Use of Evolutionary Algorithm in Radiation Therapy

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***Abstract*— This paper addresses manual treatment planning of radiation therapy. Computational intelligence in general and Evolutionary Algorithm in particular can be used to Automate and control radiation therapy. Some radiation treatments can be used as alternatives to surgery for tumors. In a manual treatment location of size of radiation shots are decided manually. This study develops a treatment plan using Evolutionary Algorithm and applying 3-Dimensional optimization model to create a radiation path for shot location. The algorithm will also decide for the number, size and the location of the radiation shots. The research compares the automation and optimization of the proposed techniques as well as the speed of treatment with that of conventional procedure.**

Keywords: Optimization, Radiosurgery, Skeletonization, Evolutionary Algorithm.

I. INTRODUCTION

The gamma knife is a powerful clinical technique to provide an advanced stereotactic approach to the treatment of tumors, vascular malformations, and pain disorders within the head. The gamma knife delivers 201 beams from cobalt-60 radioactive sources through 201 holes in the protective hemisphere helmet. The beams are focused so they intersect at the same location in the target region. The result is an approximately spherical dose distribution at the effective dose level. The treatment plan can be customized to treat lesions of varying sizes and shapes, which typically consist of a number of shots, of possibly different shot sizes ($w \in \{4mm, 8mm, 14mm, \text{ and } 18mm\}$) and shot duration, centered at different shot location in the tumor.

In most clinical setting, the patient's treatment plan is developed by undertaking through a trial-and-error process. Most of the planning time is spent on fine-tuning the shot configuration in order to obtain a clinically optimal plan. A slightly more complicated target shape can significantly increase the planning time.

A number of models and techniques have been investigated for automating the planning of multiple shots for three dimensional radiosurgery. In 1996, Wu and Bourland [10] introduced a shape based treatment planning approach. In this approach, an image process technique called Skeletonization (Medial Axis Transform) is adopted to assist treatment planning. This strategy considers the shape of the target from the beginning. First, the skeleton of target is generated, and then the shot locations are limited on the skeleton. The number of shots is included in the solution as a variable, which is different from previous approaches. Hence the number of shots, shot locations, sizes, and weights for targets can be adjust quickly if the targets have different shapes and volumes.

To date, there are many optimization algorithms used in radiotherapy, in particular in intensity-modulated radiotherapy (IMRT). Most borrow the intelligence from the natural process and are inherit in a global search mechanism [2]. The typical examples are simulated annealing (SA) [7], [8], genetic algorithm (GA) [1], [3], [9], and exhaustive search techniques [5], [6]. The results reported have been promising and encouraging for further research in this field. Due to many parameters needing to be optimized, GA has been demonstrated its feasibility to solve the beam angle optimization problem in IMRT planning [4].

This research focuses on the shot location and size determination (SLSD) procedures in the treatment planning. The objective is to develop a Evolutionary algorithms based shot placement model which will allow treatment team to design treatment plan in a much simpler, faster, and more effective way, rather than current time-consuming, manual procedures.

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II. Optimization Models

A. Assumptions

This paper focuses on the shot location and size determination (SLSD) process in Radiosurgery treatment planning. The objective is to determine where to place shots and how large to make them initially. The process can be divided into two major phases. First, the skeleton (center line) is generated. Second, along the skeleton, different number and size of shots are tried to place on the target to find the optimal configuration.
Due to all physical limitations and biological uncertainties involved in the Radiosurgery Treatment Planning, several assumptions are defined before the process is presented in detail:

- A three dimensional simulated computer target is treated as an accurate representation of the actual tumor.
- The shape of the target should not be too irregular, its volume is bounded, and all dimensions of the target should not be larger than 35mm.
- The target volume is modeled as a 3D grid of points (voxels) and divided into two subsets, the subset of points in and out of the target. Each outsize voxel of the target is denoted by 0, while each inside voxel is denoted by 1.
- There are four interchangeable outer collimator helmets with beam channel diameters w = {4, 8, 14, 18} mm available for irradiating different volumes.
- For a target volume larger than one shot, multiple shots can be used to cover the entire target. There is a boundary on the number of shots, typically it should be less than or equal to 15 shots.
- The does cloud is perfectly spherical, or the overlap of radiation from the use of non-spherical shots can be negligible.

B. Skeleton Generation

At this phrase, distance transformation/coding method is use to generate a 3D skeleton. The first step in the skeleton generation is to compute the contour map containing distance information from the point to a nearest target boundary. Then based on the contour map, the skeleton extraction method designed by Zhou, Kaufman and Toga [11] is used. The reason this method is used is because it has demonstrated its accuracy and timely performance on medical images.

C. Shot Placement

After skeleton is generated, the approach restricts attention on it and evaluates each voxel to determine which one is a good location to place a shot. At this phase, GA method is adopted to look for the best point to place a shot and determine the shot size.
The fitness function is very important for GA method. This GA method will provide a fitness function that is based on one designed by Ferris et al. [6]. Ferris et al. developed a set of objective functions, which are shown in eq. 1 to eq. 3:

1. $\oint_{sh}(x, y, z) := (\text{spread}(x, y, z) - \text{height}(x, y, z))^2$ 1
2. $\oint_{sw}(x, y, z, w) = (\text{spreads}(x, y, z) - w)^2$ 2
3. $\oint_{hw}(x, y, z, w) := (\text{height}(x, y, z) - w)^2$ 3

Where:

- Spread: the approximate Euclidean distance between the current skeleton location and the end-point at which we started.
- Height: the approximate Euclidean distance to the nearest target boundary.
- w: the shot size.

The first function eq. 1 ensures that we pack the target volume as much as possible, that is the current spread between shots should be close to the distance to the closest target boundary. And then, the second function eq. 2 is used to choose a helmet size that fits the skeleton best for the current location. At last, the third function eq. 3 favors a location that is the appropriate distance from the target boundary for the current shot size.
To ensure that the height, the spread and the shot size *w* are as close as possible, the fitness function is represented as the sum of these three squared differences between three quantities. After every shot is placed on the target, the fitness function ensures that the target area will receive maximum coverage of the radiation and the surrounding normal tissues will receive minimum radiation to avoid harm. The fitness function is given as follows:

4. $F = \oint_{sh}(x, y, z) + \oint_{sw}(x, y, z, w) + \oint_{hw}(x, y, z, w)$ 4

The key steps of GA-based shot location and size selection are described as follows:

1. Initialize the first population:

- *1.1 Detect all end points based on the skeleton of targets*
- *1.2 Detect the boundary points of targets*
- *1.3 Encode the first population:* Permutation coding technique is used to initialize the population. All points on the skeleton is represented by a one-dimensional integer string. One integer denotes one point. For instance, there are five points on the skeleton in total. The first population in this case can be decoded into a five integers string, which looks like (1 2 3 4 5).
- 1.4 *Set GA operator parameters:* The crossover rate (*Pc*), the mutation rate (*Pm*), the desired fitness value, and the number of generations (*Ng*) are all defined at this step.

2. Initialize the first generation: The first generation is *m* points, which are selected randomly from all the point in the skeleton. They are treated as chromosome. Normally, the number of the first generation is set as 10 percent of whole population. For example, if the skeleton of a target has 1000 points (voxels). The first generation may contain 100 points.

3. *Reproduce the new generation:* GA operators, mutation and crossover, are run in this step to generate the new generations. As mentioned above, single point crossover and order changing mutation are applied.
4. *Evaluate the fitness of the points in both generations:* The quality of each chromosome (point) is evaluated by a fitness value, and the purpose of optimization is to find the individual with minimum fitness. The fitness value of each chromosome is calculated by fitness function F (1), which is explained above. The distance between each chromosome to the boundary, the distance between each point to the end points and the shot size will be compared to each other in this step. The fitness value of all the points are stored in a one-dimensional sequence, which is prepared for the following steps.
5. *Sort all the points according their fitness value:* After this operation, the chromosome in the both generations is sorted in ascending order.
6. *Approach the current best chromosome, and update generation:*

According to the previous steps, if one of the points satisfies the desired fitness value, the GA stops. At this time, the best shot is chosen. Otherwise, the points that corresponding to the first m fitness value based on the step 5 are selected to run in new loop. The rest of the points are removed both from sequences and the population.

Terminated GA: The optimization process will be terminated if the predefined desired fitness value is satisfied, or the algorithm has run *Ng* generations. The point, which has the smallest fitness value, is the best shot. The rest of the target is considered in whole as a new target. Steps 1 to 6 are repeated until the smallest shot size cannot be inserted into the rest of the target.

III. Computational Results

GA-based shot placement model was tested in several simulated targets with different shapes and sizes. The simulated targets are both in two-dimensional and three-dimensional.

Initially two dimensional targets were tested and then, the tests were expanded on to three dimensional targets. The algorithms in this model are coded in Matlab, and run by using Matlab R2009a in an IBM T61 laptop with 2.0 GHz Intel Core 2 Duo processor and 2.0 GB DDR2 667 RAM. To test its robustness, the proposed model independently runs 5 times for each of the cases.

The following are several two-dimensional and three-dimensional examples that show the resulting of GA based shot location and size determination solution.

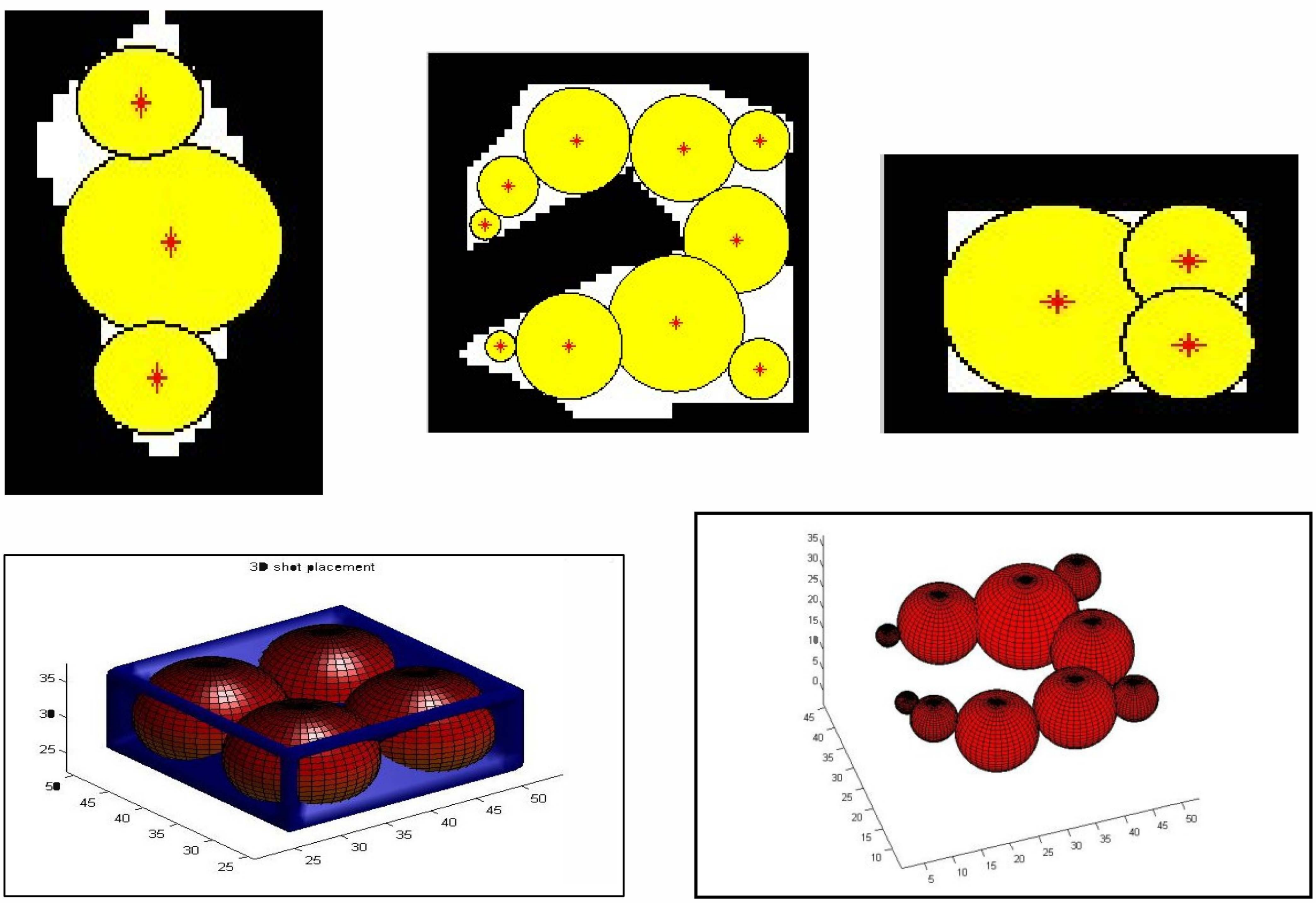

Figure 4.1 Optimization solution for Target 4.1 – 4.5

Targe t	Target Size	Shot Sizes	Number of shots
4.1	35mm by 35mm	4mm 8mm 14mm 18mm	2 3 4 1
4.2	15mm by 35mm	8mm 14mm	2 1
4.3	20mm by 15mm	8mm 14mm	2 1
4.4	25mm by 25mm by 10mm	14mm	4
4.5	35mm by 35mm by 35mm	4mm 8mm 14mm 18mm	2 3 4 1

Table 4.1 Execution Time of Five Targets

In this section, results generated by GA-based shot placement model are compared based on three different attributes: 1. Execution time before the optimum solution is found, 2. How many shots to be chosen, and 3. Coverage on targets.

The lines depict each specific fraction of the target that is covered by shots, which receives a particular dosage. The blue line representing the 4mm shot declines faster than the lines representing the bigger size shots. While the line representing the 18mm shot decreases slightly.

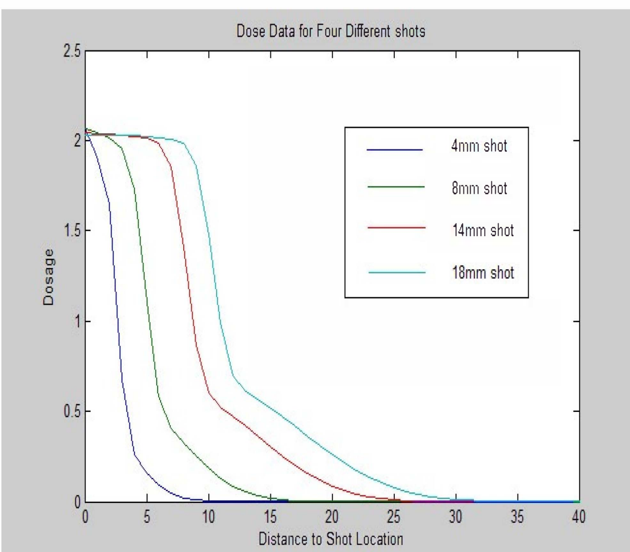

Figure 4.2 Dose Data for Four Different Shots

Neurosurgeons commonly use isodose curves as means of judging the quality of a treatment plan. They wish to impose a requirement that the entire target is surrounded by an isodose line of x%. In general, the isodose curves higher than 50% are considered having effective execution. In the Figure 4.6, the dosage varies from 0 to 2. In this way, different shot has different radius of effective execution. Only those voxel that embraced by that radius can receive adequate dosage and be cued efficiently. The following table lists the radius of effective execution for different shots

Shot	Radius of Effective Execution
4mm	2.67mm
8mm	5.21mm
14mm	8.75mm
18mm	10.97mm

Table 4.2 Radius of Effective Execution

The optimized solutions for all of the five targets are shown in Table 4.4, together with execution time for all of targets. Ordinal shot location and size determination technique is compare with GA-based model. Ordinal SLSD is similar to GA-based shot placement, but it evaluates skeleton points one-by-one in a sequence rather than select points randomly.. GA-based model takes less time to execute Target 4.1, 4.4 and 4.5 than ordinal SLSD does. There three targets are more irregular and larger (three-dimensional) than the other two. However, for simple and small two-dimensional examples, like Target 4.2 and 4.3, execution time generated by GA-based model are not less than that of ordinal ones. It can be concluded that, GA-based model has faster performance on irregular or three-dimensional cases. It can speed up the shot location and size determination procedures. On the other hand, all optimized solutions cover above 90% of the targets with number of shots less than 15. GA-based shot placement model is a useful tool for assisting in the selection of the appropriate number of shots and shot sizes. Also they demonstrated that this model satisfies the requirements of optimal treatment planning.

Target	Execution time		Coverage by 50% Isodose
	GA-based	Ordinal	
4.1	43 seconds	63 seconds	92%
4.2	25 seconds	23 seconds	90%
4.3	32 seconds	27 seconds	96%
4.4	121 seconds	243 seconds	95%
4.5	150 seconds	N/A	94%

Table 4.4 Radius of Effective Execution

I. CONCLUSION

In this paper, A variety of modeling and techniques are used to develop a model for solving the shot location and size determination problem in the Gamma knife treatment planning. The skeleton generation methods can speed the process of shot placement, and improve the effectiveness of optimization-based model. The GA-based shot placement model can help treatment team to place an optimum shot quickly and precisely. The methods and approaches used here can generate more effective and better treatment plans in shorter time. The GA-based shot location and size determination model is a useful tool in the selection of the appropriate number of radioactive shots and shot sizes.

No model and no solution come without limitation, more work need to be done for improving the model used in this thesis. At first, the actual shape of shots is not perfectly spherical, but slightly distorted. In future works, ellipsoids may instead of spheres to fit shots in the target. Additionally, the model has not been tested on actual patient data. Whether the model can handle the real medical cases with very irregular shapes needs to be examined in future. Finally, there is no guarantee that there is not a better solution. Some more evolutionary computation algorithms, such as Bees algorithm and Ants colony can be considered.

REFERENCES

[1] Haas, O. C. L., Burnham, K. J., & Mills, J. A. (1998). Optimization of beam orientation in radiotherapy using planar geometry. *Physics in Medicine & Biology.* 43 (8), 2179.

[2] Lei, J., & Li, Y. (2009). An approaching genetic algorithm for automatic beam angle selection in IMRT planning. *Computer Methods and Programs in Biomedicine, 93*(3), 257-265.

[3] Li Y, Yao J, & Yao D. (2004). Automatic beam angle selection in IMRT planning using genetic algorithm. *Physics in Medicine and Biology.* 49 (10), 1915-32.

[4] Li, Y., Yao, D., Zheng, J., & Yao, J. (2006). A Modified Genetic Algorithm for the Beam Angle Optimization Problem in Intensity-Modulated Radiotherapy Planning. *Lecture Notes in Computer Science.* (3871), 97-106.

[5] Meedt, G., Alber, M., & Nusslin, F. (2003). Non-coplanar beam direction optimization for intensity-modulated radiotherapy. *Physics in Medicine & Biology.* 48, 2999-3020.

[6] Meyer, J., Phillips, M. H., Cho, P. S., Kalet, I., & Doctor, J. N. (2004). Application of influence diagrams to prostate intensity-modulated radiation therapy plan selection. *Physics in Medicine & Biology.* 49, 1637-1654.

[7] Meyer, J., Hummel, S. M., Cho, P. S., Austin-Seymour, M. M., & Phillips, M. H. (2005). Automatic selection of non-coplanar beam directions for three-dimensional conformal radiotherapy. *The British Journal of Radiology, 78*(928), 316-327.

[8] Pugachev, A. B., Boyer, A. L., & Xing, L. (2000). Beam orientation optimization in intensity-modulated radiation treatment planning. *Medical Physics, 27*(6), 1238-1245.

[9] Schreibmann, E., Lahanas, M., Xing, L., & Baltas, D. (2004). Multiobjective Evolutionary optimization of the number of beams, their orientations and weights for intensity-modulated radiation therapy. *Physics in Medicine & Biology.* 49, 747-770.

[10] Wu, Q. J., Bourland, J. D., Robb, R. A., & Conference. (1996). Fast 3D medial axis transformation to reduce computation and complexity in radiosurgery treatment planning [2710-56].

[11] *Zhou, Y., Kaufman, A., & Toga, A. W. (1998). Three-dimensional skeleton and centerline generation based on an approximate minimum distance field. The Visual Computer 14(7), 303-314.*

[12] Clancey, O.; Witten, M. (2011). A memetic algorithm for dosimetric optimization in CyberKnife robotic radiosurgical treatment planning; *Evolutionary Computation (CEC), 2011 IEEE Congress on Digital* Object Identifier: 10.1109/CEC.2011.5949711, Page(s): 880-885, 2011.

[13] Hongchu Chen ; Xiaoming Wang ; Junsheng Wu ; Shuyan Luo, The study and implementation of dose calculation method in OUR-Body Gamma Knife, Biomedical Engineering and Informatics (BMEI), 2010 3rd International Conference on, Volume: 4 Digital Object Identifier: 10.1109/BMEI.2010.5639383, 2010 , Page(s): 1360- 1363