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A hybrid neural network goal attain optimization for failed sensor(s) radiation pattern in linear array

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ABSTRACT

Array sensors are widely used in various field such as radar, wireless communications, autonomous vehicle applications, medical imaging, and astronomical observations fault diagnosis. Array signal processing is accomplished with beam pattern which is produced by the signal's amplitude and phase at each element of array. The beam pattern can get rigorously distorted in case of failure of array element and effect its Signal to Noise Ratio (SNR) badly. This paper proposes on a Hybrid Neural Network layer weight Goal Attain Optimization (HNNGAO) method to generate a recovery beam pattern which closely resembles the original beam pattern with remaining elements in the array. The proposed HNNGAO method is compared with classic synthesize beam pattern goal attain method and failed beam pattern generated in MATLAB environment. The results obtained proves that the proposed HNNGAO method gives better SNR ratio with remaining working element in linear array compared to classic goal attain method alone.

Keywords: Backpropagation; Feed-forward neural network; Goal attain; Neural networks; Radiation pattern; Sensor arrays; Sensor failure; Signal-to-Noise Ratio (SNR).

1. Introduction

In recent times, correction in sensor array beam pattern for failed elements are gaining attention because of its usage in important fields such as radar and communication system (Khan et al., 2014). Directional signal transmission and reception uses spatial filtering technique or also known as beamforming in arrays of sensor to combine signals. Directional signal is achieved by constructive interference of some angles in an array of sensors and destructive interference of other angles in the same array (Barry D. Van Veen & Kevin M. Buckley, 1988).

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One or more sensor failure in an array can severely damage radiation pattern and lead to higher side lobe levels, weakening of null depth and null shifting in the system because there will be only few

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sensors operating actively in the system. It is significant for the system to get desired or ideal radiation pattern to function properly (Keizer, 2007). The detection system behaves differently than expected (Higger, Akcakaya, & Erdogmus, 2013) if the radiation pattern is distorted. The common way of handling this issue is to replace the hardware which is difficult and it increases the maintenance cost (Patidar, Mahanti, & Muralidharan, 2017).

Current works on sensor failure are focusing on detecting the failure elements using methods like optimization (Xu, Christodoulou, Barbin, & Martínez-Ramón, 2007), neural network (Vakula & Sarma, 2009), case based reasoning method (Iglesias, Ares, Rodriguei, Bregains, & Barro, 2008) and compressive-sensing method (Oliveri, Rocca, & Massa, 2012). While, other recent works are concentrating on the failed pattern corrections by evolutionary algorithms, such as genetic algorithm (Yeo & Lu, 1999), firefly algorithm (Patidar et al., 2017) and flower pollination algorithm (Patidar & Mahanti, 2017). Recovering failed signal with linear symmetrical array antenna is discussed in (Klhan, Qureshi, Shoib, & Naveed, 2016) with Dolph-Chebyshev and Taylor pattern. Meanwhile, Chen Y. and Tsai I. in (Chen & Tsai, 2018), have discussed on detecting failure elements by cumulative sum method and correcting it by least-squares method. Whereas in (Patidar & Mahanti, 2017), the authors have mentioned on geometry optimization of elements by flower pollination algorithm for failure pattern correction. But, very less number of studies is on failed pattern recovery with neural network methods.

In this paper, HNNGAO method is proposed to restore failed radiation pattern by adjusting neural network weights using Goal attain method with the remaining active elements. The presence of neural network in this method provide a platform to learn, adapt, make decision and display new behavior as trained in the network (Sanders, 2008). Neural Network (NN) with eight hidden layer is trained with ideal pattern as target and failed pattern as input. Hidden layers provide a total of 31 NN weights which is known as values of the connection and also bias values. The failed pattern is compared and NN weights is updated through goal attain optimization until the failed pattern matches the ideal beam pattern. Comparison of classic Goal attains optimization method and HNNGAO method is also discussed in this paper.

The rest of this paper is organized as follows. In Section 2, 16 sensors linear array beam pattern and failed beam pattern generation is formulated. Classic Optimization method and proposed method is presented in Section 3. Details of performance measure of the radiation pattern is given in Section 4. In Section 5, numerical simulation results and comparison with classic method are discussed. This paper is concluded in Section 6.

2. Beam Pattern Generation

2.1 Array Beam Pattern Generation

Spatial Signal Processing also known as beamforming is transmitting or receiving a sound wave in required direction. Directional beams can be achieved by time delaying and phase shifting. Generally, beam forming techniques is used because its advantage of high gain, focused directivity reduced interference, improved system capacity which produces better signal quality compared to omni-directional signals. A phased array beamforming method was adapted from (Wykes, Webb, Nagi, & Gibson, 1992) for beam pattern generation with $M = 16$ elements, ultrasonic frequency of $f_c = 100kHz$, and the speed of sound in air at $20°C$ is $c = 344m/\sec$, the inter-element distance d avoiding grating is

$$\lambda = \frac{c}{f_c} = \frac{344}{100000} = 3.44mm \tag{1}$$

$$d = \frac{\lambda}{2} = 1.72mm \tag{2}$$

An equal amplitudes of $w(m) = 1$ was set to normalize the array factor of the beam pattern. Linear array beamforming is formed by (3).

$$G(\theta) = \sum_{m=1}^{M} w(m) e^{i(2m-M-1)*\arg} \tag{3}$$

where

$$\arg = \pi d[\sin(\theta - \frac{\pi}{2} - \gamma)$$

θ is scanning angle,
γ is steering angle
$w(m) = [1,1,1,\ldots,M]$, uniform weight on each element
d Inter-element distance between array elements
$M = 16$ Array elements and m is the index

Figure 1 shows 16 elements in an array with uniform inter-element distance

Figure 1. 16 elements in an array with uniform inter-element distance

2.2 Failed Beam Pattern Generation

Failed array weights, $w_f(q)$ are used to simulate failed beam pattern. Failed element weights in $w_f(q)$ were assigned as zero instead of one as in $w(m)$. For this purpose, array element number 2, 4 and 7 is randomly failed. An example of $w_f(q)$ is shown in (4) with failed elements in the array.

$$w_f(q) = [1, 0, 10, 1, 1, 0, 1, \ldots, Q = M - P] \tag{4}$$

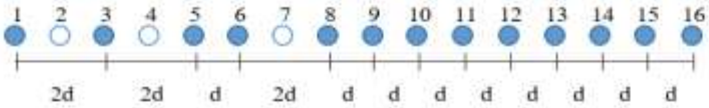
Where the number of remaining working elements is Q; P is number of failed elements, while q and p are their index respectively.

Beam pattern formulation of failed elements is adapted from (Nagi & Hung, 2007) as (5).

$$G_f(\theta) = \sum_{q=1}^{Q} w_f(q) e \quad G_f(\theta) = \sum_{q=1}^{Q} w_f(q) e^{i(2(q+p)-Q-1)*\arg} \tag{5}$$

In (5), index $q + p$ is increased inter-element distance with multiple of d as Figure 2.

Figure 2. Non-uniform inter-element distance



Contribution from failed elements are avoided with $w_f(q)$ and $q+p*d=(1,2,3,..)*d$

3. Optimization Methods

3.1 Classic Goal Attain Optimization

The classic method for failed pattern correction is goal attain method as in (Nagi & Hung, 2007). This optimization method is referred as 'Classic Goal Attain' method in this paper. For this method, remaining working element's weight were optimized to compensate the failure elements in an array. The objective function of this optimization is failed beam pattern $G_f(w_f)$. Relative amplitude of remaining working element amplitude is influenced by each weight, w_o. The weights are adjusted such that $G_f(w_f)$ is optimized to $G_f(w_o)$ and approaches closest to the goal $G(q)$. The optimized beam patterns is described as (6) (Nagi & Hung, 2007).

$$G_f(w_f - w_o) = \sum_{m=1}^{M} w_o(m) e^{i(2(m+p)-M-1)*\arg} \tag{6}$$

The block diagram of Classic Goal Attain method is as shown in Figure 3. The corrected pattern from this method is compared with the proposed HNNGAO method in the result section.

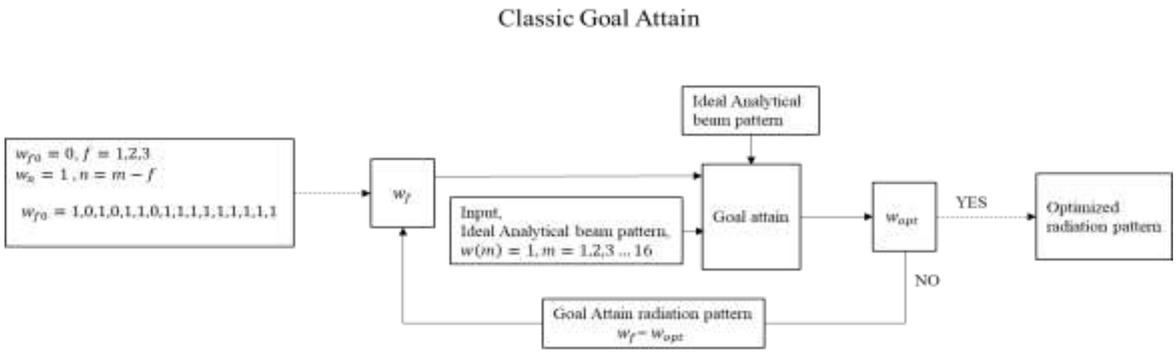


Figure 3. The block diagram of Classic Goal Attain method

3.2 HNNGAO Optimization Method

In this paper, HNNGAO method is introduced where both NN and Goal attain method is used to optimize weights of NN weights to recover failed radiation pattern.

First, The NN is configured with beam pattern with failed elements in an array as input and ideal beam pattern as target generated by (5) and (3) respectively. Each beam patterns consist of 179 points resembling the signal's amplitude at respective scanning angle. Figure 4 shows a feed-forward neural network back-propagation training with three-layers to obtain NN weights.

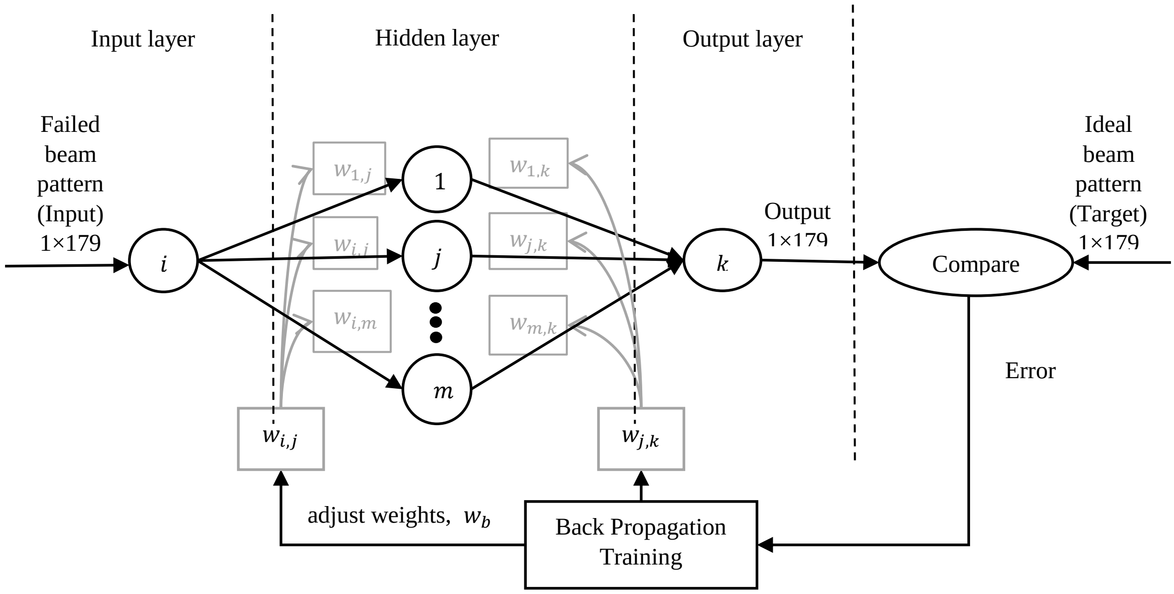


Figure 4. Feed-forward neural network back-propagation training (V Nourani et al., 2012)

In feed forward networks, neuron is connected from input layer to hidden layer or hidden layer to output layer. Neurons are not interconnected within a layer. Input layer, hidden layer and output layer is referred as i, j, and k respectively while applied weights by the neuron is denoted by w.

The output is computed with equation below (Vahid Nourani, Pradhan, Ghaffari, & Sharifi, 2014)

$$Output = f_o[\sum_{j=1}^{M=10} w_{kj} \cdot f_h(\sum_{i=1}^{N_N} w_{ji} x_i + w_{jo}) + w_{ko}) \quad (7)$$

where w_{ji} represents a weight in hidden layer, connecting to j^{th} neuron in input layer and the j^{th} neuron in the hidden layer, w_{kj} is a weight in output layer which connects the j^{th} neuron in the hidden layer and the k^{th} neuron in the output layer, w_{jo} is bias for the j^{th} hidden neuron, w_{ko} is bias for the k^{th} output neuron, f_h is activation function of the hidden neuron, f_o is activation function for the output neuron, x_i is input variable for input layer, M is number of the neurons in the input layer and N is number of the neurons in the hidden layers (Vahid Nourani et al., 2014). For this example, we used $M = 10$ and $N = 1$. The weights in this network varies in hidden and output layers, and also changes during the network training. NN weights and bias, w_h are obtained after configuring and training the network with input and target values.

Then, a function is created with goal attain optimisation to generate a beam pattern which matches closely with ideal pattern with w_b obtained earlier. Radiation pattern simulated with w_b and Ideal beam pattern is fed into goal attain optimization. Goal attain optimization is known for optimizing towards achieving a goal. In this example, goal is ideal beam pattern. It generates optimized weight to achieve goal. In this function, the network is set with new set of weights and failure pattern is simulated with the new network weights at each iteration. The process continues until desired radiation pattern with optimized weight, w_{opt} is achieved. Then, w_{opt} is set into the network and optimised pattern with failure element in an array is simulated. The optimized NN beam pattern, G_{NN} is simulated using (8) below.

$$G_{NN}(w_{opt}) = sim(net, x) \tag{8}$$

Where net represents network and x is the failed radiation pattern. The final output pattern is evaluated with performance measure described at (9). The block diagram of HNNGAO method is as shown in Figure 5 below

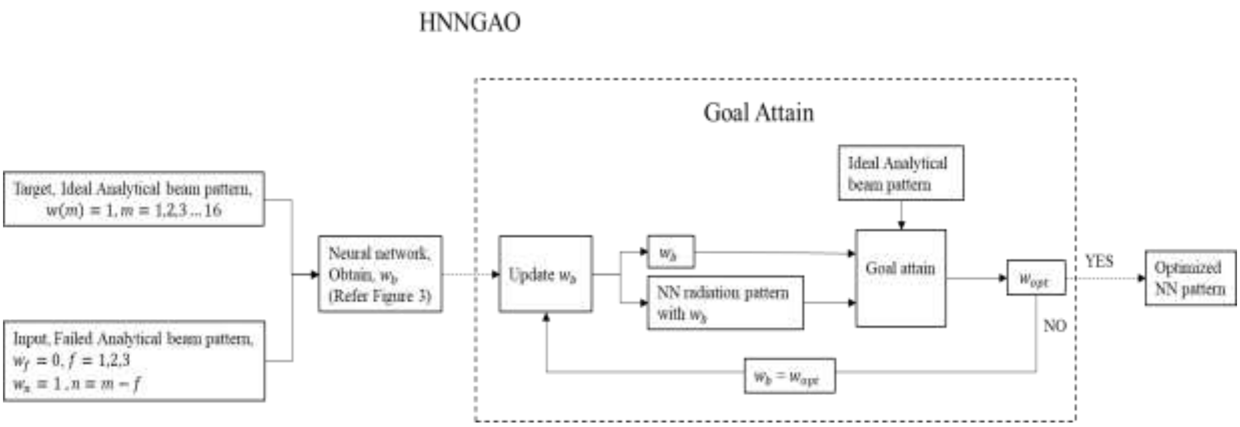


Figure 5. The block diagram of HNNGAO method

4. Performance Measure

The radiation patterns obtained after optimization is compared with the failed beam pattern to evaluate with the effectiveness of this method. Gain performance is measured with SNR, η . is set to be the ratio of the main beam above the -3db, to the side lobes as (9) (Nagi & Hung, 2007).

$$SNR, \eta_{(f,op)} = 20\log[\frac{\sum G_{BW_{3db}}}{\sum[G_f(w_o - G_{BW_{3db}})]}] \tag{9}$$

Figure 6 describes (9) where the main beam is pointing towards the desired direction while the side lobes are raised creating undesired direction while the side lobes are raised creating undesired noise entering in the receiver from other directions.

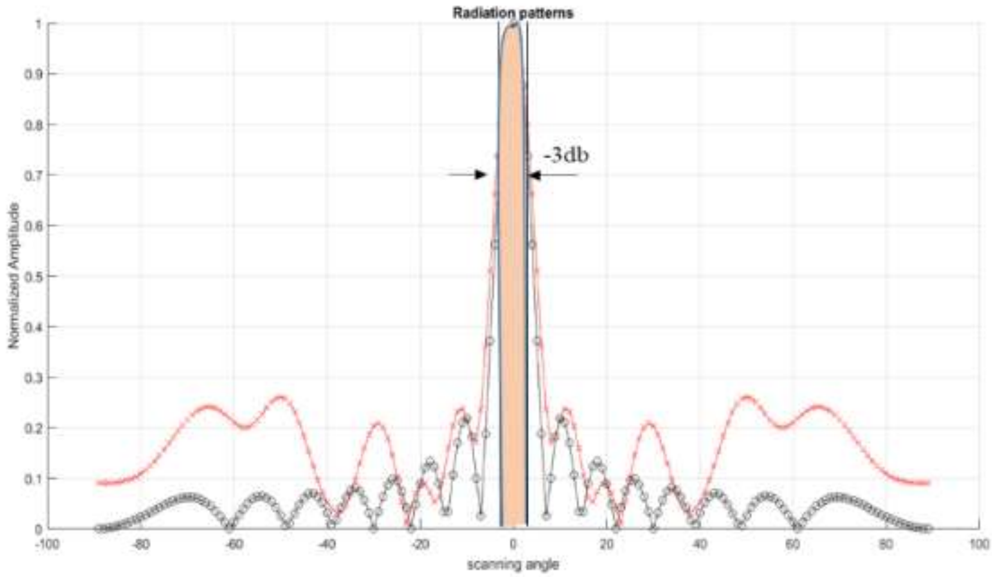


Figure 6. -3db beam width used in (9) (Nagi & Hung, 2007)

5. Simulation Results and Discussion

A beam pattern of 16 element uniform linear array through the X-axis is simulated. For linear array without failed elements and with failed element, (3) and (5) is used respectively as per literature (Sanders, 2008), (Chen & Tsai, 2018). In this example, we arbitrarily choose second element, forth element and seventh element to be faulty. Optimization results were evaluated for classic goal attain with failed sensors at same location. Figure 7 shows the beam patterns of simulation results. The ideal beam or reference pattern is in black obtained by (3); failed pattern is in red by (5); goal attain optimized is in blue by (6) and HNNGAO optimization in green with (8).

The performance measure, η was evaluated by (9). The η obtained by ideal beam pattern is 5.2405, failed pattern is 13.1546, classic goal attain optimised is 10.5523 and HNNGAO is 9.2574 respectively. The proposed HNNGAO method results clearly shows a closer match to the ideal beam pattern compared to classic goal attain method in the presence of failure elements in an array. The proposed method also provides a lower SNR, closer to the ideal beam pattern in comparison with classic goal attain method. Less noise will be received from other direction in HNNGAO side lobes in comparison with classic goal attain method.

5.1 Limitation

This method is limited to 20% of sensor failure in a linear array. Even though the method can hold up more percentage of sensor failures, it is not advisable to use the device with major number of sensor failures which will lead to inaccurate results.

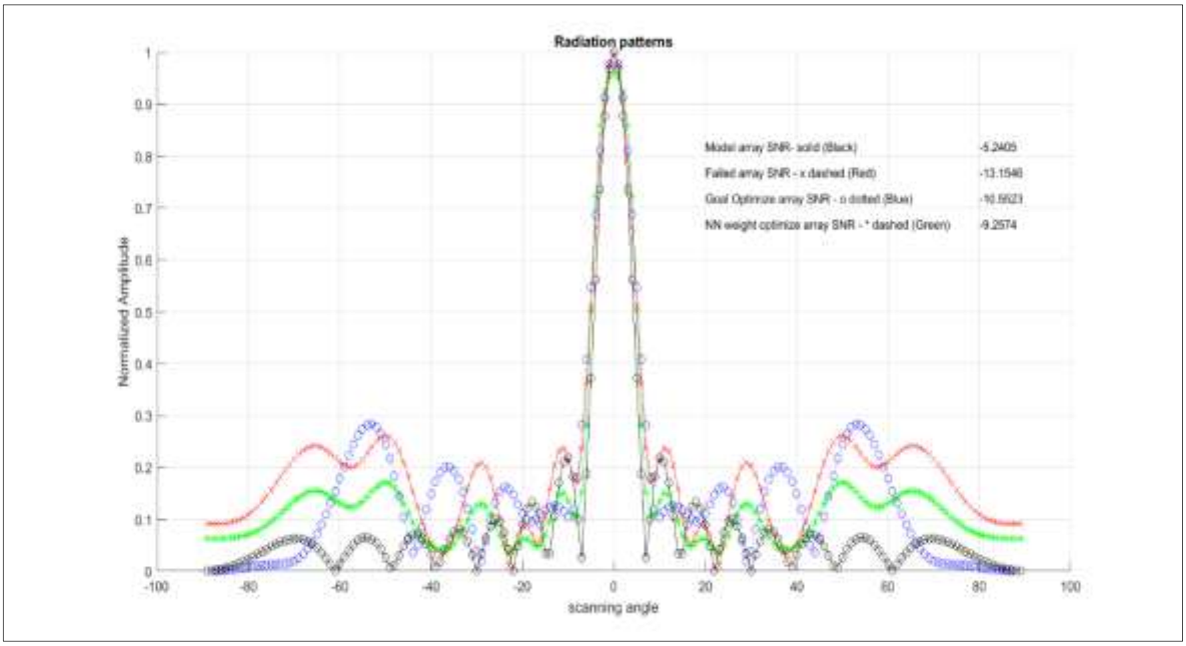


Figure 7. HNNGAO beam pattern simulation with comparison with ideal, failed and goal attain optimization

6. Conclusion

This paper presents a HNNGAO method for linear antenna array failure correction beam pattern using NN weight optimization with goal attain function. The proposed method proves that it can significantly improve SNR values compared to optimization with classic goal attain optimization method. It is observed that the radiation pattern obtained from this method closely matches with the ideal beam pattern. In addition, this method does not require any modification at remaining working elements excitation which avoids computational complexity. Obtained results clearly shows the effectiveness of the proposed approach.

For future work it is recommended to increase number of hidden layer configured to the neural network which might improve the optimized radiation pattern and provide a SNR value closer to ideal beam pattern SNR value. Other than that, it is also advised to compare this HNNAG method with other optimization method like genetic algorithm to optimize the failed radiation pattern.

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