method with no kernel (PCA-EGM).

For the suggested system, uniformly linear array of 14 sensors and 100 snapshots are used. Furthermore, PCA parameters' setting is single layer network with 14 neurons. While single layer network with 14 neuron and learning rate value = 0.02 are used for the classic model. Two scenarios with different sources' numbers are considered, in the first scenario, three sources are utilized, while four sources are considered in the second scenario.

In the first scenario the angles of incidence signals sources are set as 40º, 45º, and 50º having SNR=-5 dB. The suggested model kernel-PCA-EGM offer correct number of sources $\hat{p} = 3$ in the first examined scenario, as well traditional model provides true sources number of $\hat{p} = 3$. Nevertheless PCA-EGM with kernel-PCA-EGM performance is more speedy convergence than CGHA of traditional model as demonstrated in Figure (3).

In the second scenario the angles of incidence signals sources are set as 40º, 45º, 50º and 55º having SNR=-5 dB. The suggested model kernel-PCA-EGM method provide exact sources number of $\hat{p} = 4$, in contrast to traditional model which provide incorrect sources number of $\hat{p} = 3$.

Figure (4) displays the detection probability for two modes versus SNR in the second examined scenario, in which, the performance of suggested model more efficient than traditional model

VII. CONCLUSION

The present paper introduces an innovated model for calculating sources number in communication system via EGM forcing into the kernel output and PCA neural network. This given model is able to offer true estimation for number of sources through an integrated kernel and principal components (eigenvalues besides eigenvectors) which are obtained from input signals based on PCA neural network as an alternative of using covariance matrix, for that reason, covariance matrix computing is unneeded. The adopted model is more preferred in hardware implementation because of its good expandability, in addition to unneeded calculation of input covariance matrix, which is time consuming operation. The simulation outcomes prove the effectiveness and speedy convergence of this offered model. .

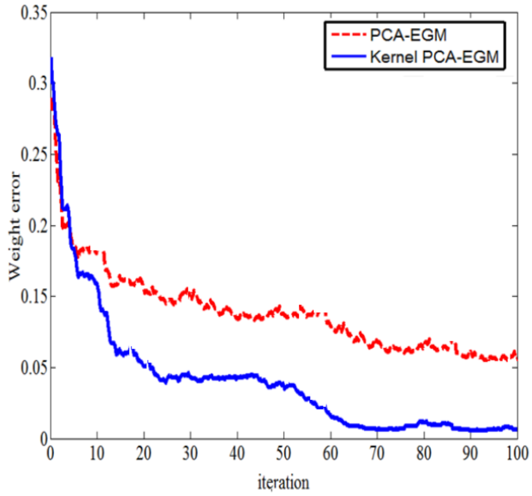

Figure 3. Curve for weight error each iteration for PCA-EMG and kernel-PCA-EMG models.

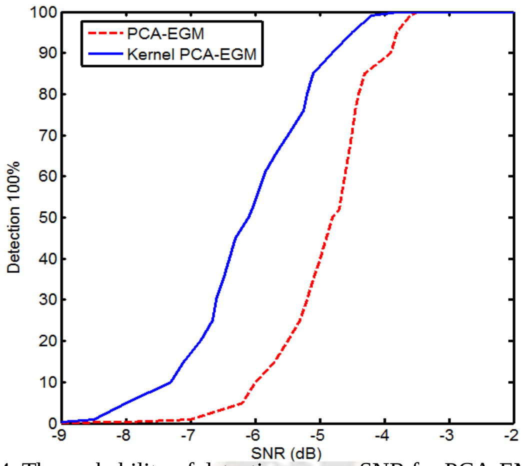

Figure 4. The probability of detection versus SNR for PCA-EMG and kernel-PCA-EMG.

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