Number of sources estimation using a hybrid algorithm for smart antenna

Mohammed Hussein Miry[1], Atheer A. Sabri[1], Ali Hussien Mary[2]
[1]Department of Communication Engineering, University of Technology-Iraq, Baghdad, Iraq
[2]Department of Mechatronics Engineering, Al-Khwarizmy College, University of Baghdad, Baghdad, Iraq

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ABSTRACT

The number of sources estimation is one of the vital key technologies in smart antenna. The current paper adopts a new system that employs a hybrid algorithm of artificial bee colony (ABC) and complex generalized Hebbian (CGHA) neural network to Bayesian information criterion (BIC) technique, aiming to enhance the accuracy of number of sources estimation. The advantage of the new system is that no need to compute the covariance matrix, since its principal eigenvalues are computed using the CGHA neural network for the received signals. Moreover, the proposed system can optimize the training condition of the CGHA neural network, therefore it can overcome the random selection of initial weights and learning rate, which evades network oscillation and trapping into local solution. Simulation results of the offered system show good responses through reducing the required time to train the CGHA neural network, fast converge speed, effectiveness, in addition to achieving the correct number of sources.

Corresponding Author:

Mohammed Hussein Miry
Department of Communication Engineering, University of Technology-Iraq
Baghdad, Iraq
Email: Mohammed.H.Miry@uotechnology.edu.iq

1. INTRODUCTION

Smart antenna techniques have taken a lot of effort during recent decades; they present one of the most important techniques that support the coming fifth-generation (5G) of wireless communication [1]–[4]. However, number of signal sources estimations is an important issue in these techniques. A public method for estimating the number of sources that imposing on multiple sensors is Bayesian information criterion (BIC) [5]–[8], this method needs covariance matrix calculation, the calculation operation costs significant time during estimation number of sources. On the other hand, complex generalized Hebbian (CGHA) neural network [9], [10] is commonly used for signal processing. Furthermore, it used as dimensional reduction, CGHA network projects the input data from the original p-dimensional vector space to q-dimensional output space, where typically $q < p$ dimensionality reduction is performed; the output vector retains most of the essential information that is resident in the input vector. Moreover, it could be used to extract the eigenvalues and its corresponding eigenvectors form the covariance matrix. However, CGHA neural network has to lack in a condition of initial connections weights determining, leading to difficulty in specifying the initial global point, accordingly, probability of acquiring the optimal global solutions is lesser. In this context, artificial bee colony (ABC) algorithm has proven its efficiency and accuracy in optimization with only a few control parameters as compared with other common optimization techniques [11]–[13]. In light of this, depending on ABC optimization and CGHA network, a new system is suggested in the present paper to estimate the number of sources using BIC without need computing their covariance matrix.

2. BIC PRINCIPLE

The array model assumes with m antennas, each antenna gathering n received samples from k sources. These samples are arranged in a matrix $S \in C^{k\times n}$. Let $H \in C^{m\times k}$ is the channel matrix accompanied by the elements $\{h_{ij}\}$, where $i = 1, 2, \ldots, m$ and $j = 1, 2, \ldots, k$, that represent the channel gains concerning j-th source and i-th sensor. Lastly, assume $V \in C^{m\times n}$ is the matrix of the additive Gaussian noise. Then the matrix of the received samples will be [14], [15]:

$$X = HS + V \tag{1}$$

it can suppose that ($k \le m$). Then covariance matrices of data vector (X) is [16]–[18].

$$R = E[XX^{\dagger}] \tag{2}$$

In practice, the accurate covariance matrices cannot be gotten due to the finite snapshots data, only the estimation $\hat{R}$ of real R can obtained according to (3).

$$\hat{R} = \frac{1}{n}\, X\, X^{\dagger} = \sum_{i=1}^{m} \hat{\lambda}_i\, \hat{u}_i \hat{u}_i^H \tag{3}$$

Where † means complex conjugate and transpose, $\hat{\lambda}_i, i = 1, \ldots, m$ are the eigenvalues and $\hat{u}_i, i = 1, \ldots., m$ are the corresponding eigenvectors. The eigenvalues are sorted descendant as: $\hat{\lambda}_1 \ge \hat{\lambda}_2 \ge \ldots. \ge \hat{\lambda}_k \ge \hat{\lambda}_{k+1} = \ldots\ldots = \hat{\lambda}_m$, where $\hat{\lambda}_1, \hat{\lambda}_2, \ldots\ldots, \hat{\lambda}_k$ are the eigenvalues corresponding to the sources, and $\hat{\lambda}_{k+1}, \ldots\ldots, \hat{\lambda}_m$, are the eigenvalues corresponding to the noise [19], [20].

The BIC method uses the previously statistical derivations if the estimated eigenvalues are given, in order to detect number of sources. BIC estimation function can be shown [21], [22]:

$$BIC(i) = -2n(m-i)log\left(\frac{\prod_{j=1+i}^{m} \lambda_j^{\frac{1}{m-i}}}{\frac{1}{m-i}\sum_{j=i+1}^{m} \lambda_j}\right) + [i(2m-i)+1]logn\ for\ i = 0,1,2,\ldots,m-1 \tag{4}$$

where λ_j denote the eigenvalues of $\hat{R}$. The number of sources is the value of i, which minimizes the cost function in (4).

3. CGHA NEURAL NETWORK

The complex generalized Hebbian algorithm (CGHA) is a way that applied in extracting the rest of the eigenvectors. The model has q dimensional output vector:

$$Y = [y_1, \ldots, y_q]$$

and m dimensional input vector.

$$X = [x_1, \ldots., x_m]$$

There is only feed forward connection between input and output which is a linear function of the input (consider) the feed forward network shown in Figure 1. For the n-th complex vector $X(n)$ that offered to CGHA network, the complex output value $y_i(n)$ of neuron (j) is obtained by [10].

$$y_j(n) = \sum_{i=1}^{m} w_{ji}^{*}(n) x_i(n) \quad j = 1,2, \ldots \ldots, q \tag{5}$$

Where $w_{ji}(n)$ denotes the complex weight of the synapse which joins the (i-th) input node to the (j-th) output neuron at iteration (n) and "*" represent the complex conjugate operator. The initial value of synapse weight can be arbitrarily set.

The synapse weight vector $w_{ji}(n)$ is updated according to [23].

$$w_{ji}(n+1) = w_{ji}(n) + \Delta w_{ji}(n)$$
$$= w_{ji}(n) + \eta conj[y_i(n)].[x_i(n)y_i(n)w_{ji}(n) - \sum_{h=1}^{j} w_{hi}(n)y_h(n)]$$
$$i = 1,2, \dots, m \text{ and } j = 1,2, \dots, q \quad (6)$$

Where η is the learning rate parameter. The components of Y vector are usually ordered according to decreasing variance. The vectors $W_1, \dots \dots, W_q$ present the first q eigenvectors of the covariance matrix R_{xx}, such that $W_1 = [w_{11}, \dots, w_{1m}]^T$ corresponds to the largest eigenvalue (λ_1) of R_{xx}, $W_2 = [w_{21}, \dots, w_{2m}]^T$ corresponds to next-largest eigenvalue (λ_2) and $W_q = [w_{q1}, \dots, w_{qm}]^T$ corresponds to the smallest eigenvalue (λ_q). Output vector Y elements are uncorrelated and their variance is equal to covariance matrix R_{xx} eigenvalues. Whereas eigenvectors that related to the largest eigenvalues represent the principal eigenvectors. While Y vector elements represent the principal components.

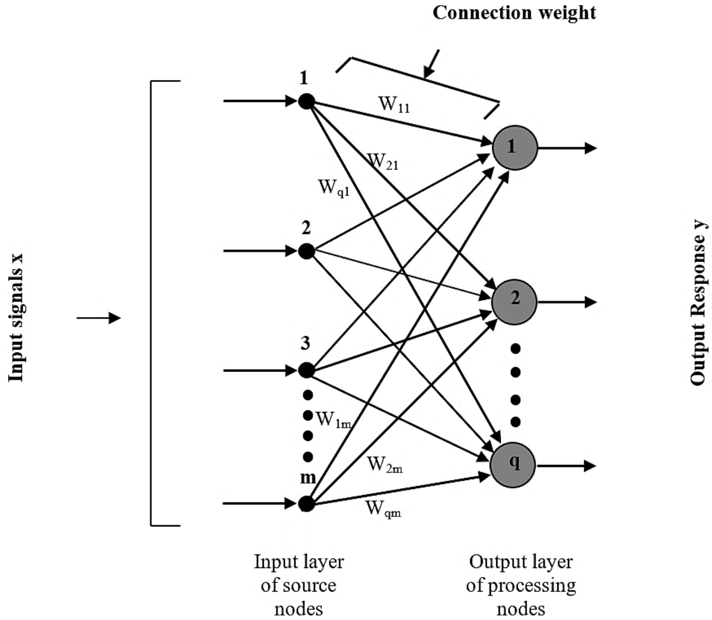

Figure 1. The CGHA neural network architecture

4. ARTIFICIAL BEE COLONY OPTIMIZATION

ABC optimization [24]–[26] represents one of the warmest swarm intelligent based schemes, which is introduced to simulate the foraging behavior of honey bee colonies. The construction of ABC optimization procedure is generally encompassing three collections of artificial bees; which are employed, onlooker, and scout bees. Each individual employed bee is linked to a food source (possible solution) in the population, and shares its location information besides the fitness cost with onlooker bees for further treatment; which will responsible to determine the most suitable solution in related to the process of probability selection. When the given solution does not get better for a predefined number of attempts (limit parameter value), the solution is abandoned and its relative employed bee transmutes into a scout bee. In more particulars:

- Initialization phase: In this phase, a random population of solutions for initialization is generated. Afterward, the fitness functions for these initial solutions are evaluated.
- Employed bee phase: Neighborhood search around previous solutions to find new solutions. Subsequently, a greedy selection between them, depending on their fitness evaluation values is performed.
- Onlooker bee phase: After probability calculation for each solution according to its fitness value, onlooker bees choose the solution that has the maximum probability assessment. Afterward, likewise the mechanisms of solution amendment and greedy selection are performed to keep the better solutions.
- Scout bee phase: The solution that has not been improved after the limit value of endeavors is abandoned, and its corresponding employee becomes a scout that generates a new random solution. The optimal output is acquired from the best obtained solution after repeating the above three phases for a predetermined maximum number of cycles.

5. PROPOSED MODEL

The main procedure of the proposed system for the BIC technique based on ABC and CGHA neural network is explained below, and shown in Figure 2.

- Stage one: in this stage, signal $x(t)$ is received by antennas.
- Stage two: this stage employs ABC algorithm to speed up the entire learning process. The ABC optimization achieves the optimal initial points that used in the third stage. However, every food source is utilized for encoding weights besides CGHA network learning rate. Where the total sum squared system error is taken as the objective function.
- Stage three: in the current stage, the best food source is utilized to set the initial weights besides learning rate for the CGHA network, resulting in compute the actual output of the feed-forward CGHA network, compute the output (y) and weight coefficients W for the CGHA network by using (5) and (6) respectively.

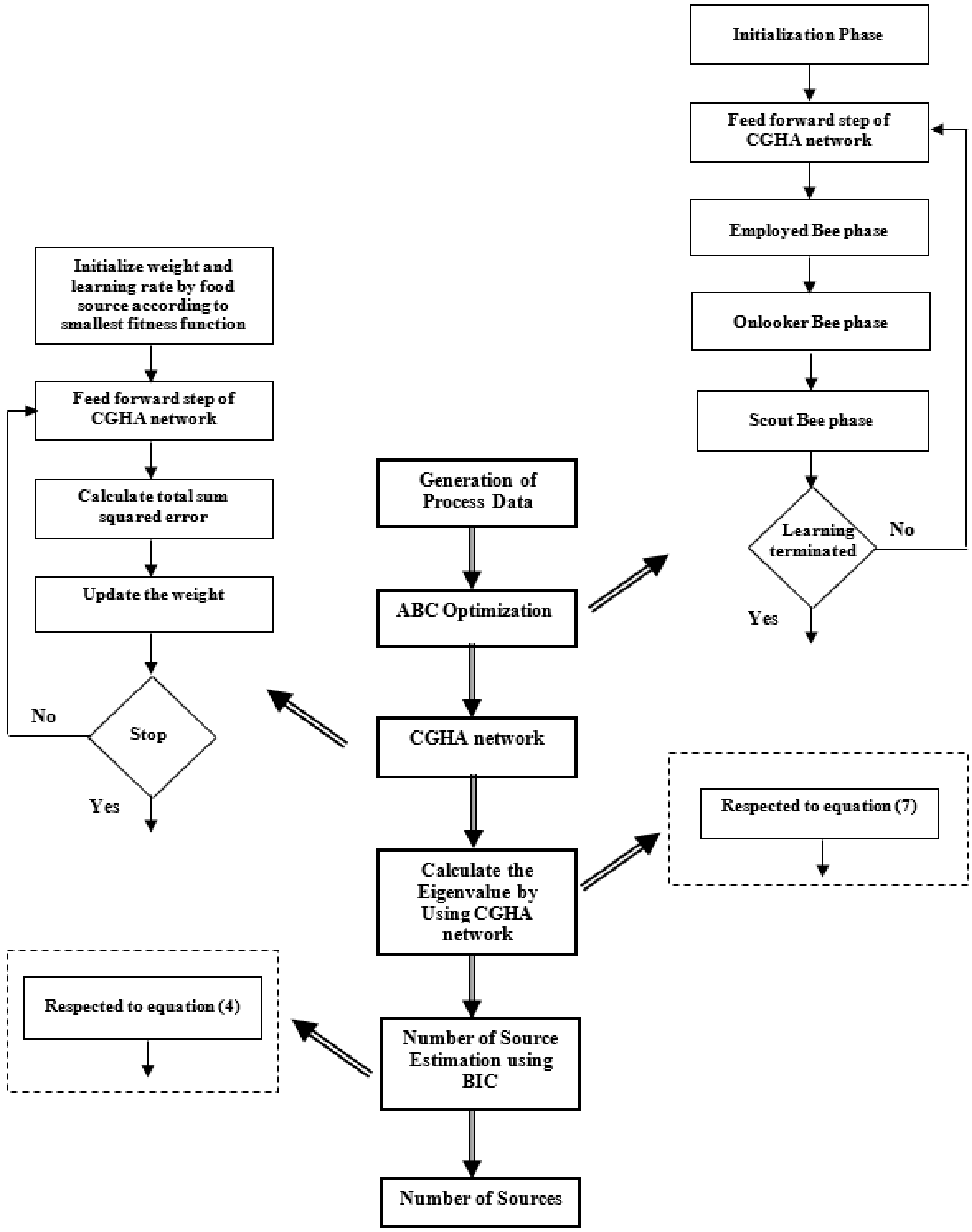

Figure 2. Block diagram of the proposed model

- Stage four: in this stage; eigenvalues of the data covariance matrix is calculated by means of a conjugate multiply to CGHA network output using (7)

$$\hat{\lambda}_j = y_j y_j^H, j = 1,2, \dots, P \tag{7}$$

where $\hat{\lambda}$ denotes data covariance matrix eigenvalues, whereas y denotes CGHA network output.
- Stage five and six: the primary function of these stages is to utilize the BIC method to estimate sources number using (4).

6. SIMULATION AND RESULT

Simulation experiments using MATLAB 2019 have been performed to investigate the efficiency of the proposed method. We consider a uniform linear array with M=12 elements used with N=100 snapshots. In this section, the performance of the suggested system; sources estimation considering artificial bee colony and CGHA neural network for BIC method (ABC-CGHA-BIC) is compared with the non-optimized system; sources estimation considering CGHA neural network with BIC method devoid of ABC optimization (CGHA-BIC).

In the proposed system, control parameters of ABC are set as 60 to population size, 80 to limit, with maximum cycle number of 5,000. CGHA neural network is setup as: 12 neurons, and the values of initial weights and learning rate are automatically extracted using ABC algorithm. While the CGHA neural network in the non-optimized system is set as: single layer network consisting of 12 neurons with a learning rate of 0.02.

Two cases are considered with varied sources number. The first one uses two sources (K=2) involving SNR=-3 dB, where first source was placed at 50°, whereas the next source was at 54°. It can be noticed that, both the proposed and the non-optimized systems attain the right number of two sources. Nevertheless, CGHA response for each neuron in the proposed system has faster convergence speed as compared with the non-optimized system as displayed in Figure 3.

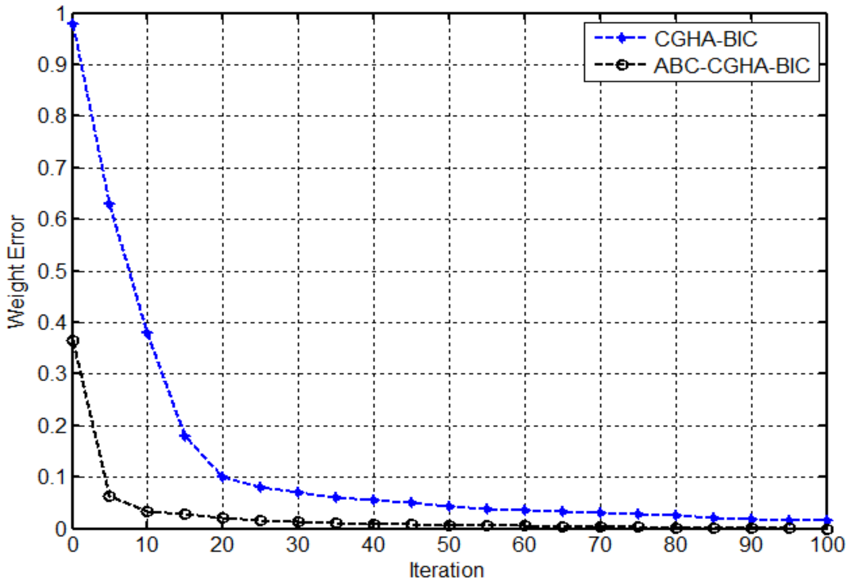

Figure 3. Curves of weight error coefficients per iteration for CGHA-BIC and ABC-CGHA-BIC methods

While the second case considers three sources number (K=3) having SNR=-3 dB, first source was placed at 50°, and second one was at 54°, while the last was at 58°. The proposed system in this case can attain a right number of three sources, whereas the non-optimized system provides wrong number of two sources. Figures 4 to 6 show the probability of detection for the comparative systems, which reveal that the proposed ABC-CGHA-BIC system gives almost the same original BIC detection probability, but actually surpasses the CGHA-BIC system.

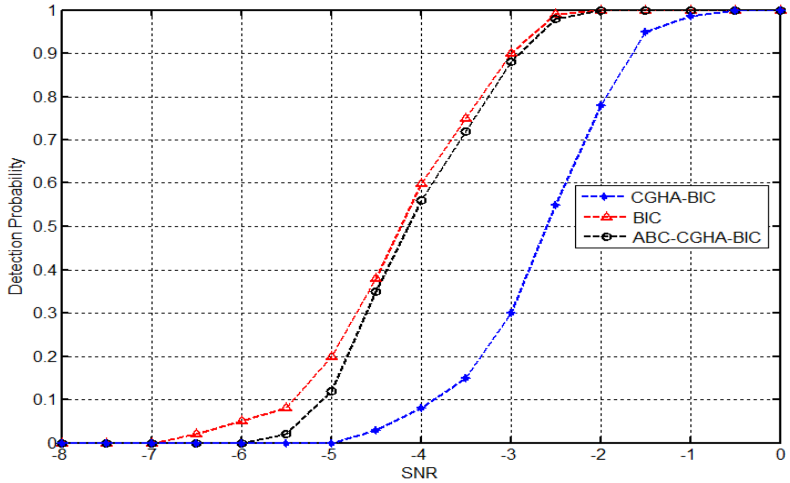

Figure 4. The probability of detection versus SNR with N=100, M=12, K=3, $\{\theta_1, \theta_2, \theta_3\} = \{50^o, 54^o, 58^o\}$ for BIC, CGHA-BIC and ABC-CGHA-BIC methods

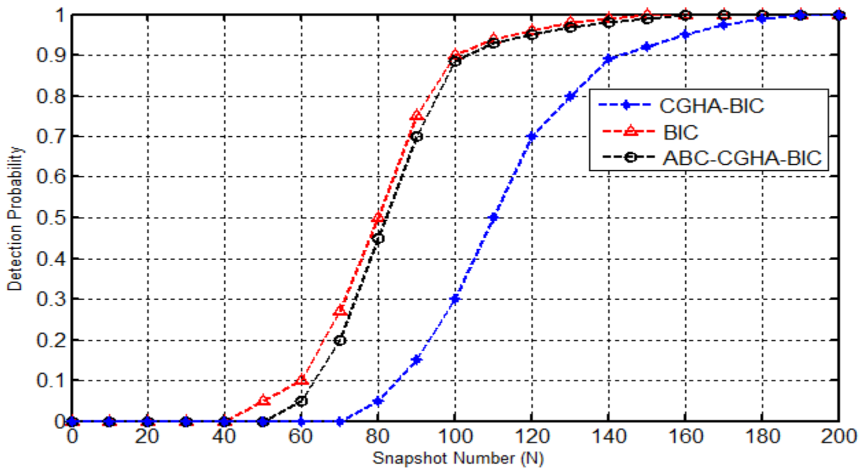

Figure 5. The probability of detection versus snapshot number (N) with SNR=-3dB, M=12, K=3, $\{\theta_1, \theta_2, \theta_3\} = \{50^o, 54^o, 58^o\}$ for BIC, CGHA-BIC and ABC-CGHA-BIC methods

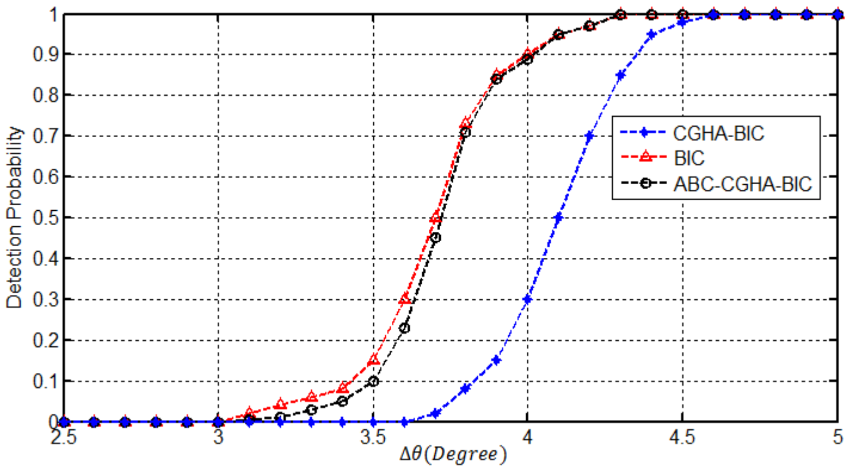

Figure 6. The probability of detection versus angle separation $\Delta\theta$, $\{\theta_1, \theta_2, \theta_3\} = \{0, \Delta, 2\Delta\}$ with SNR=-3 dB, N=100, M=12, K=3 for BIC, CGHA-BIC and ABC-CGHA-BIC methods

7. CONCLUSION

The current work introduces a hybrid scheme to support the number of sources determining in smart antenna through carrying out BIC to the outcome of CGHA neural network that based on artificial bee colony optimization. The proposed scheme implies optimization to solve the dilemmas of the random initial weights specifying besides determining the training condition of the CGHA neural network, which frequently causes network training oscillations. Furthermore, the proposed scheme is able to catch an accurate number of sources estimation, taking the principal components that computed directly from the input signals by using CGHA neural network rather than computing them from the covariance matrix, accordingly, determining the covariance matrix is not required. Simulation results of the proposed scheme verify its effectiveness through diminishing the required time to train the neural network, fast converge speed, with almost the same anticipation possibility as compared to the original BIC method.

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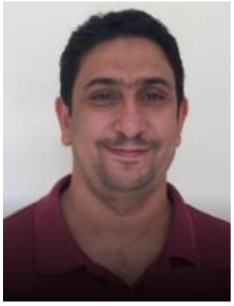
BIOGRAPHIES OF AUTHORS

Mohammed Hussein Miry received his bachelor and master degree in communication engineering from the University of Technology (UOT), Iraq and Ph.D. from the Department of Electrical Engineering at the Basra University, Iraq. He is working as an associative professor in Department of Communication Engineering at University of Technology- Iraq. His main fields of interests are smart antenna, adaptive filter, digital signal processing, communication system, and microwave engineering. He can be contacted at email: Mohammed.H.Miry@uotechnology.edu.iq.

Atheer A. Sabri was born in Baghdad, Iraq in 1975. He received his B.Sc. degree in 1997 from Al-Nahrain University, while the M.Sc. and Ph.D. degrees in 2000 and 2006 respectively from University of Technology- Iraq. Since 2013, He has been Assistant Professor at the University of Technology. Also, from 2015 he worked as deputy head of communication Engineering Department at the University of Technology. He can be contacted at email: Atheer.A.Sabri@uotechnology.edu.iq.



Ali Hussien Mary was born in Baghdad in 1976. He graduated from the electrical engineering department in University of Baghdad, Iraq, in 1998. He got the MSc degree in electrical engineering/computer and control division from University of Baghdad Iraq in 2001. He received a Ph.D. degree in control engineering from Gaziantep University Turkey in 2017. He published many papers in different journals. Research interests are robust control, nonlinear systems and robotics control. He can be contacted at email: alimary76@kecbu.uobaghdad.edu.iq.