ADAPTIVE BEAMFORMING USING GENETIC ALGORITHMS

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Abstract

The presented submission describes how genetic algorithms can be applied to the control of adaptive antennas. The proposed optimization method is easily implementable on one hand, but relatively slowly converging and depending on the parameters of the genetic algorithms on the other hand. The disadvantages as well as some possible improvements are discussed in this paper.

Keywords

Adaptive Antennas, Pilot Signal System, Genetic Algorithms.

1. Introduction

In today's society, radio communications play an important role: they are used in TV and radio broadcasting, mobile telephony, satellite communications and in other applications without which the today's civilisation cannot exist. Radio communications are based on the propagation of electromagnetic waves in free space which enable coverage of large areas by the signal on one hand but which are unfortunately subject to environmental perturbation such as atmospheric interference or jamming on the other hand.

Antennas are important components of radio communication systems since the way, energy is collected from and distributed into the environment has great influence on the effective use of spectrum, and also on the quality of services provided by radio communication systems including these antennas.

Beamforming is a subject of considerable interest. It is used in antenna systems to attenuate interferences which come from different directions than the desired signal. Adaptive beamforming is particularly attractive since it permits radio communication systems to respond to a time-varying environment.

There are numerous applications of adaptive antennas: they are used in radars to preserve a very weak signal reflected from a target for strong interferences, they are explored in radio communications to enable decreasing the power of transmitters due to the elimination of interferences by the antenna, they are applied in satellite as well as mobile communications to track main lobes of antennas in order to keep main lobe axes of transmitting and receiving antennas in the same direction, etc.

An adaptive antenna is a system which automatically sets minims of its directivity pattern to directions from which the most powerful interferences come. While retaining desired signal beam characteristics, it can reduce sidelobe levels in the directions of interferences and steer nulls in real time. Such systems usually consist of an array of antenna elements and an adaptive processor adjusting its weights in real time according to a selected control algorithm in order to maximize the output signal-to-interference ratio (SIR).

In the open literature, an emphasis has been put on control of adaptive antennas using gradient algorithms yet, e.g. Least Mean Squares [1], Linear Random Search [2], Recursive Least Squares [3], Kalman Filter [4], Simplified Kalman Filter [5] etc. This is given by the fact that these algorithms are rather simple to implement on one hand and they exhibit relatively good adaptation properties (high rate of convergence, low misadjustment, relatively good stability, etc.) on the other hand. Unfortunately, these algorithms are unable to handle with correlated signals if special de-correlation techniques are not used [6].

In this submission, a control of adaptive antennas, which is based on the use of genetic algorithms, is developed in order to find out in which situations they can work better than gradient algorithms.

In the presented paper, adaptive beamforming using genetic algorithms is discussed. Section 2 describes the general principals of genetic optimization. In section 3, an application of genetic algorithms to the control of adaptive antennas is described. In section 4, the results of simulations are discussed.

2. Genetic Optimization

Genetic algorithms (GA) are global numerical optimization methods which mimic the natural processes of genetic recombination and evolution [7] - [11]. Such algorithms are particularly efficient to handle with optimization problems with a large number of unknowns.

Usually, the algorithms encode parameters of an optimized system into binary sequences called *genes*. All the parameters of the optimized system are then encapsulated as sets of genes called *chromosomes*.

GA usually use four steps to solve problems [9]:

1. An initial population of chromosomes is randomly generated. By this way, *the first generation of chromosomes* is created.
2. A *fitness value* is assigned to each chromosome in the population in order to expressing how well the chromosome meets requirements to the optimized system. The function which performs the described assignment is called the *cost function* or the *fitness function*.
3. A new population of chromosomes is generated by selecting the best existing chromosomes and creating new ones by *crossover* and *mutation* which will be explained later. The phase of creating new generation is usually referred as *mating*.

   Step **3** is iterated k times. This means that k generations of chromosomes are created in order to find as good chromosomes as possible (i.e. chromosomes meeting the desired parameters of the optimized system as much as possible are searched).
4. The result of the genetic optimization is obtained as the best chromosome at the k^{th} iteration.

Contents of the steps **1**, **2**, and **4** are obvious but the step **3** has to be explained. Let's start with *mating*.

Mating consists of a phase of selection and a phase of creation.

Dealing with the first phase, there are many selection techniques [9]. Here, the most popular ones are described:

Proportionate selection (or *roulette-wheel selection*) chooses chromosomes according to a probability of selection depending on the fitness of the chromosomes ($p_i = f_i \,/\, \Sigma_n f_n$ where f_i and p_i are respectively the fitness and the probability of selection of the individual i).

Ranking selection (or *population decimation*) evaluates chromosomes according to their fitness value and only the best fifty percents of them are kept. This is the simpliest selection technique.

Tournament selection is characterized by choosing N chromosomes from the initial population and by selecting the most fit chromosome in the sub-population (all of the sub-population chromosomes are replaced into the population and the process is repeated).

Elitist strategy is based on testing the best individuals of a new generation whether their fitness is higher than in the previous generation. In the opposite, the best individuals from the previous generation are copied to the new one.

Thus, unacceptable individuals are discarded, leaving a superior species-subset of the original list.

Dealing with the phase of creation, a so called *crossover* is based on the recombination of two parent's chromosomes which yields two new child's chromosomes (or *offspring*). Parents can be paired randomly or in another way (a lot of strategies were so far developed). Parents are chosen from the chromosomes which remain in the population after selection. Once paired, a random cut site, defining where the chromosome is broken, is chosen for the couple of chromosomes. Finally, the exchange of genetic material is performed.

Dealing with *mutation*, this is a random alteration of some chromosomes of the population - one or more bits of chromosomes of the population are changed. Typically, the probability of mutation for a chromosome is between 1% and 10%. Mutation prevents the algorithm from getting stuck in a local extreme.

Now, let's try to apply the above described principles of the genetic optimization to the control of adaptive antennas.

3. Genetic Control of Adaptive Antennas

In this chapter, a linear adaptive antenna array consisting of N omni-directional elements, which are half-wavelength-spaced, is assumed. Each antenna element is completed by a complex weight implemented by a Finite Impulse Response (FIR) filter (Fig.3.1). The FIR filter consists of a tapped delay line connected to a processor which adjusts gains (also called FIR's weights) of the signals derived from the delay line and sums them to obtain an output signal. GA's role is to find FIR's weights in order to maximize SIR at the antenna output.

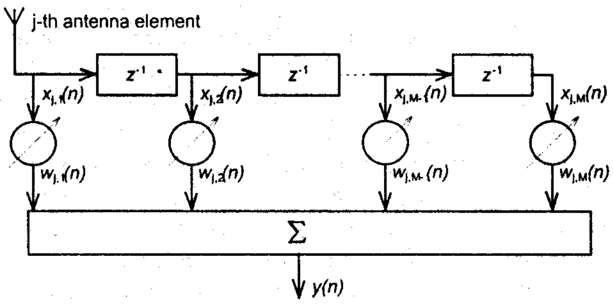

Fig. 3.1 An antenna element completed by an adjustable broad-band complex weight

The complex weights permit to modify the phase and the magnitude of broad-band signals at the outputs of the antenna elements in order to control input currents, and consequently, directivity pattern of the antenna system. If the adaptive array consists of N elements then the output signal can be expressed by the equation [4]

$$y(n) = \mathbf{W}^{T}(n)\,\mathbf{X}(n) \qquad (3.1)$$

where $y(n)$ is the sample of the signal at the antenna output, $\mathbf{W}(n)$ is the column vector of FIR's weights of all the antenna elements $\mathbf{W}^{T}(n) = [w_{1,1}(n), w_{1,2}(n), ..., w_{1,M}(n), ..., w_{N,M}(n)]$, and $\mathbf{X}^{T}(n)$ is the column vector of signals at the delay lines' taps of FIRs of all the antenna elements $\mathbf{X}^{T}(n)$ equals $[x_{1,1}(n), x_{1,2}(n), ..., x_{1,M}(n), x_{N,M}(n)]$ and ^{T} denotes transpose.

Our adaptive antenna system is based on the method of the pilot signal which was developed in the late sixties by B. Widrow [1]. The pilot signal $d(n)$ is a deterministic signal which is synchronously generated both in the transmitter and in the receiver. The adaptive change of the weighting vector $\mathbf{W}$ is asked then to enforce the signal at the antenna output $y(n)$ to meet the desired one $d(n)$.

Complex weights, by which antenna elements of the receiving antenna are completed, are calculated so that the mean squared error (mean value of the squared difference between the pilot signal and the output one) is minimized. Minimizing error signal means minimizing power of interferences in the output signal (in the ideal case, the output signal consists of the pilot only and all the interferences are suppressed). This can be interpreted as setting minima of the directivity pattern to the directions from which the most powerful interferences come [1]. Therefore, interferences can be rejected or at least attenuated.

The pilot signal system was used here as the simplest approach to the control of adaptive antennas. The minimum of the mean squared error was searched in an iterative way by LMS algorithm serving here as a reference and by genetic optimization techniques.

Concentrating on the genetic optimization, every adaptive antenna is described by a chromosome consisting of $N.M$ genes (FIRs' weights which can be changed during the optimization process) where N is the number of antenna elements and M is the number of FIRs' weights per antenna element. Our cost function computes for each chromosome the mean squared error on T samples of the signal (T is another parameter of our program). The ranking selection method was chosen as a selection technique. And chromosomes were paired in an easy way: the best one with the second best one and so on.

We implemented a first version of GA using binary encoding and decoding of parameters (conventional way of implementing GAs). Then since binary encoding and decoding of parameters were time consuming, we decided to implement a genetic version working directly on real weights [8]. In this version, real weights are genes of our GA and sets of $M.N$ genes are chromosomes. The use of real weights also allows the use of a much simpler cross-over function. Indeed, a child's chromosome can then be obtained from additions and subtractions of parent's chromosomes (and then there is no need to choose a random cross-over point to perform partial exchange of genetic material). Cross-over function is important since it is important for children to inherit good features from their parents. So, as it is suggested in [8], in this genetic algorithm, from two parents A and B, the three following children were produced: $C_1 = (A+B)/2$ which is the average of A and B, $C_2 = (3A-B)/2$ and $C_3 = (3B-A)/2$ which are two extrapolation points of C_1.

Let's recapitulate parameters of our program:

- Simulation of an antenna array is described by number of antenna elements N, by order of FIR filters M, by parameters of desired signal and interferences (mean, variance, direction of arrival), by sampling frequency f_s and by number of samples T for the estimation of statistical parameters of signals (ergodicity of signals is assumed).
- GA is described by the size of the population, by number of bits per gene, by number of iterations and by mutation probability.

In the next section of the paper, results of the simulation of the described genetic control of adaptive antennas are presented.

4. Results of Simulations

4.1 Narrow-Band Systems

Assume that both the interferences and the desired signal consist of only one harmonic. Computer simulations of a five-element antenna array (omni-directional elements spaced the half wavelength) with a two-tap FIR filter at the output of each antenna element were performed. Four interferences were simulated. The desired signal came from the main lobe direction with the amplitude S = 0.01 mV. The interferences came from θ_1 = -70°, θ_2 = -17°, θ_3 equals +17° and θ_4 = 80°. All the interferences had the same amplitude R = 10 mV.

Using binary encoding of parameters, the adaptation process was observed during 500 iteration cycles (mutation probability=5%). The simulation was executed twice. We chose here a time vector consisting of T = 51 samples.

As shown in Fig. 4.2 and Fig. 4.4, the genetic algorithm is converging, but even after 500 iterations, the mean squared error is still quite high. In term of speed of convergence, a mutation probability of 5 % seems to be optimal here. We didn't raise the number of iterations (i.e. number of generations) since, first, it is time-consuming, and second, attenuations were already set in the right directions (θ_1 = -70°, θ_2 = -17°, θ_3 = +17°, θ_4 = 80°) as shown in Fig. 4.1 and Fig. 4.3.

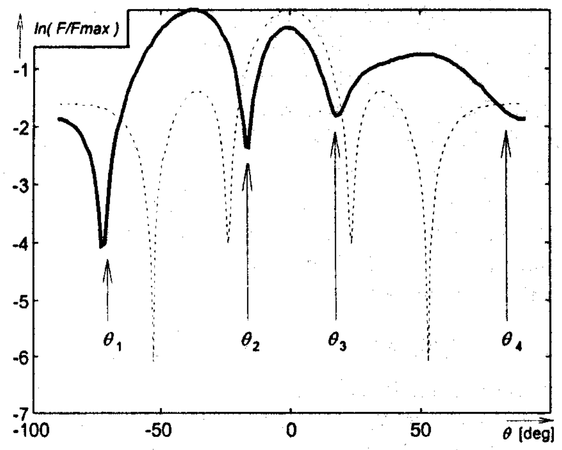

Fig. 4.1 Directivity pattern of the narrow-band non-adapted antenna (dotted) and the genetically optimized antenna (solid) after 500 iteration steps (first execution).

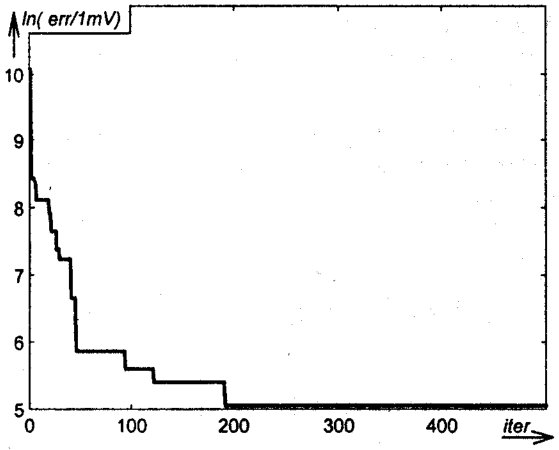

Fig. 4.2 Time course of the mean squared error of the narrow-band genetically optimized adaptive antenna in the described interference environment (first execution).

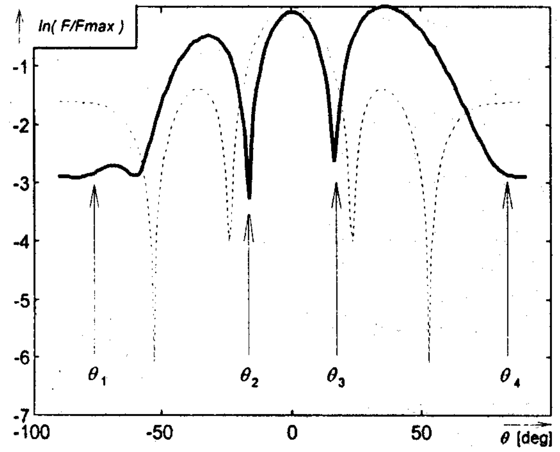

Fig. 4.3 Directivity pattern of the narrow-band non-adapted antenna (dotted) and the genetically optimized antenna (solid) after 500 iteration steps (second execution).

Two executions of the same program under the same conditions show that results of GA are sometimes worse (Fig. 4.1 and Fig. 4.2), and sometimes better (Fig. 4.3 and Fig. 4.4). Raising the amplitude of one of the interferences in a factor less than 10 doesn't seem to influence the GA. In particular, the strongest attenuation doesn't correspond to the most powerful interference. If one of the interference is at least ten times stronger than the other interferences, the algorithm attenuates it in priority sometimes without attenuating at all the other interferences.

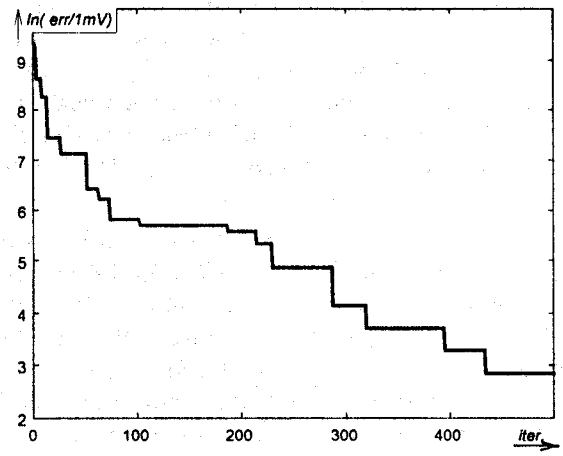

Fig. 4.4 Time course of the mean squared error of the narrow-band genetically optimized adaptive antenna in the described interference environment (second execution).

In the next simulation, both the antenna system and the electromagnetic environment stayed the same but adaptation process was performed by a GA without binary encoding of parameters. The adaptation process was observed during only 300 iteration cycles (mutation probability = 10%)

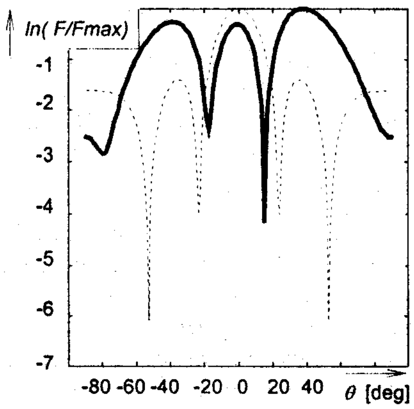

Fig. 4.5 Directivity pattern of the narrow-band non-adapted antenna (dotted) and the antenna genetically optimized without binary encoding (solid) after 300 iteration steps.

The average error between the desired signal and the control system output can be computed using the relation

$$err = \sqrt{resultat(K)/size(t)} \qquad (4.1)$$

where *resultat(K)* contains the mean squared error of the signal at the step K, and *size(t)* is the number of samples on which the mean squared error is computed. In this experiment (Fig. 4.5 and Fig. 4.6), err = 0.0032 for an amplitude of the desired signal of 0.01 mV. It confirms the fact that the error is converging toward zero. Raise the number of generations is useless since attenuations are already set in the right directions as it is shown in Fig. 4.5. In this experiment, we raised the mutation probability from 5 to 10% in order to increase the speed of the algorithm. A mutation probability of 10 % seems to be optimal in the conditions of last experiment. We also chose here a time vector consisting of 51 samples. So the mean squared error is computed over 51 points. It is a trade-off between results and speed of the algorithm.

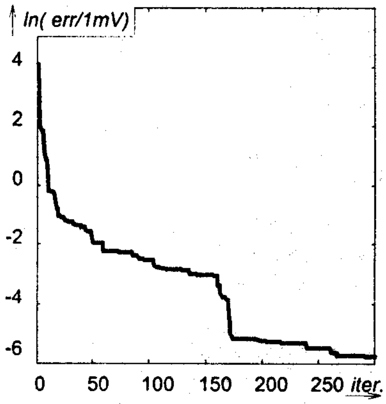

Fig. 4.6 Time course of the mean squared error of the narrow-band adaptive antenna genetically optimized without binary encoding in the described interference environment.

Now, the following conclusions can be drawn:

1. The GA is well minimizing the mean squared error causing attenuations in the directions of interferences.
2. The GA without binary encoding and decoding of parameters is quicker because avoiding encoding and decoding procedures saves CPU time and because using real genes allows the use of a simpler cross-over function. This method very well suits to real time adaptation in our simple case.
3. The GA is a resistant search algorithm able to handle as many interferences as it should (N-1 for a N element antenna array) provided that the number of generations is big enough. One can fear that raising the number of antenna elements as well as the number of interferences increase computational time in such a way that it would be difficult to perform adaptation in real time. On the other hand processors are getting quicker and quicker, making the GAs, algorithms of the future.

4.2 Broad-Band Systems

In broad-band systems, both the interferences and the desired signals are supposed being white noises. In this case, a two tap FIR filter is replaced by a M-tap FIR filter with M>2. In the conditions of our experiments, best results were obtained from M = 4 against M = 15 for a system adapted with a LMS algorithm. Computer simulations using a five-element antenna array were carried out. Desired signal (white noise, variance 6.45) coming from $\theta = 0°$ and two interferences, first one (white noise, variance $6.45.10^6$) coming from $\theta = 90°$, and the second one (white noise, variance $1.61.10^6$) coming from $\theta = 60°$ were used. Both the interferences and the desired signal were *white* between f_1=100kHz and f_2=500kHz.

Dealing with the simulation, 2000 iteration steps were performed with a mutation probability set to 5%, with *err* = 0.0142. The learning curve corresponding with the described situation is depicted in Fig. 4.7.

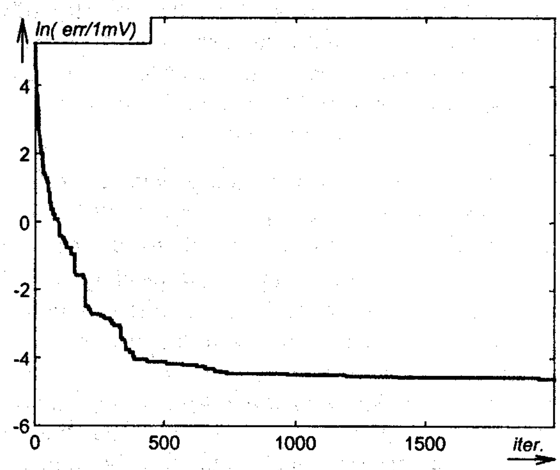

Fig. 4.7 Time course of the mean squared error of the broad-band genetically optimized adaptive antenna.

As the mean squared error is converging toward zero (mean squared error=0.0126 at the last iteration), it can be concluded that both interferences are attenuated.

Comparing GA to LMS, the convergence of the GA is slower. Even more, good convergence of GA is conditioned by choosing a good initial condition and a smaller search space.

From our experiments, GA seems to suit to adaptive beamforming of broad-band signals. But the complexity of real-life systems will probably lead to heavy computational loads making the algorithm unliveable for real-time adaptation. Therefore, the results of our simulations should be confronted to real life experiments.

5. Conclusions

The presented paper describes genetic beamforming of antenna arrays. As control algorithms, the genetic algorithms with binary encoding of genes and without it were chosen.

The genetic algorithms were used for the control of adaptive antenna arrays based on the pilot signal system which was chosen for the presented development for reasons of simplicity. The pilot signal control was used in conjunction with a linear five-element half-wavelength-spaced antenna array to which up to four interferences coming in different directions and presenting different amplitudes and phases were allowed to fall.

In narrow-band systems, properties of the GA and LMS algorithms are quite the same in simple cases (e.g., a five-element antenna array subject to only one interference). Unfortunately, performance of some more comparisons in a noisier environment was impossible to carry out, due to a problem of correlation of signals appearing when applying an LMS algorithm to the control of our antenna system.

Dealing with broadband systems, the properties of GA and LMS algorithms are not equivalent neither. Indeed, the LMS is quicker but requires a high FIR filter order whereas the GA performs comparable results in more time but requires a much lower FIR filter order.

In our work, we implemented a genetic algorithm for the above described specific application in Matlab 5.1. The genetic control turned out to be capable to reject all interferences in a simple narrow and broad-band system. The principal GA operators (selection, cross-over and mutation) were discussed as well as their role in the resolution of the optimization problem. We notably showed their influence on the speed of the algorithm which leads us to elaborate a non conventional GA without binary encoding and decoding of parameters which was already applied to sidelobe reduction in array pattern synthesis [8].

In conclusion, the robustness of genetic algorithms has been shown, at least in our specific application. Their properties allow them to handle a large number of parameters which make them very useful in the electromagnetic field. In particular, they make them suitable to adaptive beamforming. When the environment is getting more complex, the LMS is not capable to provide an exploitable result. This shows that genetic algorithms are much less sensitive than LMS algorithms to correlation of incoming signals. Yet, genetic algorithms also have their drawbacks: they are time consuming and the question of real-time adaptation will probably appear in the much more complex real-life systems. Yet, since processors are getting quicker and quicker, properties of genetic algorithms allow us to think them as algorithms of our future.

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Zbyněk RAIDA - for biography see the June's issue of this journal.