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Research Article

Detection of Defective Sensors in Phased Array Using Compressed Sensing and Hybrid Genetic Algorithm

Shafqat Ullah Khan,[1] Ijaz Mansoor Qureshi,[2] Aqdas Naveed,[3] Bilal Shoaib,[3] and Abdul Basit[3]

[1] *School of Engineering & Applied Sciences, ISRA University, Islamabad 44000, Pakistan*
[2] *Electrical Department, Air University, Islamabad 44000, Pakistan*
[3] *Electronic Department, International Islamic University, Islamabad 44000, Pakistan*

Correspondence should be addressed to Shafqat Ullah Khan; shafqatphy@yahoo.com

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A compressed sensing based array diagnosis technique has been presented. This technique starts from collecting the measurements of the far-field pattern. The system linking the difference between the field measured using the healthy reference array and the field radiated by the array under test is solved using a genetic algorithm (GA), parallel coordinate descent (PCD) algorithm, and then a hybridized GA with PCD algorithm. These algorithms are applied for fully and partially defective antenna arrays. The simulation results indicate that the proposed hybrid algorithm outperforms in terms of localization of element failure with a small number of measurements. In the proposed algorithm, the slow and early convergence of GA has been avoided by combining it with PCD algorithm. It has been shown that the hybrid GA-PCD algorithm provides an accurate diagnosis of fully and partially defective sensors as compared to GA or PCD alone. Different simulations have been provided to validate the performance of the designed algorithms in diversified scenarios.

1. Introduction

Nowadays array testing is of great interest in the research community. Moreover, the estimation of the power pattern and detection of faulty sensors in antenna arrays are an important issue in radar, remote sensing, and mobile and satellite communications [1–3]. There is a possibility of getting one or more antenna elements defective which results in degradation of radiation pattern of the array [4–6]. Prior to the correction of the patterns, it is necessary to first diagnose the defective antenna element in the array. Several traditional techniques are available to detect the number and the positions of faulty elements from the observation of healthy array and damaged power pattern [7, 8]. The most commonly used techniques for array detection are matrix method [9], back propagation algorithm [10], and exhaustive searches [11]. However, these techniques are computationally expensive as they require that the number of measurements should not be less than the number of antenna elements in the array.

In array diagnosis, the purpose is to locate the faulty elements in linear array. The sparse vector is defined as the deviation between the weights of the healthy reference array and the array under test [12]. In practical scenario, the number of defective elements is small. Thus the new array is very sparse with a small number of active elements, allowing a less number of measurements for the detection of faulty elements. The failure detection problem using the recovery techniques of signals in compressed sensing allows the harmonic estimation of sparse signals using a small number of data [13, 14]. The measurement matrix must satisfy the restricted isometry property to avoid information in the actual signal from distortion. In such a framework, an inventive turnup for the detection of defective linear arrays from far-field measurement has been proposed [15] enchanting the benefit of the compressed sensing technique.

Compressed sensing (CS) is a signal processing technique, in which one can recover a signal from a set of linear measurements instead of a signal itself, where the number of

the measurements is less than the signal. As a consequence, the original signal has to be recovered from the measurement matrix, which is ill-posed due to the reduced dimension. CS technique [16–19] states that it possible to recover the underlying signal from less number of measurements below the Nyquist sampling rate, under the suitable conditions such as restricted isometry property (RIP). In literature several techniques are available for solving the ill-posed recovery problem. These techniques can be classified into a number of algorithm families with their problem varying approach [20–22].

Among the researchers in engineering, GA and PCD algorithm have required special attention. GA is bioinspired technique that has been used successfully for different optimization problems in numerous fields of engineering [23–25]. On the other hand, PCD, with the idea taken from coordinate descent method, is also used for different minimization problems.

In this paper, taking into account the promising performance of GA and PCD, we have introduced a CS based array diagnosis technique. This technique is based on the measurement data of the far-field pattern. The system relating the difference between the field measured using the healthy reference array and the field radiated by the array under test is solved using GA, PCD algorithm, and GA hybridized with PCD algorithm. The major advantage of this hybrid technique is the avoidance of slow and early convergence of GA. The performances of all of these algorithms have been compared with each other in terms of convergence and mean square error (MSE). The GA-PCD algorithm provides an accurate diagnosis of fully and partially defective sensors as compared to the individual GA or PCD algorithm alone. Different simulations have been provided to validate the performance of the designed algorithms.

The remaining of paper is organized as follows. The problem formulation is discussed in Section 2, while in Section 3, we have designed GA, PCD, and hybrid GA-PCD. Section 4 describes the simulations and results, while Section 5 concludes the work and recommends some future directions.

2. Problem Formulation

Let us consider a linear array of N elements along z-axis, whose far-field patterns are given as [1]

$$A(\theta_i) = \sum_{n=1}^{N} w_n \cos\left[\left(\frac{2n-1}{2}\right) kd \sin\theta_i\right], \qquad (1)$$

where w_n is the weight vector of the nth antenna element, k is the wave number, i is the ith measurement pattern, and d is the distance between the consecutive elements. The noisy far-field pattern of the array under test is expressed as

$$F_m(\theta_i) = \sum_{\substack{n=1\\ n\neq m}}^{N} a_n \cos\left[\left(\frac{2n-1}{2}\right) kd \sin\theta_i\right] + r(\theta_i), \qquad (2)$$

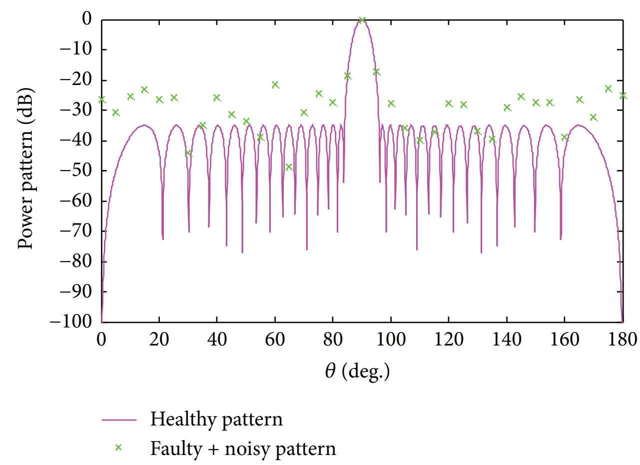

Figure 1: The Chebyshev healthy and noisy faulty pattern with $N = 30$ and SLL = −35 dB.

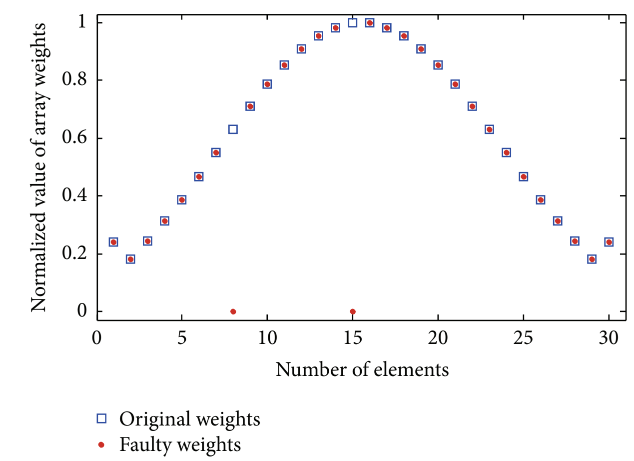

Figure 2: The Chebyshev healthy and faulty (8th and 15th) weights with $N = 30$ and SLL = −35 dB.

where $r(\theta_i)$ is the ith sample of an additive zero mean complex Gaussian noise with variance σ and a_n is the nth weight vector of the array under test. In (2), a_n is given as

$$a_n = \begin{cases} 0 & \text{with propability } \phi \\ w_n & \text{otherwise,} \end{cases} \qquad (3)$$

where $\phi < 1$ is the fraction of faulty elements. The original and noisy faulty Chebyshev power pattern with $N = 30$ and SLL = −35 dB are shown in Figure 1. The normalized Chebyshev weights of the original and faulty array with 8th and 15th elements not working are depicted in Figure 2. The difference field pattern between the ideal and the array under test is given [11] by the following equation:

$$p(\theta_i) = A(\theta_i) - F_m(\theta_i) \qquad (4)$$

or it can be written as follows:

$$p(\theta_i) = \sum_{n=1}^{N} x_n \cos\left[\left(\frac{2n-1}{2}\right) kd \sin\theta_i\right] - r(\theta_i), \qquad (5)$$

where $\mathbf{p} = \{p(\theta_i),\ i = 1, 2, 3, \ldots, K\}$ and x_n is the nth element of the array under test failure vector which is given by

$$x_n = w_n - a_n. \tag{6}$$

To solve the array detection problem, we find x_n. In practical scenario, some element failure occurs; thus the failure vector turns out to be sparse. The array detection problem can be reformulated in sparseness frame work [13]. Given the difference vector $\mathbf{p}$ find the minimum l_0 norm that satisfies the equation

$$\mathbf{p} - \mathbf{E}\mathbf{x} = \mathbf{r}$$
$$\mathbf{E} = \begin{bmatrix} \exp(jnkd\sin\theta_1) & \cdots & \exp(jNkd\sin\theta_1) \\ \vdots & \ddots & \vdots \\ \exp(jnkd\sin\theta_K) & \cdots & \exp(jN\sin\theta_K) \end{bmatrix}, \tag{7}$$

where $\mathbf{E}$ is the measurement matrix [14]. Given the difference vector and the measurement matrix, the algorithm looks for the finest solution of inverse problem under a definite constraint. If the measurement matrix is square and invertible then the unique solution can be found through matrix inversion. In practical scenario, the measurement matrix is ill-conditioned, which leads to underdetermined system of linear equations. Thus we find the sparsest solution.

3. Proposed Methodology

In compressed sensing (CS), sparsity in signals allows us to undersample the signal below the Nyquist minimum sampling criterion. In CS, less number of measurements in sparse signal contains complete information compared to its dimensions, so that exact recovery from less number of measurements is possible [16, 17]. CS has many applications, that is, communications and Magnetic Resonance Imaging (MRI) [15, 18]. Restricted isometry property (RIP) should be fulfilled by measurement matrix to avoid information in the actual signal from distortion, such as Gaussian matrices. For the exact recovery, the number of measurements taken is; that is, $m \geq S\log(N/S)$, where m measurements are taken from a signal of length N having S defective elements; then sparse signal could be recovered with high probability [20]. The minimum l_2 norm based solution minimizes the total energy of the approximated signal and has a unique solution. However, solution is generally nonsparse. l_0 norm minimization makes use of sparsity constraint for finding an estimate of solution with few defective elements in linear array. However, it has nonconvex formulation for finding the sparse solution and is computationally intractable as it involves an exhaustive search $\binom{N}{S}$ for defective elements.

There is temptation for l_2 norm minimization given in (8) due to its unique solution and because it is computationally tractable. Consider

$$\hat{x} = \arg\min_x \|p - Ex\|_2^2. \tag{8}$$

Sparse approximation problems such as l_0 minimization in (9) use the sparsity constraint as a regularizer to find an approximate solution with few defective elements in the antenna array. One has

$$\hat{x} = \arg\min_x \|p - Ex\|_2^2 \quad \text{subject to} \quad \|x\|_0 \leq S. \tag{9}$$

The l_1 norm is convex and promotes sparsity in solution, whereas, l_0 norm in (9) is generally not tractable and nonconvex. Thereby, we can replace l_0 norm by l_1 norm to remodel the problem in (9) by

$$\hat{x} = \arg\min_x \left(\|p - Ex\|_2^2 + \|x\|_1\right). \tag{10}$$

3.1. Genetic Algorithm (GA). GA is a nature inspired metaheuristic optimization technique which is based on the ideology of inheritance. The algorithm starts with the initialization of chromosomes. Each chromosome in the inhabitants acts as a candidate solution. The elements of a chromosome are called genes. The price of each chromosome is determined through a fitness function. With the help of crossover, the genes of different chromosomes can be combined in a variety of ways to produce the offspring having different fitness values. The new population is formed with the normal selection by combining the best parents and offspring. In this way the GA proceeds to search for the best candidate solution. Nature inspired metaheuristic algorithms are preferred for the problems which are NP-hard. When the optimization involves constraints the application of GA [23] becomes more difficult as the crossovers are blind to the constraints.

Constraints can be included in the fitness function as well as in the chromosome. However indirect constraint usage does not work well for the sparse problems. In our proposed algorithm the constraint is used to guarantee the preferred sparsity level before and after the crossover during hard thresholding. One of the main problems in GA is the early convergence which is linked to the loss of inherited variety of the population. To avoid this problem we pass through the mutation process. However for sparse signal recovery the ordinary mutation will not work, making the chromosome denser and compromising the sparsity constraint. The proposed algorithm avoids this problem by using the PCD algorithm when the population tends to converge prematurely.

3.2. Parallel Coordinate Descent Algorithm (PCD). PCD is an algorithm that minimizes the function. The idea of PCD is taken from the coordinate descent method in which the fitness function minimizes one coordinate at a time [20]. In order to get the new solution, it updates all the coefficients in parallel instead of doing it sequentially. The update equation of the algorithm is given by

$$x_{k+1} = x_k + \mu(e_s - x_k), \tag{11}$$

where μ is a constant and is computed through line search. In the proposed algorithm we replace it with a random number. The starting value of the solution can be either an estimate of

the least square solution or a zero vector. In (11) the term e_s is computed by the following expression:

$$e_s = \left(x_k + \operatorname{diag}\left(E^T E\right)^{-1} E^T r_k\right). \quad (12)$$

Here $r_k = p - Ex_k$ is the residue. The pseudocode of PCD is given as follows.

The Pseudo Code of Parallel Coordinate Decent (PCD) Algorithm

Task. Find the value of $\mathbf{x}$.

Input. The inputs are measurement matrix $\mathbf{E}$ and compressed measurement $\mathbf{p}$.

Output. The output is the result of $\mathbf{x}$.

Initialization. Initialize $k = 0$ and set the following:

The initial solution $x_0 = 0$.

The initial residual $r_0 = b - Ex_0 = b$.

Prepare the weights $Q = \operatorname{diag}(E^T E)^{-1}$.

Main Iteration. Increment k by 1, and apply these steps: that is, $k = k + 1$.

Back Projection. Compute $e = E^T r_k$.

Shrinkage. Compute $e_s = \operatorname{shrink}(x_k + Qe)$.

Line Search. Choose μ to minimize the real value function $f(x_k + \mu(e_s - x_k))$.

Update Solution. Compute $x_k + \mu(e_s - x_k)$.

Update Residual. Compute $r_{k+1} = b - Ex_{k+1}$.

Stopping Rule. If $\|x_{k+1} - x_k\|_2^2$ is smaller than some predetermined threshold, stop, or else apply another iteration.

Output. Result is x_{k+1}.

The proposed algorithm modifies the regular PCD to accelerate the convergence of GA. In order for PCD to interact with GA, randomness is introduced in it at various levels. PCD is used to update chromosome when the fitness of the best chromosome does not change in a few consecutive iterations thereby preventing the convergence issue. The interaction of PCD in the proposed algorithm is a random phenomenon. PCD algorithm each time is accessed by GA. The residue is computed using the current best chromosome while in (11) and (12) a chromosome from the current generation is selected randomly to replace r_{k-1}.

3.3. Hybrid Genetic Algorithm

3.3. Hybrid Genetic Algorithm. The flow chart of the proposed hybrid GA with PCD algorithm is shown in Figure 3 while its pseudopod is given as follows.

The Pseudo Code of Hybrid GA for the Detection of Faulty Elements

Input. The inputs are measurement matrix E, measurement vector p, population size P, and faulty element S.

Output. Find the vector x.

(1) Population Generation. Generate random P chromosomes:

$$\begin{gathered} G = \left[g_1, g_2, \ldots, g_P\right], \\ \operatorname{card}\left(g_i\right) \le S \\ \forall i \le 1 \le P. \end{gathered} \quad (13)$$

(2) Calculating Fitness of Parents and Sorting. Calculate the fitness of each chromosome based on (9) and sort them in the descending order:

$$\begin{aligned} f_p &= \operatorname{fit}\left(g_1, g_2, \ldots, g_P\right) \\ &= \left[f_{p1}, f_{p2}, \ldots, f_{pP}\right] \\ f_{pi} &= \left(Eg_i - p\right)^\tau \left(Eg_i - p\right) \\ \left[f_{ps}\ \text{index}\right] &= \operatorname{sort}\left(f_p, \text{descend}\right) \\ f_{ps} &= \left[f_1, f_2, \ldots, f_P\right] \\ &\qquad \text{with } f_1 < f_2, \ldots < f_P \\ G_s &= G\left(\text{index}\right) = \left[g_{s1}, g_{s2}, \ldots, g_{sP}\right] \\ &\qquad \text{where } g_{si} \text{ has fitness } f_i. \end{aligned} \quad (14)$$

(3) Crossover. Offspring of size half of the population are generated in random manner:

$$\begin{gathered} C = \operatorname{crossover}\left(G_s\right) = \left[c_1, c_2, \ldots, c_{P/2}\right] \\ c_j = \left\lfloor g_{sj} + \gamma\left(g_{sj} - g_{\text{srnd}i}\right)\right\rfloor_s \quad 1 \le j \le \frac{P}{2},\ 1 \le i \le P. \end{gathered} \quad (15)$$

(4) Calculating Fitness of Children and Sorting. It is the same as Step 2 but executed for offspring:

$$\begin{gathered} f_c = \operatorname{fit}\left(c_1, c_2, \ldots, c_{P/2}\right) \\ \left[f_{cs}\ \text{index}\right] = \operatorname{sort}\left(f_c, \text{descend}\right) \\ C_s = c\left(\text{index}\right) = \left[c_{s1}, c_{s2}, \ldots, c_{sp/2}\right]. \end{gathered} \quad (16)$$

(5) PCD Algorithm. If f_1 remains the same during the specified consecutive iterations then execute:

$$e_s = \left(g_{\text{srnd}} + w_{\text{rand}} \otimes \left(E^\tau \left(p - Eg_{s1}\right)\right)\right). \quad (17)$$

(6) Generating New Population. Generate new population using half of the best parents and all children:

$$G_1 = \left[g_{s1}, g_{s2}, \ldots, g_{sp/2} c_{s1}, c_{s2}, \ldots, c_{sp/2}\right]. \quad (18)$$

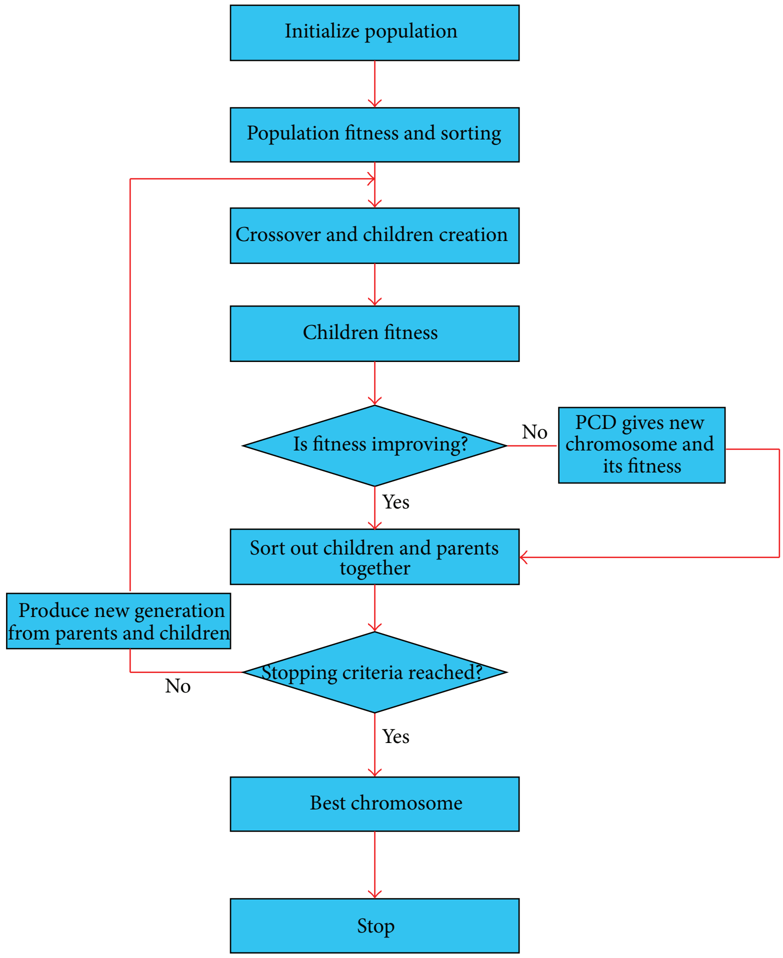

FIGURE 3: The flow chart of hybrid GA with PCD algorithm.

(7) Output. The chromosome with best fitness is the candidate solution $x = g_{s1}$.

The symbol card(Z) is used to indicate the cardinality of the vector Z whereas index represents a vector containing the indices when sorted in the descending arrangement. The data $\otimes$ represents the element-by-element product. The program can be stopped after either achieving the desired fitness function calculated in Step 2 or reaching maximum number of cycles.

4. Simulation Results and Discussion

In this section, first we consider a Chebyshev array of 20 elements with $\lambda/2$ interelement spacing that is used as the reference antenna. The power pattern in this case represents a -35 dB peak side lobe level with the nulls at the particular angles. The normalized MSE that is determined in detecting the faulty elements at the jth iterations is given by the following equation:

$$\text{MSE} = \frac{\left\| \widehat{x}_j - x_0 \right\|_2^2}{\left\| x_0 \right\|_2^2} \qquad j = 1, 2, \ldots, 350, \tag{19}$$

where $j = 1, 2, \ldots, 350$ is the number of iterations and the signal to noise ratio (SNR) is given by

$$\text{SNR} = \frac{\left[\sum_{i=1}^{K} \left| A\left(\theta_i\right) \right|^2 \right]}{\left[\sum_{i=1}^{K} \left| r\left(\theta_i\right) \right|^2 \right]}. \tag{20}$$

To examine the simulation results the radiation pattern is sampled and 37 samples were taken from the pattern. To check the validity of the proposed method we use Matlab as a programming tool. At the first instant, we consider that the 3rd and 7th elements in the array become damaged as shown in Figure 4. Now we use the PCD algorithm to detect the location of faulty elements. After simulation with the PCD algorithm, the number and the location of faulty elements are recovered; this is shown in Figure 4. The blue square represents the original weights of the Chebyshev array, green circle represents faulty elements, and red cross represents the diagnosed fault.

The same scenario is repeated to detect the number and location of faulty elements by using GA. After using GA, the fault diagnosed is shown in Figure 5. Now we check the same fault with the hybrid GA which is depicted in Figure 6.

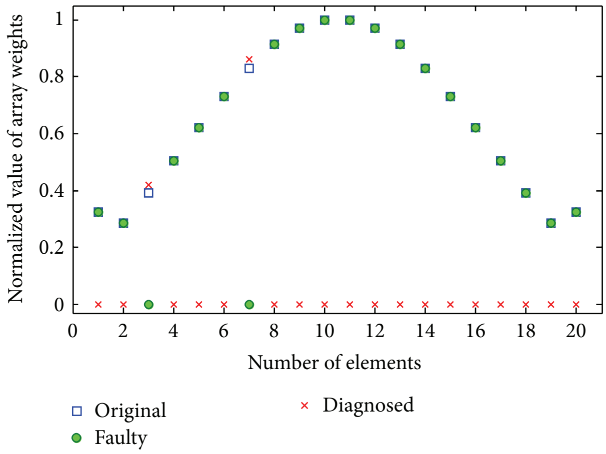

Figure 4: Detection of faulty sensors through PCD.

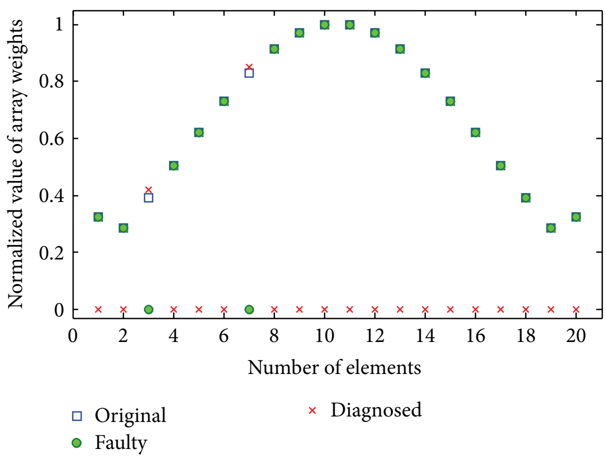

Figure 5: Detection of faulty sensors through GA.

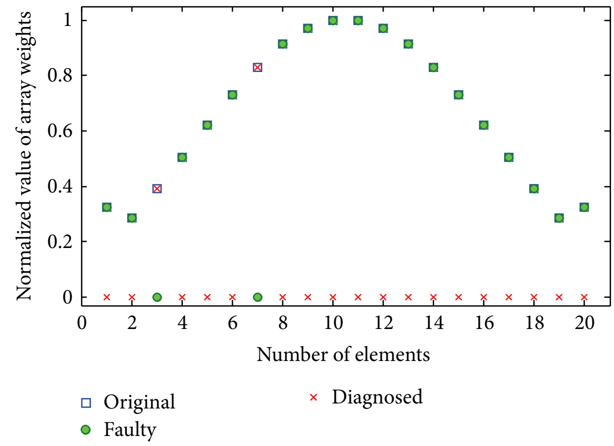

Figure 6: Detection of faulty sensors through proposed hybrid GA algorithm.

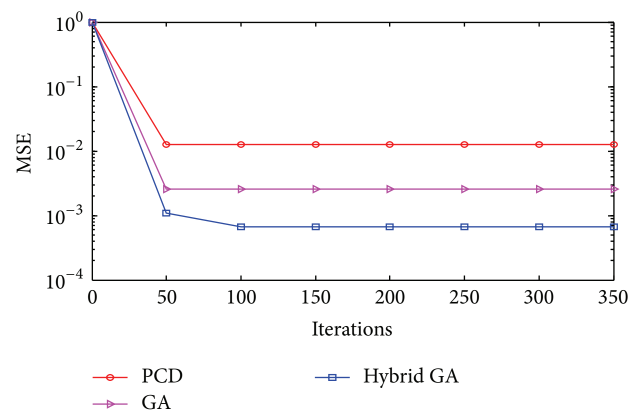

Figure 7: Comparison of PCD, GA, and hybrid GA with PCD based on MSE.

Now we detect the 3rd and 7th element failure by applying hybrid GA algorithm. The fault diagnosed through hybrid GA is depicted in Figure 6. By using the hybrid GA, we diagnosed the number and location of faulty elements more accurately than PCD and GA alone.

The performance of the proposed hybrid GA was compared with PCD and GA alone based on the normalized MSE which is computed at each run of 350 iterations by using (19). Figure 7 is the comparison of the MSE of the PCD, GA, and hybrid GA. From Figure 7 it is clear that the MSE of the hybrid GA detect the number and location of faulty elements more accurately as compared to PCD and GA alone.

Figure 8 shows the performance of the diagnosis error for different values of SNR for PCD, GA, and hybrid GA. From Figure 8, it is clear that, for lower value of SNR, we have a greater value of MSE. For the value of SNR ≥ 45, the value of MSE is lower and stable. Hence the hybrid GA performs better than PCD and GA alone for different value of SNR.

Now we test the proposed hybrid technique for different number of array sensors. In this case we consider an array of 30, 40, and 50 sensors. We assumed that 4 sensors are damaged. The fault is assumed at 5th, 10th, 15th, and 25th locations in an array of 30 and 40 sensors. Now we applied the proposed hybrid technique to detect the faulty sensors. The hybrid GA with PCD algorithm detect the positions of faulty sensors more accurately and the MSE graph is shown in Figure 9. Now the hybrid GA with PCD algorithm is tested for an array of 40 sensors. Again the position of fault is assumed at 5th, 10th, 15th, and 25th locations; after applying the proposed hybrid GA with PCD algorithm the fault is diagnosed. From the simulation results of Figure 9 it is clear that as the array size increases while keeping the number of faulty sensors fix, we achieved minimum MSE. The same scenario of faulty sensors is repeated for an array of 50 sensors; again the hybrid GA with PCD algorithm detects the faulty sensors positions more accurately as shown in Figure 10. From Figure 9, it is clear that the MSE curve of an array of 50 sensors is lower than the array of 30 and 40 sensors. It is clear, from simulation results, that as we increase the array size while keeping the number of faulty sensors fixed, we received accurate detection and better MSE curve. The advantages of the proposed method have been fully examined. The disadvantage is when the array size increases, the method deteriorates.

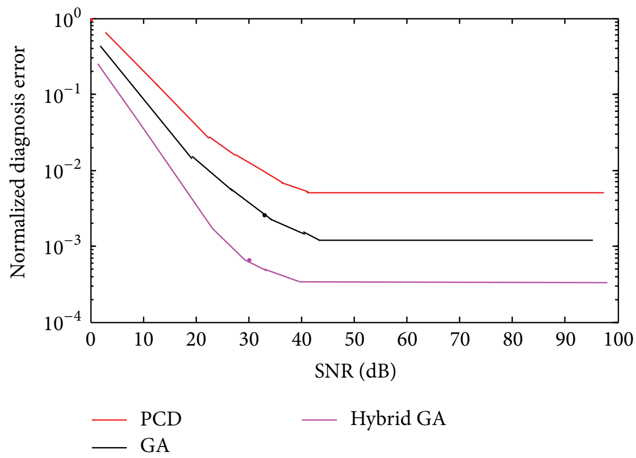

FIGURE 8: Diagnosis of faulty elements for different values of SNR.

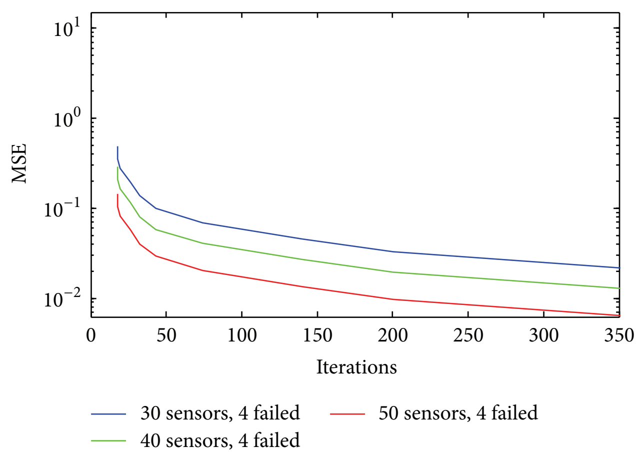

FIGURE 9: Comparison of hybrid GA with PCD based on MSE for different array.

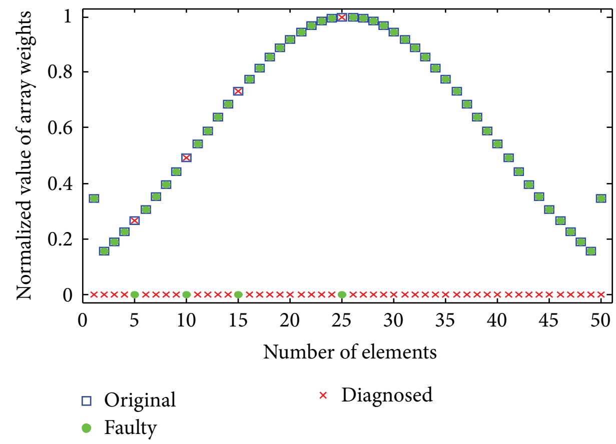

FIGURE 10: Detection of faulty sensors through hybrid GA with PCD algorithm.

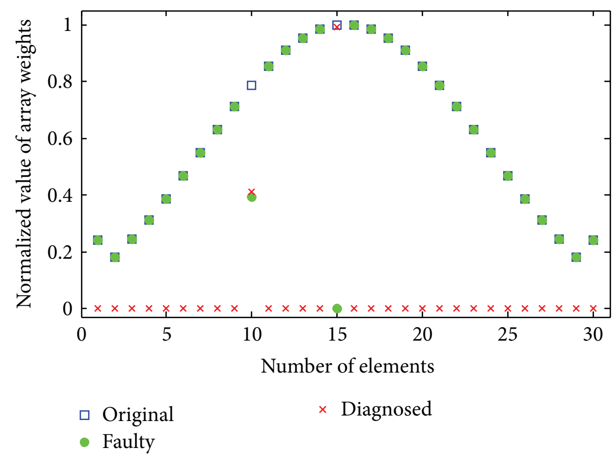

FIGURE 11: Detection of partial and complete fault through proposed algorithm.

4.1. Diagnosis of Partial Faults. If some elements in the array become faulty but radiate some power that is, its weight excitation is a fraction of the original but not equal to zero. The mathematical formula for partial fault is given by the following expression:

$$a_n = \begin{cases} \kappa w_n & \text{with propability } \phi \\ w_n & \text{otherwise,} \end{cases} \tag{21}$$

where $\kappa < 1$ is the partial failure factor. In this case, we consider the complete as well as partial fault. We assume that the 10th element is partially faulty (50% faulty) and the 15th element is completely faulty. The proposed technique detects the partial and complete fault more accurately which is depicted in Figure 11.

5. Conclusion and Future Work

In this paper, a compressed sensing based array diagnosis technique has been presented. This technique starts from collecting the measurement of the far-field pattern. The system linking the difference between the field measured using the healthy reference array and the field radiated by the array under test is solved using a GA, PCD algorithm, and GA hybridized with PCD algorithm. These algorithms are tested for the detection of fully and partially defective antenna elements and their simulation results validate that the proposed algorithm gives better results in terms of failure detection with a small number of measurements. The slow and early convergence of GA is prohibited by hybridizing with PCD algorithm. The hybrid GA-PCD algorithm makes the diagnosis of defective sensors (fully or partially) more accurate as compared to GA and PCD alone. Different simulation results are provided for Chebyshev array to validate the performance of the designed algorithms.

Conflict of Interests

The authors declare that there is no conflict of interests regarding the publication of this paper.

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