

# A new genetic algorithm technique in optimization of permanent $^{125}\text{I}$ prostate implants

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Real time optimized treatment planning at the time of the implant is desirable for ultrasound-guided transperineal  $^{125}\text{I}$  permanent prostate implants. Currently available optimization algorithms are too slow to be used in the operating room. The goal of this work is to develop a robust optimization algorithm, which is suitable for such application. Three different genetic algorithms (sGA, sureGA and securGA) were developed and compared in terms of the number of function evaluations and the corresponding fitness. The optimized dose distribution was achieved by searching the best seed distribution through the minimization of a cost function. The cost function included constraints on the periphery dose of the planned target volume, the dose uniformity within the target volume, and the dose to the critical structure. Adjustment between the peripheral dose, the dose uniformity and critical structure dose can be achieved by varying the weighting factors in the cost function. All plans were evaluated in terms of the dose nonuniformity ratio, the conformation number and the dose volume histograms. Among these three GA algorithms, the securGA provided the best performance. Within 2500 function evaluations, the near optimum results were obtained. For a large target volume (5 cm $\times$ 4 cm $\times$ 4.5 cm) including urethra with 20 needles, the computer time needed for the optimization was less than 5 min on a HP735 workstation. The results showed that once the best set of parameters was found, they were applicable for all sizes of prostate volume. For a fixed needle geometry, the optimized plan showed much better dose distribution than that of nonoptimized plan. If the critical structure was considered in the optimization, the dose to the critical structure could be minimized. In the cases of irregular and skewed needle geometry, the optimized treatment plans were almost as good as ideal needle geometry. It is concluded that this new genetic algorithm (securGA) allows for an efficient and rapid optimization of dose distribution, which is suitable for real time treatment planning optimization for ultrasound-guided prostate implant. © 1998 American Association of Physicists in Medicine. [S0094-2405(98)02412-2]

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## I. INTRODUCTION

An ultrasound-guided transperineal  $^{125}\text{I}$  permanent implant technique was first described by Holm *et al.*<sup>1</sup> and later refined by Blasko and Ragde *et al.*<sup>2,3</sup> During this procedure a transrectal ultrasound (TRUS) probe is inserted into the rectum to visualize the prostate and a perineal template is attached as a guide. Needles are then inserted transperineally through the template into the prostate under ultrasound visualization and the radioactive seeds are placed within at predetermined positions.

Prior to the actual implant, computerized dosimetric "pre-planning" is performed which is generally based upon a set of transverse contours obtained a day or two before using computed tomography (CT) or ultrasound imaging. The planned placement of needles and radioactive seeds is guided by classical brachytherapy "rules" (Quimby or Paterson-Parker)<sup>4,5</sup> or published nomograms<sup>6,7</sup> and modified according to the anatomic shapes using a combination of clinical judgement and "trial and error." Since there is a large number of possibilities for arranging the needle and

seed positions, it can be very difficult to obtain a good needle and seed arrangement using this manual approach. Tools to assist the pre-planning have been developed using either home-designed codes or codes, which incorporate the existing treatment planning system.<sup>8</sup> Although acceptable dose distributions can be obtained, the numerous manual iterations can require several hours to complete and is highly dependent on the skill and experience of the individual planner.

It has been reported that a least-square optimization method when applied to prostate implants can reduce the pre-planning time by a factor of 10 compared to the manual approach.<sup>9</sup> This substantial improvement clearly indicates the direction to be followed. However, optimization using a local search algorithm, such as least-square fit, may end up in a local minimum<sup>10</sup> and the optimized plan may not be the best plan. For a large configuration space, especially one in which a desired global minimum is hidden among many inferior local minima, an efficient global search strategy must be used. Simulated annealing (SA) and genetic algorithm

(GA) have the potential and ability to explore the entire configuration space and eventually reach the global minimum. These two random search algorithms have been recently introduced in the literature for radiation therapy optimization applications.<sup>11-18</sup> Among these, a fast simulated annealing (FSA) and genetic algorithm were used for optimizing prostate implants. The computer time needed for optimizing a seed distribution based on assumed needle geometry using FSA was reported to be about 15 min using a SUN SPARC5.<sup>15</sup> Optimization of both a needle and seed distribution using GA was reported to be about 30 min on a similar computer.<sup>17</sup> Although these two random search algorithms have the ability to find a better treatment plan in less time than with the manual methods, they may not be able to improve the actual implant. The overall size and shape of the prostate can change by the time the real implant is performed, perhaps several days or even several months (considering the current status of seed availability) later after the plan is created. In addition the needles may be deflected upon insertion and not end up parallel as designed. The optimized pre-plan may no longer represent the optimized treatment for the actual implant. Using this argument it is evident that realtime optimized treatment planning at the time of the implant is necessary for true optimization of the treatment delivery. Thus, it is desirable to develop an optimization algorithm, which is fast enough so that after all the needles are inserted into the prostate, a quick seed optimization can be done based on the actual anatomic contours and needle geometry from the post-insertion TRUS. Afterwards the seeds can be loaded according to the realtime optimized plan.

In this article, three GA algorithms were developed for the application of the realtime optimization. The comparison was made amongst these three algorithms of the number of function evaluations and the corresponding fitness values. The securGA was found to be the best among these three algorithms and used to optimize the dose distribution for all cases studied in this paper. The computer time needed for the optimization of a large prostate (5 cm $\times$ 4 cm $\times$ 4.5 cm) involving 20 needles is less than 5 min. This new genetic algorithm allows for an efficient and rapid optimization of dose distribution, which is suitable for realtime treatment planning for ultrasound-guided prostate implant.

## II. METHODS AND MATERIALS

### A. Genetic algorithm

A genetic algorithm is a model of machine learning that derives its mechanisms from Darwinian's principle "survival of the fittest."<sup>19-22</sup> An initial population of size  $n$  is created from a random selection of the parameters in the parameter space. Each parameter set represents the individual's chromosomes. Each of the individuals is assigned a "fitness" based on how well each individual's chromosomes allow it to perform in its environment. There are three operations, which occur in GA's to create the next generation: (1) selection, (2) crossover, and (3) mutation. Fit individuals are selected for mating, while weak individuals die off.

Mated parents create a child with a chromosome set that is some mix of the parent's chromosomes. The process of mating and child creation is continued until an entirely new population of size  $n$  is generated with the hope that strong parents will create a fitter generation of children; in practice, the average fitness of the population tends to increase with each new generation. The fitness of each of the children is determined and the process of selection-crossover-mutation is repeated. Successive generations are created until very fit individuals are obtained.

Several concepts are important to understand the genetic algorithm techniques. These include the following: (1) Binary coding is a coding method that the parameters are discretized into a number of possibilities. The chromosome length is based on the total number of possibilities in a binary format. For example, a string of length 4 would represent 16 possibilities. (2) Single point crossover is a crossover process that a crossover point is randomly chosen where the chromosome set of the second parent overwrites the chromosome set of the first parent. For example, parent "abcde" and "ABCDE," after crossover, one possible chromosome set for the child is "abcDE," where the position between the "c" and "D" is the randomly determined single crossover point. (3) Uniform crossover is a crossover method that each chromosome position has a probability for a crossover with the second parent. It is possible to obtain any combination of the two parent chromosomes; e.g., the child could end up with chromosome set "aBcDe." For single point crossover it is possible that the child could retain the entire chromosome set of either parent, but in uniform crossover it is unlikely. (4) Jump mutation is a mutation method that produces a chromosome that is randomly picked to be in the defined parameter range. For example, the child ends up with chromosomes "abcDM," where "M" was not a chromosome from either parent. (5) Creep mutation is the mutation process that produces a parameter value that is randomly picked to be larger or smaller than its parent values. For example, the child ends up with chromosome "abcDF," where "F" was not a chromosome from either parent, but is only one increment away from second parent's chromosome value of "E." (6) Elitism is the operator that is used to insure that the chromosome set of the best parent generated to date is reproduced.

Krishnakumar<sup>23</sup> found that a micro-GA avoided premature convergence and demonstrated faster convergence to the near-optimal region than did a simple GA (sGA) for the multimodal problems he studied. Krishnakumar's results are quite intriguing for the multimodal, seed implantation application of this study. Very briefly, a micro-GA starts with a small random population (5 individuals), which evolves in normal GA fashion and converges in a few generations (typically 4 or 5). From this a new random population is created while keeping the best individual from the previously converged generation ("elitism") and the evolution process restarts. GA concepts, which are employed in the micro-GA, are those of elitism, single-point crossover, and a restart mechanism to reinfuse new genetic information into the population when it converges. Mutations are eliminated from