Genetic Algorithm Based Weight Optimization for Minimizing Sidelobes in Distributed Random Array Beamforming

S. Jayaprakasam, S.K.A. Rahim, Chee Yen Leow
Wireless Communication Centre,
Universiti Teknologi Malaysia (UTM),
Johor 81310, Malaysia.
{sharulkamal, bruceleow}@fke.utm.my.

K.R. Ramanathan,
Board Design Centre Malaysia (BDCM),
Intel Microelectronics (M) Sdn. Bhd.,
Kulim 09000, Malaysia.

Abstract—This paper proposes solution to optimize the peak side lobes level (PSLL) in a distributed random antenna array (RAA) when locations of the nodes in the array cannot be manipulated. Using the conventional beamforming method, RAA produces a poor beam pattern with high sidelobe level, which greatly reduces the performance and the efficiency of the antenna. Existing literature focuses on finding the best position of antenna placement in RAA to lower the sidelobes. This is not feasible when the user has no autonomy over the position of the antenna elements. Our proposed solution achieves beampattern with much lower PSLL regardless of the array size and number of nodes in the array. The proposed method also enables up to 40% of energy savings when the size of array is small and 20% of savings when bigger array size is considered.

Keywords—antenna radiation patterns; genetic algorithms; random antenna array; side lobe reduction.

I. INTRODUCTION

In accordance to the Moore's law, electronic devices are now rapidly decreasing in size while increasing in capacity. This serves as a remarkable boost to the popularity of the Internet of Things (IoT). It is conceived that in near future, all objects will be fully equipped with smart miniature electronic device that could communicate over wireless networks. This will simplify human's life tremendously. Daily chores will see changes with applications like intelligent shopping and home automation systems. A more global impact will also be felt via waste management, emergency response and similar applications [1].

One of the chief concerns when dealing with small communication devices (nodes) is the limitation of the battery life. One solution to solve this setback is employing cooperation among a few nodes via distributed and collaborative transmit beamforming [2-3]. In collaborative beamforming, a cluster of nodes can coordinate and subsequently form a virtual antenna array to send a common message to a receiver. With a fixed radiated power at each node, an ideal distributed beamforming with $N$ nodes will result in $N^2$ -fold gain in the received power at the receiver. Alternately, this technique could also enhance the energy efficiency of the communication while maintaining a fixed power at the receiver [3-5].

In practice, the positions of the distributed collaborative nodes are random, and thus the resultant beampattern is also random. This randomly placed nodes over a specified radius, and collectively form an array for beamforming purposes is known as a virtual Random Antenna Array (RAA). Though the RAA has its niche applications, it has to be noted that the sidelobes of the RAA tend to be higher compared to uniform antenna arrays. The number of elements in RAA influences the level of the largest sidelobe, or the peak sidelobe level (PSLL) to be higher if compared to the PSLL of a uniform array. Having high sidelobes will cause and incur interference, which reduces the transmission and reception efficiency of the system.

Previous researchers have proposed to reduce the side-lobes in antenna arrays by strategically placing the nodes according to pre-calculated optimized positions using various optimization algorithms [6-10]. Of these, the Genetic Algorithm (GA), inspired by the principle of evolution and the survival of the fittest concept, is one of the most common optimization methods [8-9]. However, in the existing literature, the GA is used to find the best arrangement of the nodes to minimize the sidelobes. While these solutions work well for centralized array, element spacing perturbation is not feasible in a practical distributed scenario, where the position of the nodes cannot be manipulated.

We hence propose a solution to reduce the sidelobes, especially the PSLL in distributed RAAs. Contrary to most previous works where GA is used to identify the best position for each element, we instead employ GA to identify the beamforming weight vector for the antenna elements. It is desired that the optimized solution not only should achieve lower PSLL, but also reduce the overall transmit energy of the nodes.

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II. FORMULATION OF DISTRIBUTED AND COLLABORATIVE RANDOM ANTENNA ARRAY BEAMFORMING

Consider a total of \( N \) communication devices (nodes) scattered within a radius of \( R \) meters, forming an RAA with a geometrical composition as depicted in Fig. 1.

A few nodes are randomly situated in a cluster, whereby each node can communicate directly with other nodes within the same cluster. One of these nodes is chosen as the cluster head (CH), which will become the geometrical reference point for all other nodes in the cluster. A source node which wishes to establish a communication is always chosen as the CH, hence hereafter, the CH also implies the source node.

The notations used in the figure are tabulated in Table 1. Only transmit beamforming is considered in this paper. Furthermore, for simplicity and generalization, the following assumptions made throughout this paper:

- **A1.** All nodes are coplanar.
- **A2.** All nodes are equipped with a single isotropic antenna with identical transmit power constraint.
- **A3.** System is operating under perfect channel conditions.
- **A4.** All nodes are static during the course of beamforming.
- **A5.** The effects of phase, time and frequency asynchrony are neglected.
- **A6.** Each node has the information on its own location coordinate.

The process of forming a beam collaboratively in a distributed network can be divided into two stages; i) information sharing stage and ii) collaborative beamforming stage.

In the first stage, the source node, CH broadcasts the data meant for the destination to all nodes within the same cluster. Each node in the cluster, after receiving data from the CH, aligns the phase of the data signal by multiplying it with a complex weight.

This phase alignment ensures that signals from all the nodes will be in-phase towards the direction of the destination when transmitted collaboratively.

During the second stage, the CH and the collaborating nodes will simultaneously transmit the data to the destination, each with a transmitting energy of \( \xi_k \). Since phase correction is made by each node during the first stage, the data will be added constructively at the destination node.

The location of the destination is \( \phi = [-\pi, \pi] \) with reference to the CH. When far field condition is assumed, the resultant array factor (AF) at \( \theta = [-\pi, \pi] \) is:

\[
AF(\theta, \mathbf{w}) = \sum_{k=1}^{K} w_k e^{-\frac{2\pi}{\lambda} \cos(\theta + \Psi_k)}
\]

where \( \mathbf{w} = [w_1, w_2, ..., w_k] \) and \( w_k \) is the \( k \)-th node's transmission weight:

\[
\Psi_k = \frac{2\pi}{\lambda} r_k
\]

The energy, \( \xi_k \) is the transmission energy and \( \Psi_k \) is the initial phase of node \( k \).

Each element multiplies the signal with the corresponding weight to align the phase of the signal. This ensures that signals from all the elements are in-phase towards the direction \( a \) when radiated. Therefore the produced main beam will be directed towards \( a \). In a closed-loop scenario, the phase synchronization is done by compensating the distance between a collaborating node and the destination. As a result, the initial phase of node \( k \) for the conventional RAA beamforming is [3]:

\[
\Psi_k = \frac{2\pi}{\lambda} r_k \cos\left(\phi - \Psi_k\right)
\]

If all nodes are assumed to be transmitting identical energy,
the receive power becomes $|N_\xi|^2$ under ideal system assumptions; while a single node transmission only yields $\xi^2$ of receive power.

The goal of the optimization in this paper is to choose $\xi$, such that the collaborative beamformer produces the best beampattern that points towards the direction of interest while maintaining low sidelobes.

III. GENETIC ALGORITHM FORMULATION

Genetic Algorithm (GA) is applied to obtain the best combination of the distributed node’s excitation energy to return low PSLL in the RAA. Each node is to broadcast a beacon periodically to inform other nodes in the cluster on its location coordinate. The neighboring nodes will then save the information a location vector table. When a CH wants to perform a distributed transmit beamforming, it will first compute the excitation energy for each nodes in the cluster using the GA based method proposed in this section. The information on the energy amount for each node will be then broadcast to the nodes along with the intended data during the information sharing stage. This will ensure that the resultant beampattern will have lower sidelobes and no unnecessary energy is wasted during the beamforming process.

The proposed GA based optimization works to obtain the best excitation energy for each node in a collaborating cluster through series of populations as described below.

Step 1. Initial Population and Chromosome Construction.

The initial population of genes is generated for $N$ sets of $M$ number of genes. The chromosome genomes are corresponding to the energy, $\xi$ excitation of nodes. Therefore, each chromosome contains $N$ number of genes.

During the first iteration ($t=1$), the genomes of this GA, the energy excitation of all nodes are set to unity, where $\xi_k = 1$ for all values of $k$. The phase excitations of the elements are fixed according to (3).

Step 2. Fitness Evaluation.

Fitness function is formulated to evaluate the sidelobe levels and get possible lowest PSLL out of all the energy combinations in the sets of genes. The fitness function is:

$$f(i) = \max [20 \log_{10}(AF(\theta_{SL}, w))]$$

where, $\theta_{SL}$ angles of the local maxima (side-lobe levels) for the AF:

$$\theta_{SL} = \arg \max \{AF(\theta, w)\}$$

Step 3. Parent Selection.

Once initial population is generated, the parent selection process takes place. This parent selection process can be done using several methods such as roulette, ranking, tournament and other. For this paper, ranking selection method was used. The ranking selection method chooses the chromosome with high fitness level from the parent and discards the lower fitness level. Hence, the top half of the parent chromosomes are chosen and lower half of the parent chromosomes are discarded.

Step 4. Crossover and Mutation.

A crossover point is randomly chosen and the part of chromosomes beyond and after the crossover points is swapped to form the offspring. After that, mutation process randomly changes the value of the genes into a random floating point within the transmit power constraint. Mutation process will be executed based on preset mutation rate value, $\mu$. The recently mutated offspring population is evaluated based on the fitness function and ranked. From the offspring chromosomes, $M/2$ best chromosomes are selected from the previous population to create new offspring population.

Step 5. Convergence Check.

The algorithm is stopped when the maximum number of iteration, $I$ is reached. If the conditions are not met, go to Step 2.

IV. RESULTS AND DISCUSSIONS

Simulations are done to compare the radiation pattern before and after the proposed GA based optimization in RAA beamforming is carried out. The elevation angle of the receiver (main beam) is set at $0^\circ$ for all cases. Other fixed parameters are $M=50$, $\mu=0.01$ and $I=100$. The transmit power constraint is set to 1mW.

In Fig. 3, the RAA indicates nodes’ arrangement and the corresponding radiation pattern when $N=4$, $N=16$, and $N=64$. PSLL of the conventional RAA beampattern and the proposed GA based RAA beampattern are labeled accordingly. For the example shown in Fig. 3, the improvement in terms of PSLL reduction are prominent for all cases, whereby the proposed GA based RAA beamforming reduces the PSLL by 2.1127dB, 4.012dB and 8.167dB for $N=4$, $N=16$, and $N=64$, respectively.

Fig. 3 also depicts the distribution of the transmit power at each node during the beamforming transmission of the proposed method. While the conventional RAA beamforming method will result in a fixed rate of 1mW at all nodes, the proposed GA based RAA suppresses the transmit power of certain nodes in the cluster and thus allows energy preservation. The nodes and amount of transmit power suppression will be determined by the arrangement of the nodes.

It is important to note that, due to the arbitrary crossover and mutation process in the GA, the obtained optimized beam pattern will not be the same even if the process is repeated on the same arrangement of the nodes.
To gauge a better overall view on the improvement provided by the proposed algorithm, Monte Carlo approach is adopted. A total of 100 different sets of nodes arrangement for \( N \) ranging from 10 to 100, and normalized disk size radius, \( R \) ranging from \( \lambda \) to 10\( \lambda \) were considered for analysis.

The average PSLL before and after the GA optimization for RAA is illustrated in Fig. 2. The PSLL for RAA decreases in a logarithmic fashion in accordance to the number of nodes. When \( N \) is varied from 1 to 10 for a fixed disk size of \( R=2\lambda \), about 2dB improvement in the PSLL is yielded, regardless of the number of nodes in the RAA. On the contrary, when \( R \) is varied from \( \lambda \) to 10\( \lambda \) for a fixed disk size of \( N=16 \), a higher improvement in PSL is achieved for a smaller disk size. An average of 7dB improvement is recorded for \( R=\lambda \) while only 2dB of improvement is seen when \( R=10\lambda \). Generally, mutual coupling affects the sidelobe level of RAA if the average spacing between elements is smaller than 2.5\( \lambda \)\cite{11}. Therefore, employing the GA based optimization to the individual nodes’ energy effectively limits the energy between two nodes with close spacing and thus reduces the mutual coupling effect for RAA of smaller disk size.

The average normalized directivity and the average power saved in the system by employing the proposed method are depicted in Fig. 5. The radius of the disk is varied from \( \lambda \) to 10\( \lambda \) while the number of nodes in the array is set to a constant \( N=16 \). The proposed method achieves a higher directivity compared to the conventional RAA beamforming in any case of disk size. The improvement in the percentage of power saved on the other hand is much higher for RAA of smaller disk size. The proposed method yield 20\% to 45\% of improvement in power savings when \( R \) is reduced from 10\( \lambda \) to \( \lambda \).

Fig. 4 shows the average convergence plot of the number of iteration over the achieved cost function during each iteration. Comparison is done between a 20 element array and a 100 element array. It is reflected in Fig. 4 that the improvement in
the PSLL reduction after the 50-th iteration is minimal for both cases, and hence an iteration of $i=50$ would be sufficient to achieve an optimal solution.

V. CONCLUSIONS

A procedure for reducing the level of the peak side lobe of distributed random antenna arrays is proposed in this paper. The proposed Genetic Algorithm based optimization efficiently determines the best excitation energy of each distributed nodes to collaboratively beamform. Results show that proposed method consistently yields beampattern with significantly lower PSLL compared to conventional scheme. The improvement in PSLL is not affected by the number of nodes in the cluster. Varying the disk size of the cluster affects the amount PSLL improvements in the system, where the proposed method shows higher improvements when the disk size is small. Up to 45% of overall energy can be saved in a cluster of nodes when the proposed method is used. Results also show that the proposed method needs only about 50 iterations to achieve the improved solutions.

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