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An Efficient Approach Combining Genetic Algorithm and Neural Networks for Eigen Value Grads Method (EGM) In Wireless Mobile Communications

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Abstract

The objective of this paper is combining Genetic Algorithm and Principal Component Analysis (PCA) neural network for Eigenvalue Grads Method (EGM) to estimate the number of sources in wireless mobile communications. The Eigenvalue Grads Method (EGM) is a popular method for estimation the number of sources impinging on an array of sensors, which is a problem of great interest in wireless mobile communications. This paper proposed a new system to estimate the number of sources by applying the output of genetic algorithm and PCA neural network with Complex Generalized Hebbian algorithm (CGHA) to EGM technique. In the proposed model, the initial weight and learning rate values for CGHA neural network can be selected automatically by using Genetic algorithm. The result of computer simulation for proposed system showed good response by fast converge speed for neural network , efficiency and yield the correct number of the sources. The important feature of new system is that, the PCA of covariance matrix are calculated based on CGHA neural network instead of determining the covariance matrix because computation of covariance matrix is time consuming.

Keywords: Principal Component Analysis (PCA) Neural Network, Complex Generalized Hebbian algorithm (CGHA), Genetic Algorithm (GA), Eigenvalue Grads Method (EGM).

الدمج الكفوء للخوارزمية الوراثية و الشبكات العصبية لطريقة EGM في اتصالات النقال اللاسلكي

الخلاصة

إن الهدف الأساسي من هذا العمل هو مزج الخوارزمية الوراثية و عناصر المركبات الأساسية العصبية (PCA) في تقنية (EGM) لتخمين عدد المصادر في الاتصالات اللاسلكية. إن طريقة (EGM)هي طريقة معروفة لتخمين عدد المصادر الساقطة على مصفوفة المتحسسات والتي هي مهمة جدا في الاتصالات اللاسلكية. هذا البحث اقترح نظام جديد لتخمين عدد المصادر بواسطة تسليط ناتج الخوارزمية الوراثية وإخراج الشبكة العصبية *PCA* مع خوارزمية (CGHA) على تقنية (EGM). في هذا النظام المقترح، قيم الأوزان الأولية وعامل معدل التعلم للشبكة العصبية تنتقي أليا بواسطة الخوارزمية الوراثية. نتائج المحاكاة الحاسوبية للنظام المقترح تبين إن النظام المقترح امثل بواسطة زيادة سرعة الاقتراب للشبكة العصبية ، نظام كفؤ و يستطيع تخمين عدد المصادر بصورة صحيحة. فائدة هذا النظام الجديد يتمثل في عدم الحاجة لحساب مصفوفة التغاير لان المركبات الأساسية للمصفوفة المتغايرة تحسب بواسطة الشبكة العصبية CGHA من الإشارة المستلمة حيث ان حساب مصفوفة التغاير يستهلك وقت.

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1. Introduction

Adaptive signal processing sensor arrays have been widely adopted in mobile systems because of their ability to estimate the number of sources with the use of EGM estimation technique. Adaptive antenna arrays also improve the performance of cellular systems by providing robustness against channels and reduced collateral interference [1]. Eigenvalue Grads Method (EGM) [2] is a popular method for estimation the number of sources impinging on an array of sensors. The Principal Component Analysis (PCA) neural network [3-4] is widely used in applications ranging from neuroscience to signal processing to extract relevant information from high dimensional data sets. The PCA neural network has been found very useful for extracting the most representative low dimensional subspace from a high dimensional vector space. Performing the Principal Component Analysis (PCA) of a stationary multivariate random process means computing the eigenvectors of its covariance matrix corresponding to the largest eigenvalues, and the projection of the samples of the multivariate process on the eigenvectors to obtain a number of principal components [5]. The PCA neural network is lacking in objective methods for determining the initial connection weight, thus lead to the difficulty in selecting the global initial point. Therefore, the possibility of Obtaining the global optimal solution is lower. Genetic Algorithm (GA) [6] is a global probability search algorithm, which emulates the biological evolution process of Darwin's genetic selection and natural elimination. It possesses self-adaptability, global optimization, and implicit parallelism, manifesting the strong capability in solving problems [7]. At present, combining genetic algorithm and neural network to make full use of their advantages is an active research field. In this paper, based on genetic algorithm and PCA (principal components) neural network, a new system is proposed to detect the number of sources using EGM. The system can estimate the number of sources without computing the covariance matrix

2. PCA Neural Networks with Genetic Algorithms Optimization

PCA neural networks and genetic algorithms are both inspired by computation in biological systems. A good deal of biological neural parameters are determined genetically. It is therefore not surprising that as some neural network researchers explored how neural system are organized that the idea of evolving neural parameters should arise. Genetic algorithms have been used in conjunction with neural network by find a set of initial weights and learning rate values for neural network

2.1 PCA Neural Network with CGHA Algorithm

Principal component analysis is a useful statistical tool for linearly reducing the dimensionality of a set of measurements while retaining as much information as possible. This is accomplished by a linear mapping from the input space to a lower dimensional representation space. Mathematically, principal component extraction carries out a linear transform from an N-dimensional zero-mean input vector space

$$X = [x_1 \quad x_2 \quad \dots \quad x_N]^T \qquad (1)$$

to an M-dimensional $(M < N)$ output vector space

$$Y = [y_1 \quad y_2 \quad \dots \quad y_M]^T \qquad (2)$$

and is related to by

$$Y = W^H X \qquad (3)$$

where W is an $N \times M$ matrix and its columns are the eigenvectors associated with the largest M eigenvalues of the input correlation matrix $R_{XX} = E[XX^H], T$ denotes transpose and H denotes conjugate transpose. The eigenvectors associated with the largest eigenvalues are called principal eigenvectors. Elements of vector are called Y principal components. With $M < N$, the dimensionality of the input vector space is reduced. An N-dimensional "data space" is compressed into an M-dimensional "feature space". Snager proposed the Generalized Hebbian Algorithm (GHA), a multiple-component method capable of extracting the rest of the eigenvectors. In many scenarios such as sensor array processing, the complex version of GHA (CGHA) is need inorder to utilize the narrowband phase-shift relationship between

Receptions of different sensors [8]. The mechanism of CGHA can be summarized in the following.

The input column vector is

$$X = [x_1 \quad x_2 \quad \dots \quad x_N]^T \qquad (4)$$

In the decreasing order of eigenvalues, the principal eigenvectors of the input correlation matrix are expressed as the following column vectors:

$$W_1 = [w_{11} \quad w_{12} \quad \dots \quad w_{1N}]^T$$

$$W_2 = [w_{21} \quad w_{22} \quad \dots \quad w_{2N}]^T$$

$$\dots$$

$$W_M = [w_{M1} \quad w_{M2} \quad \dots \quad w_{MN}]^T \qquad (5)$$

In CGHA, the initial value of $W_j \,(j = 1,2,\dots,M)$ can be randomly set. The updating rule for W_j is

$$W_j(n+1) = W_j(n) + h\,conj[y_i(n)]^* \, [X(n) - y_j(n)W_j(n) - \sum_{i<j} y_i(n)W_i(n)] \qquad (6)$$

Where n is the iteration index and

$$y_j(n) = W_j^T(n)X(n) \qquad (7)$$

and h is the learning rate factor. The vectors $W_1 \quad W_2 \quad \dots \quad W_M$ are considered as the first m eigenvectors of the covariance matrix R_{XX} and the elements of the output vector (y) are uncorrelated and have variance equal to the eigenvaules of the covariance matrix R_{XX} [9]. The output Y can be used to reconstruct the input X by a reversible PCA neural network, X reconstruction formation is $\tilde{X} = W^T Y$.

The construction square error *e* is [10]

$$\|e\|^2 = \|X - \tilde{X}\| = \|X - W^T Y\|^2 \qquad (8)$$

The CGHA can be implemented by a single-layer linear neural network, as shown in Figure 1. Each block is a linear neuron. The CGHA neural network has the following features [8]:

1. No need to compute the correlation matrix R_{XX} in

advance. The eigenvectors and eigenvalues are derived (learned) directly from the input vector. In sensor array processing, when the number of sensors is large, this advantage becomes significant because computation of R_{XX} is time consuming.

2. Implementation with local operation. This feature is favorable for parallel hardware.
3. Good expandability. Updating of the jth neuron is affected only by those neurons with number less than j.

2.2 Genetic Algorithm (GA)

The parameters which need to be searched by GA in the training are the range of initial weights (R) and initial values of learning rate. The initial weights are generated using a uniform random number generator in the range [-R,R]. The GA proposed as searching process based on the laws of the natural selection and genetics. This algorithm which is used firstly to obtain the optimal values of the initial weights and the initial value of learning rate top-level description of a simple GA is shown below [11]:

a. Randomly generate an initial population $P^0 = \left(a_1^0,\ a_2^0,\ ....,\ a_m^0\right)$

b. Compute the fitness $f\left(a_i^t\right)$ of each chromosome a_i^t in the current population p^t.

c. Create new chromosome P^{1t} of mating current chromosomes, applying mutation and recombination as the parent chromosomes mate.

d. Delete numbers of the population to make room for new chromosomes.

e. Compute the fitness of $f\left(a_i^{1t}\right)$, and insert these into population.

f. Increment number of generation, if not (end-test) go to step c, or else stop return the best chromosome.

3. EGM principle

The array model assumes the presence of M sources impinging on an L-channel array according to [12]

$$Y = AS + Z \qquad (9)$$

where $Y \in \Re^{L\times N}$ denotes the multichannel observations in the sampled time interval $t = nT$, where n is an integer, $A \in \Re^{L\times M}$ denotes the mixing (steering) matrix, $S = \Re^{M\times N}$ denotes the source signal matrix, and $Z = \Re^{M\times N}$ denotes an additive Gaussian noise component with nontrivial temporal and spatial covariance matrices. It will be assumed the number of sensors L is lager than the number of emitting sources M, i.e., $M \le L$ .The covariance matrices of the data vector (Y) would then be

$$R = E[YY^T] \quad (10)$$

In practice, because of the limitation of the data length and the influence of noise, we can only get an estimation $\hat{R}$ of the real R by [13]

$$\hat{R} = \frac{1}{N}\sum_{t=1}^{N} Y(t)Y(t)^T = \sum_{k=1}^{L} \hat{l}_k\, e_k\, \hat{e}_k \qquad (11)$$

Then the eigenvalues are $\hat{l}_k (k = 1,...,L)$. These eigenvalues will not display that good quality, but $\hat{l}_1 \ge \hat{l}_2 \ge ......\ge \hat{l}_M \ge \hat{l}_{M+1} \ge ......\ge \hat{l}_L$ instead. The remaining L-M eigenvalues are no longer equal to zero and the corresponding L-M eigenvectors span the noise subspace. When the noise is cross correlated with the signal of interest, $\boldsymbol{R_Y}$ can be expressed as [14]

$$R_Y = AR_S A^T + R_Z + AR_{SZ} + R_{ZS} A^T \quad (12)$$

where R_s is the autocorrelation of signal, R_z is the autocorrelation of noise, R_{sz} is the crosscorrelation between the signal and noise and R_{ZS} is the crosscorrelation between the noise and signal. The presence of the cross covariance terms shrinks the separation distance that should be observed to determine the subset of eigenvalues belonging to the signal subspace because of the mutual correlation of the sample eigenvalues, making it practically impossible to determine M. In good SNR conditions, the separation between the signal and noise subspaces is easily obtained. In low SNR conditions, this separation does not yield easily and the source detection problem amounts to the test to determine the multiplicity of the smallest L-M eigenvalues using the Eigenvalue Grads Method (EGM) [2]. The algorithm of Eigenvalue Grads Method (EGM):

Step 1: Calculate the auto-correlation matrix of the output data y (t) of the array by $\hat{R} = \frac{1}{N}\sum_{t=1}^{N} Y(t)Y(t)^T$

Step 2: Calculate the eigen-decomposition of $\hat{R}$, and arrange the eigenvalues by decrease order, $\hat{R} = \sum_{k=1}^{L} \hat{l}_k e_k e_k^T$, $\hat{l}_1 \geq \hat{l}_2 \geq ...... \geq \hat{l}_M \geq \hat{l}_{M+1} \geq ...... \geq \hat{l}_L$, e_k, is the corresponding eigen-vector of eigenvalue $\hat{l}_k$

Step 3: Calculate the average grads of all those eigenvalues by $\Delta \bar{l} = (\hat{l}_1 - \hat{l}_L)/(L-1)$ and each grads by $\Delta l_i = \hat{l}_i - \hat{l}_{i+1}, i = 1,......, L-1$;

Step 4: Find all the *i* satisfying $\Delta l_i \leq \Delta \bar{l}$ to construct the set $\{i_k\} = \{i | \ \Delta l_i \leq \Delta \bar{l}\}$;

Step 5: Take the i_0 that is the first one of the last continuous block of *i* in the set **{**i_k**}**, and the estimated signal number $\hat{M} = i_0 - 1$

4. Proposed Model

The proposed system for EGM technique based on genetic algorithm and PCA neural network with CGHA algorithm is shown in Figure (2). The main procedure of the system is described as follow:

First Stage

In this stage, generation of data (signal (*X*))

Second Stage

This stage using genetic algorithm with the feed-forward step uses stage to accelerate the whole learning process. The genetic algorithm performs global search and seeks near-optimal initial point for the third stage. Where, each chromosome is used to encode the weights and learning rate of CGHA neural network. The fitness (objective) function for genetic algorithm is defined as the total sum squared system error of the corresponding CGHA neural network. Therefore, it becomes an unconstrained optimization problem to find a set of decision variables by minimizing the objective function. The best fitness function value in a population is defined as smallest value of the objective in the current population.

Third Stage

In this stage, set the best chromosome as the initial weight vector and learning rate, set up the topologic structure of neural network, compute the output of the CGHA neural network (y) according to following equation

$$y_j(n) = W_j^T(n)X(n), \quad j = 1,2,\ldots,P \qquad (13)$$

Where P is the number of neurons and W is weight coefficients of CGHA neural network. Compute the updates the weight according to following equation

$$W_j(n+1) = W_j(n) + \Delta W_j(n) \qquad (14)$$

$$\Delta W_j(n) = h conj[y_j(n)].[X(n) - y(n)W_j(n) - \sum_{i<j} y_i(n)W_i(n)], \qquad (15)$$
$$j = 1,2,\ldots.,P$$

Fourth Stage

This stage calculate the eigenvalues of data covariance matrix by conjugate multiplication of the output of CGHA neural network according to following equation

$$\hat{l}_j = y_j y_j^H, \quad j = 1,2,\ldots,P \qquad (16)$$

Where $\hat{l}$ is eigenvalues of data covariance matrix and y is the output of CGHA neural network

Fifth Stage and Sixth Stage

The main procedure of the stages is described as following steps

- Calculate the average grads of all those eigenvalues according to following equation

$$\Delta \bar{l} = (\hat{l}_1 - \hat{l}_L)/(P-1), \qquad (17)$$

and each grads following equation

$$\Delta l_i = \hat{l}_i - \hat{l}_{i+1}, i = 1,\ldots\ldots, P-1 \qquad (18)$$

- Find all the i satisfying $\Delta l_i \le \Delta \bar{l}$ to construct the set $\{i_k\} = \{i \mid \Delta l_i \le \Delta \bar{l}\}$;

- Take the i_0 that is the first one of the last continuous block of *i* in the set $\{ i_k \}$

- The number of sources is taken to the value of $\hat{M} = i_0 - 1$

5. Simulation and Result Evaluation

Computer simulations have been carried out to examine the effectiveness of the proposed system. A uniformly linear array with 16 sensors is employed. Each number detection result is carried out based on 100 snapshots. In section, we compare the performance of proposed system (estimation of sources by using Genetic Algorithm and CGHA neural network for Eigenvalue Grads Method (GA-CGHA-EGM)) with classic system (estimation of sources by using CGHA neural network for Eigenvalue Grads Method without using Genetic Algorithm (CGHA-EGM)). The proposed algorithm is build by MATLAB 7. In proposed system, Parameter settings for the genetic algorithm are mutation rate=0.05, crossover rate=0.65, population size=20 and real coding to the chromosomes, CGHA neural network is setup as follow: single layer network with 16 neurons, initial weights and learning rate values can be selected automatically by using Genetic Algorithm. In classic system, CGHA neural network is setup as follows: single layer network with 16 neurons and learning rate value = 0.015. We consider two cases with different number of sources. In first case, two sources are consider with SNR=13 dB, the first source is at 40^o while the second source is at 50^o. In this case, the proposed system give correct number of sources $\hat{M}$ =2 and also the classic system give correct number of sources $\hat{M}$ =2 but the response of CGHA with proposed system is faster in speed convergence than the response of CGHA with classic system as shown in figure 3. The weight coefficients error curves versus iteration for first three neurons is shown only in figure 3, because the output of first three neurons represented the first three large of eigenvalues. Figure 4 shown the comparison between the square error of the CGHA with proposed system and CGHA with classic system. In second case, three sources are considered with SNR=13 dB, the first source is at 40^o, the second source is at 50^o and third case at 65^o. In this case, the proposed system give correct number of sources $\hat{M}$ =3 but the classic system give incorrect number of sources $\hat{M}$ =2. The detection probability for two systems versus SNR in second case is shown in figure 5. The figure shows that, the proposed system (GA-CGHA-EGM) provides almost same detection probability performance as original EGM, much better than classic system (CGHA-EGM).

6. Conclusions

In this paper, a new system has been introduced to determine the number of source for wireless mobile communication by applying EGM to the output of genetic algorithm and CGHA neural network. The proposed method based on optimizing the connection weight and learning rate of CGHA neural network can solve the problems of the randomicity of initial weight values and learning rate of the CGHA neural network. The proposed method can give precise estimation for the number of sources based on genetic algorithm and the principal components (eigenvaules and eigenvectors) which are determined from the input signals based on CGHA neural network instead of using covariance matrix, therefore no need to compute the covariance matrix. The proposed method suitable for hardware implementation because it no need to determine the input covariance matrix, the computation of covariance matrix is time consuming, and good expandability. The result of computer simulation for proposed system showed, fast converge speed for CGHA neural network , efficiency and it has almost same detection probability with original EGM method.

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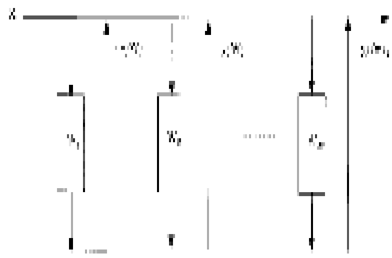

Figure (1): Implementation network for CGHA

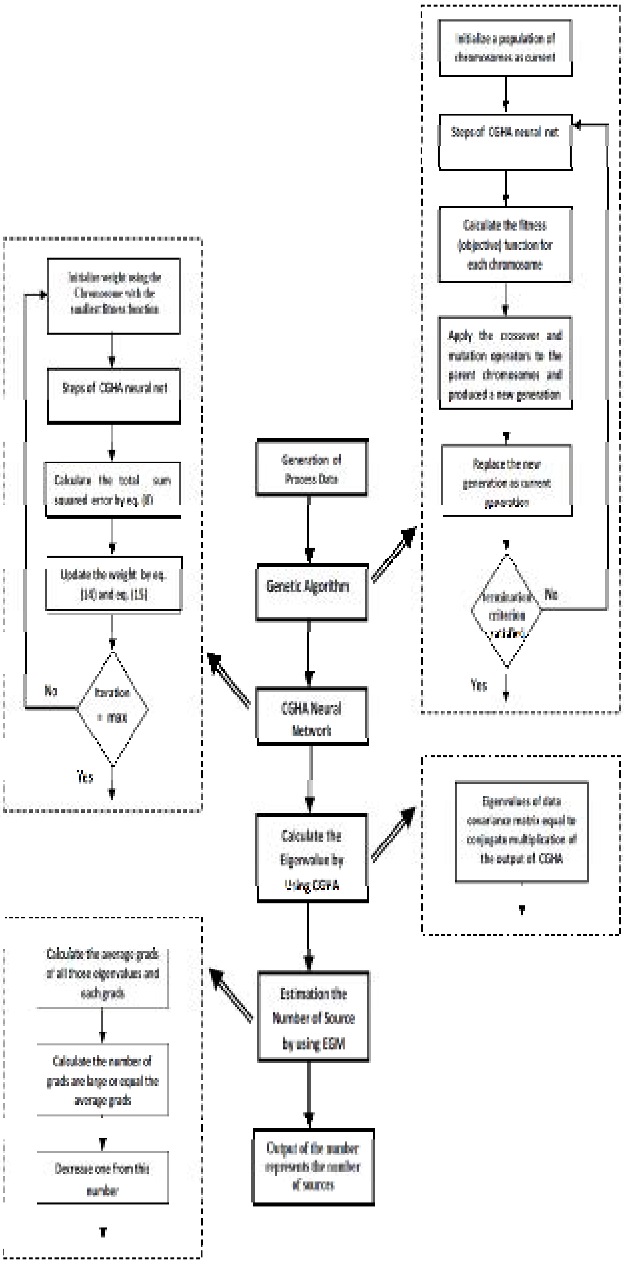

Figure 2: Flowchart of the Proposed Model

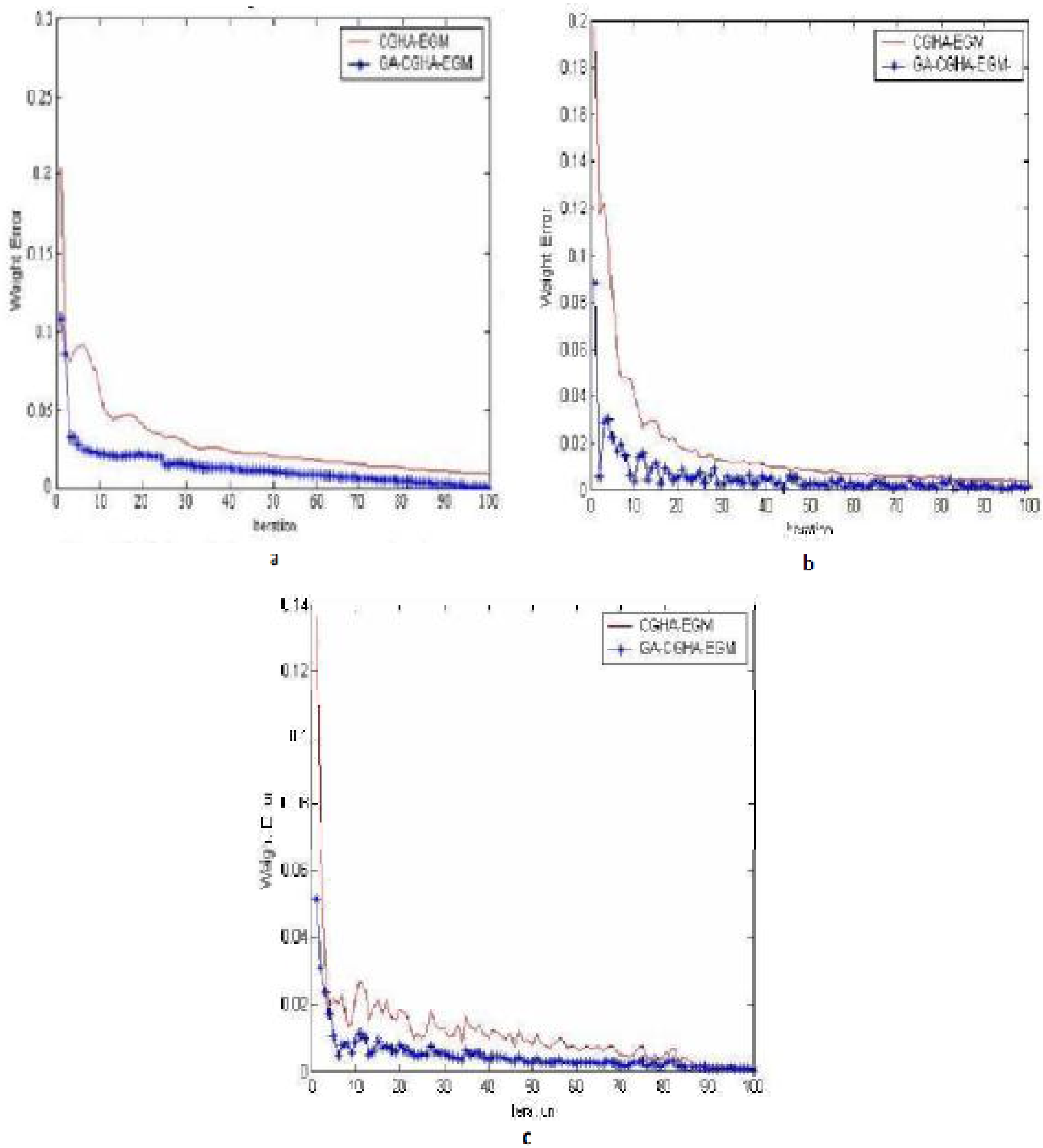

Figure (3): Weight coefficients error curves versus iteration for first three neurons. (A) First neuron (b) second neuron (c) third neuron

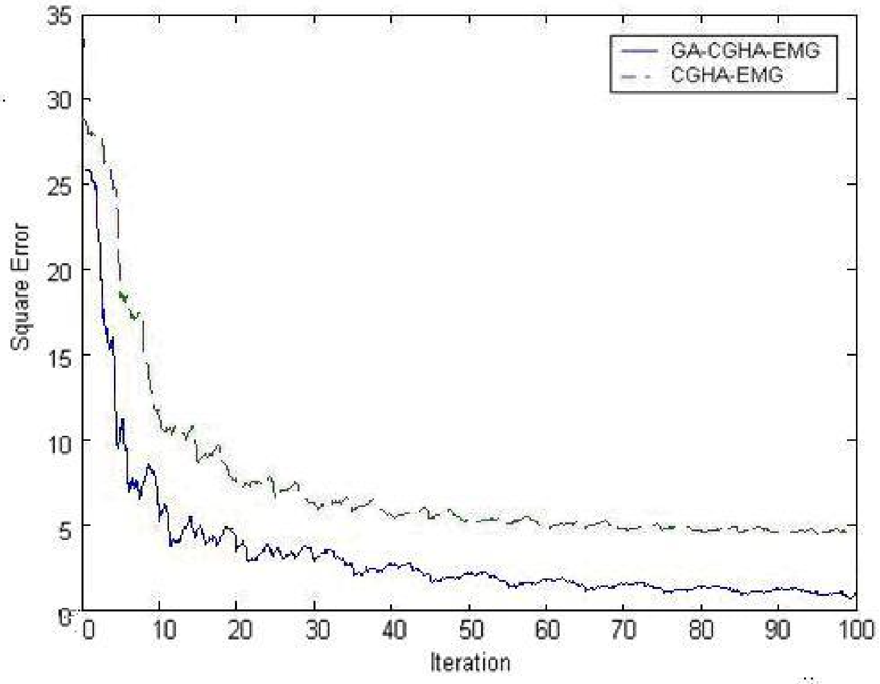

Figure (4): Comparison of square error for the CGHA-EGM and GA-CGHA-EGM

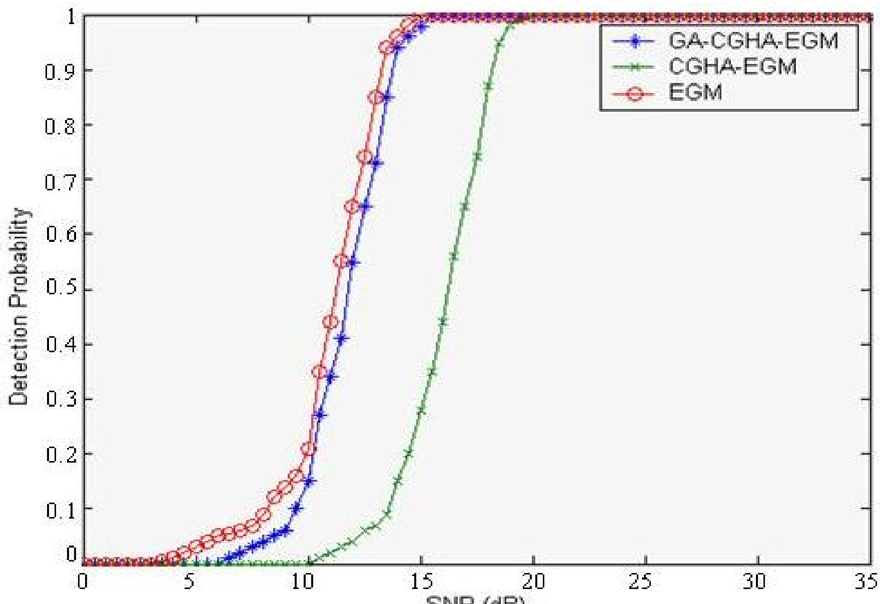

Figure (5): Probability Detection comparison for EGM, CGHA-EGM and GA-CGHA-EGM methods