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THE EVOLUTIONARY APPROACH FOR TUMOR DOSE WITH FOTELP-VOX TRANSPORT SIMULATIONS

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ABSTRACT:
This study introduces an evolutionary approach for minimizing risks to organs-at-risk during tumor therapy, utilizing the FOTELP-VOX program in voxel-based transport simulations (author R.Ilić). The use of voxels in the FOTELP program requires spatial constraints within a parallelepiped for targeted irradiation with a particle source. Particle interactions with the initial voxel are identified based on voxel density. The technique continues until the particle's fate is complete, verifying interactions on that path and modeling these processes. To simulate particle delivery, it uses Monte Carlo techniques. When particles are carried from an external source through the human body, the absorbed dose has a 3-D distribution. The CT data is used to characterize the anatomy of the patient.

The current methodology is based on a manual trial-and-error approach. In order to expedite the discovery of an optimized solution, we explored various optimization strategies, such as random search, Bayesian optimization (BO), and genetic algorithm (GA), within the framework of FOTELP-VOX. By evaluating these approaches, our research seeks to identify the most effective strategy for minimizing risks to organs-at-risk during radiation exposure. Two novel methodologies, namely FOTELP-VOX-BO and FOTELP-VOX-GA, are proposed.

The introduction of FOTELP-VOX-BO and FOTELP-VOX-GA methodologies further expands the research's potential applications and relevance within the domain of Monte Carlo transport simulations.

Keywords: *Tumor therapy, Voxel-based simulations, evolutionary optimization, Monte Carlo techniques*

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1. INTRODUCTION

Artificial Intelligence (AI) is rapidly becoming a cornerstone in a multitude of sectors within modern society, revolutionizing the way we interact with technology and make decisions [1]. Its integration ranges from enhancing user experience with personalized recommendations on social media platforms to driving the development of autonomous vehicles. Furthermore, AI plays a pivotal role in the analysis of large datasets in the business realm, providing invaluable insights that guide strategic planning and operational improvements [2]. Perhaps most critically, the application of AI in medical diagnostics and treatment has opened new frontiers in healthcare, offering the promise of more accurate diagnoses, personalized treatment plans, and improved patient outcomes. In the medical field, AI's impact is particularly profound in areas such as tumor therapy, where precision and accuracy are paramount [3]. The challenge of minimizing radiation exposure to healthy organs and tissues during treatment presents a significant obstacle, underscoring the need for innovative solutions that can enhance the safety and effectiveness of cancer therapies. This paper aims to explore the application of AI in addressing these challenges, specifically through the lens of a novel approach utilizing the FOTELP-VOX program for voxel-based particle transport simulations [4, 5]. By leveraging the capabilities of AI to optimize treatment parameters and reduce the risk of radiation damage, we can advance towards more targeted and less invasive cancer treatments.

The adoption of AI in medical treatment represents a critical step forward in our quest to mitigate the adverse effects of cancer therapies. Through a detailed examination of the FOTELP-VOX program and its application in minimizing radiation risk, we face the substantial challenge of accurately determining the FOTELP-VOX program's input parameters, which requires extensive manual effort and iterative processes to refine simulation accuracy and reduce errors. This challenge is classified as an optimization problem, which is being addressed through the application of Bayesian Optimization (BO) [6, 7], and Genetic Algorithms (GA) [8, 9], offering promising pathways to enhance the precision and efficacy of treatment planning. Leveraging real patient data from the Clinical Center in Kragujevac, the study contributes to the advancement of Monte Carlo transport simulations in medical physics, highlighting the potential for improved treatment planning and patient safety. Based on those findings, this paper proposes two novel methodologies: FOTELP-VOX-BO and FOTELP-VOX-GA, aimed at advancing the optimization process in radiation therapy planning.

2. MATERIALS AND METHODS

2.1 FOTELP-VOX Simulation framework

The FOTELP program (author R.Ilić) utilizes a sophisticated voxel-based simulation framework known as FOTELP-VOX for irradiating specific regions within a parallelepiped using particle sources [4]. In this framework, the use of voxels necessitates the definition of a limited portion of space to irradiate, including surrounding air if the particle source lies outside the irradiated region. Particle interactions with initial voxels are determined by voxel density, with each voxel assigned dimensions and six planes in the coordinate system. This process continues until the particle's fate is complete, with verification of interactions and modeling of these processes. By employing voxel addresses and temporary voxel placement coordinate levels, the framework optimizes memory usage, preventing the loading of fixed geometry planes from other programs. The GEMVOX function enables the temporary placement of the current voxel in the coordinate system, further enhancing memory efficiency. Moreover, Monte Carlo techniques are utilized to simulate particle delivery, resulting in a three-dimensional absorbed dose distribution as particles traverse the human body from an external source. Before simulation, users can choose between photon or electron beams of any shape, with an energy threshold of 1 keV required for the computation of the three-dimensional distribution. CT data is leveraged to characterize patient anatomy, enabling accurate simulations tailored to individual patients.

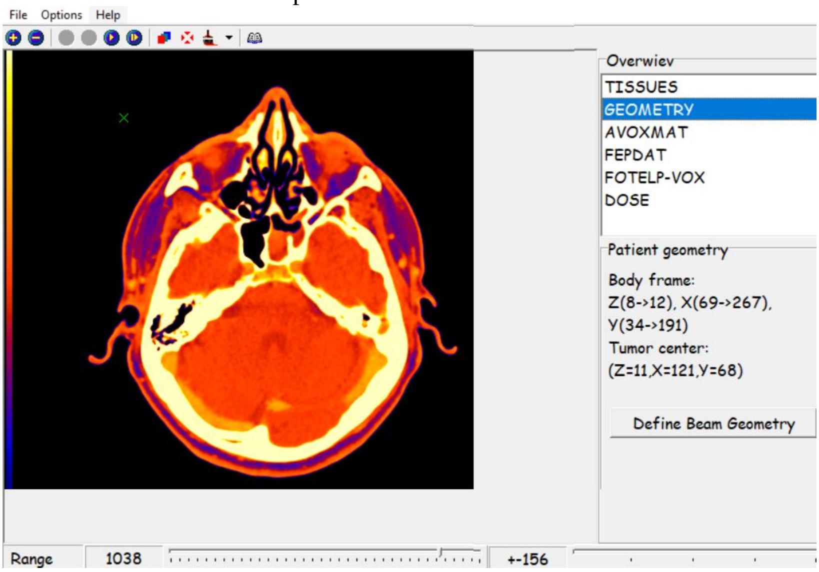

Fig. 1. View of the dose planning interface in FOTELP-VOX

3. RESULTS

This study embarks on a comprehensive examination of the FOTELP-VOX program, a cutting-edge tool designed for voxel-based particle transport simulations, to enhance the precision and efficacy of tumor therapy through radiation. By incorporating real patient data from the Clinical Center in Kragujevac, including detailed Computed Tomography (CT) scans, the research adheres to the highest ethical standards, ensuring confidentiality and informed consent throughout the data acquisition process. Central to our methodology is the adaptation of the FOTELP-VOX program to facilitate compatibility with optimization algorithms, laying the groundwork for employing advanced optimization BO, and GA – aimed at optimizing radiation therapy by accurately determining input parameters and minimizing radiation exposure risk to non-targeted organs.

3,1 Defining the objective function

The objective function in radiation therapy optimization quantifies treatment efficacy by balancing tumor eradication against minimizing radiation exposure to organs-at-risk. We define the optimization search space X as comprising all possible scenarios for patient treatment. A patient treatment $x \epsilon X$ represents a combination of FOTELP-VOX input parameters, denoted as $x = (x_1, x_2 \dots x_n)$. Based on these findings, our goal is to minimize the objective function $f(x)$ as outlined below:

$$x_{opt} \in \underset{x \in X}{\operatorname{argmin}} f(x) \,. \tag{1}$$

3.2. Optimization

In this chapter, we introduce two optimization techniques utilized in this research: the Tree-Structured Parzen Estimator (TPE), a Bayesian optimization method [6, 7], and the Genetic Algorithm.

Tree-Structured Parzen Estimator

TPE is a Bayesian optimization algorithm that efficiently explores and exploits the search space to find the optimal solution. At its core, TPE employs a probabilistic model to capture the relationship between the hyperparameters and the objective function. This model guides the search by iteratively updating its beliefs about the parameter space X, focusing on promising regions. Instead of using the Gaussian-process to model $p(y|x)$ directly, this strategy models $p(x|y)$ and $p(y)$. TPE divides the hyperparameters into two sets: "good" and "bad" and maintains separate probability density functions (PDFs) for each set. Let's denote the hyperparameters as $x \in X$, the objective function as $f(x)$, and the set of hyperparameters sampled so far as $\mathcal{L}$. TPE estimates two PDFs:

$$P(x|f(x), x \in \mathcal{L}, good), \tag{2}$$

$$P(x|f(x), x \in \mathcal{L}, bad). \tag{3}$$

TPE employs a non-parametric approach to model the PDFs using kernel density estimation. Specifically, it fits a kernel density estimator to the observed hyperparameters in each set. This allows TPE to flexibly capture the underlying distribution of hyperparameters that lead to desirable or undesirable outcomes. TPE uses the PDFs to guide the search for the next set of hyperparameters to evaluate. Instead of sampling hyperparameters uniformly or randomly, TPE samples from the "good" PDF more often than from the "bad" PDF. This adaptive sampling approach enhances efficiency by focusing computational resources on areas of high potential improvement. The strategy aims to balance exploration (sampling from areas with uncertainty) and exploitation (sampling from areas likely to yield better results). Specifically, TPE samples a set of hyperparameters $x \in X$ by maximizing the ratio:

$$\frac{P(x|f(x), x \in \mathcal{L}, good)}{P(x|f(x), x \in \mathcal{L}, bad)}. \tag{4}$$

This ratio indicates the likelihood that x belongs to the "good" set relative to the "bad" set, given the observed performance of x. After evaluating the chosen hyperparameters, TPE updates the sets of "good" and "bad" hyperparameters based on their performance. If the evaluated hyperparameters lead to a better outcome, they are added to the "good" set; otherwise, they are added to the "bad" set. This updating mechanism refines the PDFs over time, directing the search towards more promising regions of the hyperparameter space. By iteratively updating the probabilistic model and intelligently sampling from the PDFs, TPE efficiently explores the hyperparameter space X and converges to the optimal solution with fewer evaluations compared to traditional optimization methods.

Genetic Algorithm

GA is a widely recognized method in class of evolutionary optimization methods, inspired by the process of natural selection and genetics. The primary purpose of genetic algorithms is to efficiently search through large and complex solution spaces to find optimal or near-optimal solutions to optimization and search problems where traditional optimization techniques may struggle due to the complexity or non-linearity of the objective function. Rooted in the principles of natural selection, GAs emulate the process of evolution by favoring the survival and reproduction of the fittest individuals. The population in GA represents a collection of candidate solutions (individuals). Each individual in the population $x^{\psi} \in \omega \mid \omega \subseteq X$ is represented as a chromosome, often encoded as a string of binary digits, although other encoding schemes such as real-valued numbers or permutations can also be used depending on the problem domain. For this specific task, we propose integer encoding scheme where integer-based value gene x_i^{ψ} in chromosome x^{ψ} corresponds to FOTELP-VOX's input x_i.

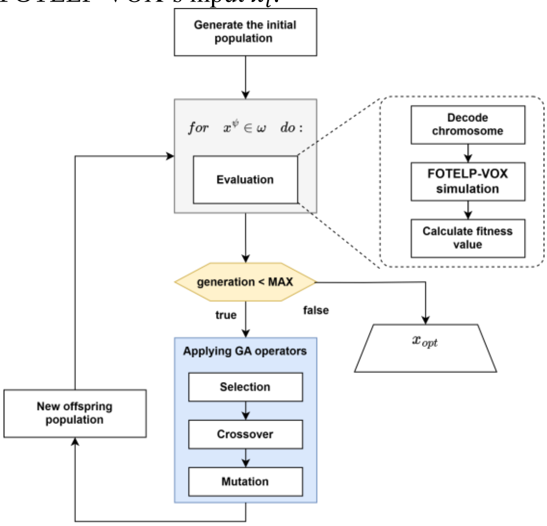

Fig. 2. FOTELP-VOX-GA algorithm

The GA operates through a series of iterative steps, known as generations or epochs. The process initiates with the creation of a randomly generated population. Each individual within this initial population is evaluated to assess their fitness. Subsequently, the population undergoes an iterative cycle comprising selection, crossover, mutation, and evaluation to produce the succeeding iteration (generation). Selection mechanisms determine which individuals are chosen to reproduce and contribute genetic material to the next generation based on their fitness values. Individuals with higher fitness values are more likely to be selected, following the principle of "survival of the fittest". We are using a selection method named binary tournament selection; two randomly selected individuals participate in the tournament and the winner is the individual with the higher fitness value. We apply crossover to selected individuals. Crossover is binary operator also known as recombination. It involves the recombination of genetic material from two parent individuals to produce offsprings with traits inherited from both parents. Combing good gene materials leads to exploration of the search space by combining promising solutions, approaching the global optimum. In single-point crossover we randomly select the crossover point cp from the set $\{1 \dots n\}$ to split chromosome to head and tail. Suppose that two parents P_1 and P_2 are given as:

$$P_1 = \left(x_1^1, x_2^1, \dots, x_{cp-1}^1, x_{cp}^1, x_{cp+1}^1, \dots, x_n^1\right), \tag{5}$$

$$P_2 = \left(x_1^2, x_2^2, \dots, x_{cp-1}^2, x_{cp}^2, x_{cp+1}^2, \dots, x_n^2\right). \tag{6}$$

The crossover application over parents P_1 and P_2 produces offsprings O_1 and O_2:

$$O_1 = \left(x_1^1, x_2^1, \dots, x_{cp-1}^1, x_{cp}^1, x_{cp+1}^2, \dots, x_n^2\right), \tag{7}$$

$$O_2 = \left(x_1^2, x_2^2, \dots, x_{cp-1}^2, x_{cp}^2, x_{cp+1}^1, \dots, x_n^1\right). \tag{8}$$

Mutation is the key part in searching for global optimum, it provides an escape mechanism from the local optimum. The mutation operator introduces random variations into the population by modifying a small proportion of individuals' chromosomes. This stochastic process helps maintain genetic diversity within the population, preventing premature convergence to suboptimal solutions. If a mutation discovers an individual with high fitness value, there is a high chance that this genetic material will be passed on to subsequent generations, directing the search into a new unexplored area of the search space. On the other hand, if the mutation has resulted in an individual with low fitness, due to the low probability of selecting that individual for crossover, the search will not be directed towards lower fitness solutions. The mutation operator is applied under a certain probability, we suggest a small mutation probability rate of 0.05.

4. CONCLUSION

This study demonstrates the significant potential of using artificial intelligence (AI) optimization strategies, particularly Bayesian Optimization (BO) and Genetic Algorithms (GA), to enhance radiation therapy planning. These methods effectively minimized radiation exposure to non-targeted organs while maintaining accurate tumor targeting. Bayesian Optimization showed a notable balance between precision and efficiency, whereas Genetic Algorithms excelled in quickly finding optimal solutions. This research underscores AI's role in improving medical treatment precision, offering a pathway to more personalized and effective radiation therapy approaches. The findings encourage further exploration of AI in healthcare, promising advancements in treatment planning and patient outcomes.

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