



Optimization for the Relative Side Lobe Level of the NXN Ultrasound Phased Array Using Genetic Algorithm to Treat Large Intestine Tumores

Mazhar Tayel, Nour Ismail, Ashraf Talaat,
 Alexandria University, Faculty of Eng., Electrical Eng. Dept., Alexandria, Egypt.21544
ashraftalaat@yahoo.com

Abstract

This paper presents how to optimally thin an array using genetic algorithm (GA). The GA determines which elements are turned off in a periodic array to yield the lowest maximum relative side lobe level (rsll). Simulation results for 400 elements ultrasound NXN phased array are shown. The array is thinned to obtain the lowest maximum values of rsll and a desired temperature therapeutic values at the volume of tumor in the large intestine.

1. Introduction

The ability of ultrasonic waves in the 0.4- 1 .0-MHz frequency range to penetrate deep inside the body gives ultrasound a unique advantage as a modality for deep hyperthermia when compared with other noninvasive techniques. However, when plane ultrasound waves are used for heating, unwanted hot and cold spots can result in the heating pattern. Hot spots in normal tissue lead to toxicities which can severely limit hyperthermia sessions [1]. On the other hand, cold spots in the tumor volume lead to treatment failures or recurrences [1]. Focused scanned ultrasound hyperthermia systems can achieve precise control of localized heating patterns by steering a small focused beam around the periphery of the tumor. Scanning systems currently in clinical use employ some kind of mechanical movement of the transducer(s) for steering the focus [2], [3]. Although mechanical scanning systems demonstrate the fact that focused ultrasound is probably the best noninvasive modality for deep localized hyperthermia, the mechanical movement of transducer(s) complicates the machine-patient interface and may increase the patient discomfort during treatment [1]. Periodic arrays are largely employed in communication systems. Array antennas can be easily implemented and presents the flexibility to control the direction of radiation, gain, side lobe levels, etc [1].

These periodic arrays generate a low side lobe amplitude taper by strategically positioning equally weighted elements. Simple analytical methods for deriving the element

positions to obtain a desired side lobe level are not available [2]. Probabilistic methods can also be applied for controlling relative side lobe level (rsll), but these are not accurate enough [3]. Haupt [4] presented the meaning of thinning an array by turning off some elements in a periodic array in order to improve the rsll. The method presented used the GA technique and normally arrived at optimized thinning configurations for large arrays, where other methods can not be applied. The aim of this paper is to present an exercise of optimization of array antennas by using the GA technique, for which it is necessary to define the chromosome information and fitness function. The chromosome will contain the information about the uniform phase variation along the array, and also amplitude excitation level of each array element as input parameters. The fitness function will take into account the desired direction of the main lobe and the rsll. (rsll). A GA was used to numerically optimize circular phased array applicator. The algorithms perform the genetic operations of reproduction, crossover, natural selection, and mutation to arrive at the optimum solution. These algorithms arrive at better thinning configurations for arrays than previous optimization attempts or statistical attempts. Other optimization methods cannot be applied to large-arrays, while statistical methods cannot find optimum solutions. Excellent results are obtained using GA to optimize an NXN ultrasound phased array applicator with 20X20 elements at 0.5 MHz frequency.

2. The Genetic Algorithm

The goal of the GA is to find a set of parameters that minimize the output of a function. GA differs from most optimization methods such as Fuzzy method for

thinning arrays because they have the following characteristics ;

- 1-It works with a coding of the parameters, not with the parameter themselves,
- 2-It searches from many points instead of a single point,
- 3-It doesn't use derivatives, and
- 4-It uses random transition rules, not deterministic rules.

GA is a search technique used in computer science to find approximate solutions to optimization and search problems. GA is a particular class of evolutionary algorithm that use techniques inspired evolutionary biology such as inheritance , mutation , natural selection and recombination (crossover) .GAs are typically implemented as a computer simulation in which a population of abstract representations (called chromosomes) of candidate solution (called individuals) to an optimization problem evolves toward better solutions. Traditionally, solutions are represented in binary as strings of 0s and 1s, but different encodings are also possible. The evolution starts from a population of completely random individuals and happens in generations. In each generation, the fitness of the whole population is evaluated, multiple individuals are stochastically selected from the current population (based on their fitness), modified (mutated or recombined) to form a new population, which becomes current in the next iteration of the algorithm [5].

Operation of a GA

Two elements are required for any problem before a genetic algorithm can be used to search for a solution: First, there must be a method of *representing* a solution in a manner that can be manipulated by the algorithm. Traditionally, a solution can be represented by a string of bits, numbers , characters or by a special struct. Second, there must be some method of measuring the *quality* of any proposed solution, using a fitness function.

For instance, if the problem involves fitting as many different weights as possible into a knapsack without breaking it , a representation of a solution might be a string of bits, where each bit represents a different weight, and the value of the bit (0 or 1) represents whether or not the weight is added to the knapsack. The fitness of the solution would be measured by determining the total weight of the proposed solution: The higher the weight, the greater the fitness, provided that the solution is possible.

Initialization

Initially many individual solutions are randomly generated to form an initial population. The population size depends on the nature of the problem, but typically

contains several hundreds or thousands of possible solutions. Traditionally, the population is generated randomly, covering the entire range of possible solutions (the *search space*). Occasionally, the solutions may be "seeded" in areas where optimal solutions are likely to be found.

Selection

During each successive epoch, a proportion of the existing population is selected to breed a new generation. Individual solutions are selected through a *fitness-based* process, where fitter solutions (as measured by a fitness function) are typically more likely to be selected. Certain selection methods rate the fitness of each solution and preferentially select the best solutions. Other methods rate only a random sample of the population, as this process may be very time-consuming. Most functions are stochastic and designed so that a small proportion of less fit solutions are selected. This helps keep the diversity of the population large, preventing premature convergence on poor solutions. Popular and well-studied selection methods include roulette wheel selection and tournament selection.

Reproduction

Main articles: crossover and mutation and _ The next step is to generate a second generation population of solutions from those selected through genetic operators: crossover (or recombination), and mutation. For each new solution to be produced, a pair of "parent" solutions is selected for breeding from the pool selected previously. By producing a "child" solution using the above methods of crossover and mutation, a new solution is created which typically shares many of the characteristics of its "parents". New parents are selected for each child, and the process continues until a new population of solutions of appropriate size is generated. These processes ultimately result in the next generation population of chromosomes that is different from the initial generation. Generally the average fitness will have increased by this procedure for the population, since only the best organisms from the first generation are selected for breeding, along with a small proportion of less fit solutions, for reasons already mentioned above.

Termination

This generational process is repeated until a termination condition has been reached. Common terminating conditions are (1- a solution is found that satisfies minimum criteria 2-Fixed number of generations reached 3-Allocated budget (computation time/money)

reached 4-The highest ranking solution's fitness is reaching or has reached a plateau such that successive iterations no longer produce better results 5-Manual inspection 6-Combinations of the above).

Observations

There are several general observations about the generation of solutions via a GA [6]:

- In many problems with sufficient complexity, GAs may have a tendency to converge towards local optima rather than the global optimum of the problem. The likelihood of this occurring depends on the shape of the fitness landscape. Certain problems may provide an easy ascent towards a global optimum, others may make it easier for the function to find the local optima. This problem may be alleviated by using a different fitness function, or by using techniques to maintain a diverse population of solutions.
- Operating on dynamic data sets is difficult, as genomes begin to converge early on towards solutions which may no longer be valid for later data. Several methods have been proposed to remedy this by increasing genetic diversity somehow and preventing early convergence, either by increasing the probability of mutation when the solution quality drops (called triggered hypermutation), or by occasionally introducing entirely new, randomly generated elements into the gene pool (called random immigrants). Recent research has also shown the benefits of using biological exaltation (or preadaptation) in solving this problem.
- Selection is clearly an important genetic operator, but opinion is divided over the importance of crossover versus mutation. Some argue that crossover is the most important, while mutation is only necessary to ensure that potential solutions are not lost. Others argue that crossover in a largely uniform population only serves to propagate innovations originally found by mutation, and in a non-uniform population crossover is nearly always equivalent to a very large mutation (which is likely to be catastrophic).
- Often, GAs can rapidly locate good solutions, even for difficult search spaces.
- For specific optimization problems and problem instantiations, simpler optimization algorithms may find better solutions than genetic algorithms (given the same amount of computation time). GA practitioners may wish to try other algorithms in addition to GAs.
- GAs cannot effectively solve problems in which there is no way to judge the fitness of an answer other than right/wrong, as there is no way to converge on the solution. These problems are often called "needle in a haystack" problems.
- As with all current machine learning problems it is worth tuning the parameters such as mutation

probability, recombination probability and population size to find reasonable settings for the problem class you are working on. A very small mutation rate may lead to genetic drift (which is non-ergodic in nature) or premature convergence of the genetic algorithm in a local optimum. A mutation rate that is too high may lead to loss of good solutions. There are theoretical but not yet practical upper and lower bounds for these parameters that can help guide selection.

- How the fitness function is evaluated is an important factor in speed and efficiency of the algorithm.

A gene with N, B-bit parameters have a total of $2NB$ possible genes. If the parameters are continuous, then the GA limits performance due to quantization errors associated with the binary encoding of the parameters. On the positive side, GAs are ideally suited for optimization of functions with discrete parameters. A thinned array has discrete parameters. One bit represents the element state as "on" = 1 or "off" = 0. For example, a six element array may, be represented by 101101, where elements 2 and 5 are turned "off." Assuming the linear array is symmetric about its center allows the $2N$ element array to be represented by a gene with N bits. Thus, six-element array example can then be represented by the gene 101. The fitness associated with this gene is the maximum rsl1 of its associated field pattern. The function in this paper is the relative field pattern of an array of point sources. Its output to be minimized is the maximum rsl1. The parameters affecting the output are whether an array element is on or off.

3. Optimally Thinned Array

Cancer can occur in any part of body . Carcinoma of the gastrointestinal tract is one of cancer types. Carcinoma of the large intestine is the most common malignant tumor of the alimentary tract. The variation in incidence of the disease between different countries has led to the speculation of the dietary factors and differences in the bacterial flora of the bowel may be of etiological significance. The sites of the tumor in the large intestine according to the frequency are as follows: sigmoid colon 29%, rectum 26%, right colon 19%, transverse colon 18%, left colon 8%. Macroscopically the tumor may be proliferative and fungating. Ulcerating and infiltrative. Polypoid. In this paper the layers considered from the anterior abdominal wall till reaching the tumor include skin, fat, muscle, peritoneum, and a layers of the intestine containing the tumor[7]. We will try to treat this cancer by using the NXN ultrasound phased array . The array factor for the NXN ultrasound phased array applicator given as[8].

$$AF(\theta, \varphi) = 4 \sum_{n=1}^N \sum_{m=1}^M i_{mn} \cdot \cos[(2m-1)\pi l_x \cdot u] \cdot \cos[(2n-1)\pi l_y \cdot v] \quad (1)$$



Where

- M = Number of elements in the x-direction
- N = Number of elements in the y-direction
- d_x = Spacing in the x-direction
- d_y = Spacing in the y-direction
- i_{mn} = Excitation of the element $mn=0$ or 1
- $u = \sin(\theta) \cdot \cos(\varphi)$
- $v = \sin(\theta) \sin(\varphi)$
- θ = Steering angle.

φ = angle measured from line passing through the center of applicators.

This equation assumes that the array lies in the x-y plane and has a symmetry about the x-axis and y-axis. Using (1) to calculate the array factor for the NXN array shown in figure (1).

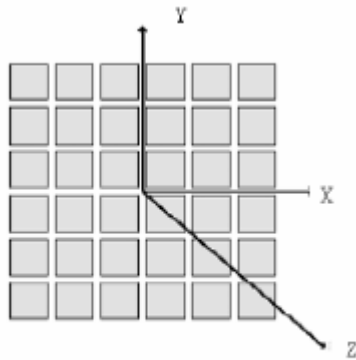


Fig 1. The NXN ultrasound phased array applicator.

The array factor for the 20X20 elements array is given as shown in figure (2)

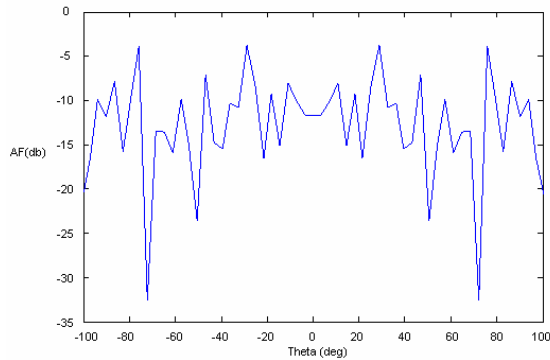


Fig.2. The array factor for the NXN array before using GA.

Applying the 3-D steady state bioheat equation

$$k \nabla^2 T - W C_b (T - T_a) + Q_p = 0 \tag{2}$$

to find the temperature distribution in the large intestine Where k is the thermal conductivity in the tissue in (W/m/°C), T is the tissue temperature (°C), W_b is the blood perfusion rate (kg/m3/s), C_b is the corresponding blood specific heat (J/kg/ °C), T_b , is the arterial blood temperature (37°C), Q is the local power deposition (W/m3) , and

$$Q = \alpha \frac{|p^2|}{2\rho c} \tag{3}$$

Where

α is the attenuation coefficient, p is the pressure, ρ is the density of layer, c is the ultrasound velocity in layer. Boundary conditions of 25°C on all of outer surfaces, the parameter of tissues are given in table (1) , and the simulated model under test is shown in figure (3).The actual model used is composed of layers of skin,fat,muscle, Peritoneum and large intestine as shown in figure (4)[9]. The large intestine tumor is located at $Z=9$ cm from the transducer surface , The foci points are selected to be found at [0,0,9cm], [0,1cm,9cm].

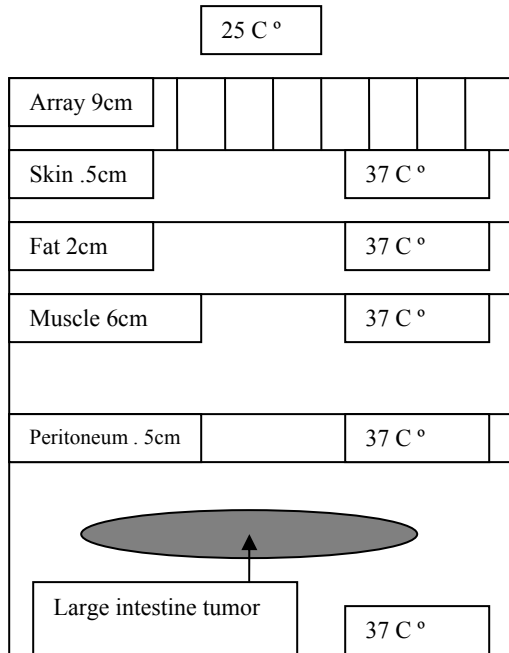
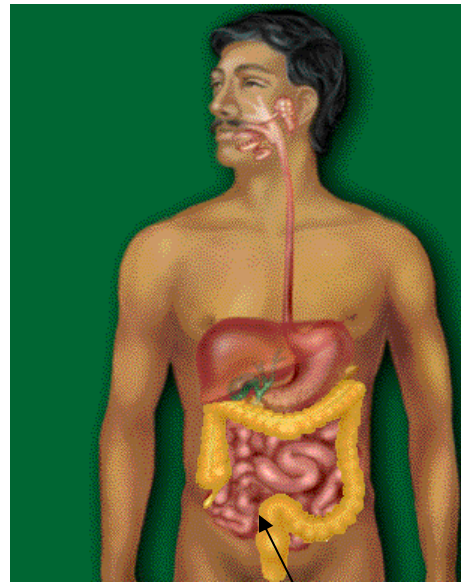


Fig.3. The simulated model under test.

Table .1.Tissue parameters

	ρ kg/m ³	C_b J/kg/°C	K W/m/°C	α N _p /m
Skin (.5cm)	1050	3610	.48	5.5
Fat (2cm)	1300	1005	.192	.006
Muscle (6cm)	1060	3720	.5	6
Peritoneum (.5cm)	1.07*1000	3.5*1000	.55	4
Large intestine	1.05*1000	3.1*1000	.50	4.06



(Large intestine)

Fig.4. The actual model under test.

The temperature distribution is shown in figure (5) before applying the GA. The array factor, after the GA for the same array is shown in figure (6).

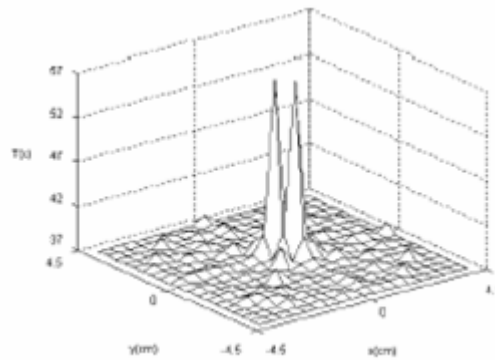


Fig.5. The temperature distribution in large intestine tissue at [0,0,9cm],[0,1cm,9cm] before using GA

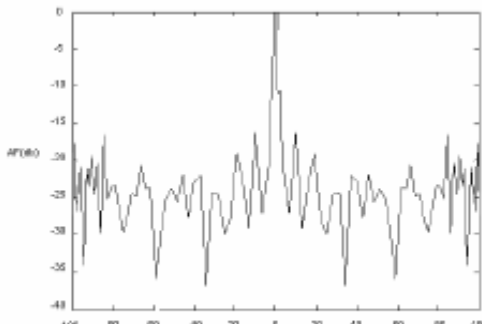


Fig.6. The array factor for NXN array after using GA

The temperature distribution, after applying the GA and after reducing the rsl1 from -5 db to -17 db is shown in figure (7).

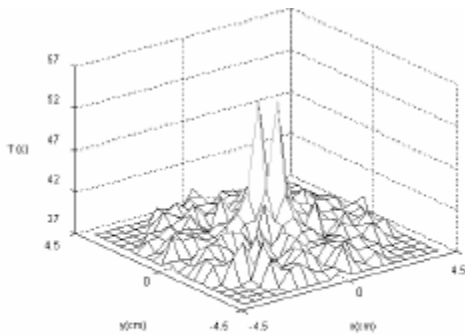


Fig.7. The temperature distribution in large intestine tissue at [0,0,9cm],[0,1cm,9cm] after using GA.

5. Conclusion

The above sections had introduced the use of GA for thinning the NXN ultrasound phased array applicator to obtain the lowest possible maximum values of rsl1 and to minimize the number of array elements. Matlab tools are used to optimize the number of element using GA. The program initiating by a chromosome length of 400 binary bits representing 400 elements of the array .The program includes a random crossover and mutation depending on a specified cost function (AF). After 100 iterations the optimization process is ended . The results show that the number of active elements is reduced to 256 elements instead of 400 elements . Also a reduction from -5db to -17db is observed for the rsl1. The GA intelligently had searched for the best thinning that produces low side lobe levels. Thus this algorithm is quite useful for optimizing the array design.

6.Refrances

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