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Bio-inspired optimization technique for optimal beam angle selection in radiotherapy application

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Abstract: A human planner's expertise is currently the most important consideration for determining optimal beam angles for external beam radiotherapy. The necessity of automatically selecting beam angles is especially important in intensity-modulated radiation therapy (IMRT) since fewer modulated beams are utilized in conformal radiotherapy. For an automated beam angle selection (ABAS) approach, the ideal coplanar beam angles correspond to the lowest objective function (OF) value of the dose distributions produced from this collection of candidate beams' intensity-modulated maps. Because of the task's intricacy and the large search space concerned, the ABAS and optimization of intensity maps are addressed independently and repeatedly. The Modified Artificial Bee Colony (MABC) optimization, the integration of Artificial Bee Colony (ABC), and a Firefly algorithm are employed to choose suitable beam angles, and the conjugate gradient (CG) technique is employed to fasten the optimized intensity maps for every selected beam. A 3D full scatter convolution (FSC) approach based on the pencil beam is employed for dose assessment. The effectiveness of MABC is examined using a more difficult instance representing a prostate tumor, and 2 simple cases The simulated MABC output is compared to the ABC optimization method. The results illustrate the reliability and efficiency of the suggested MABC-based ABAS can improve dosage distributions with clinically acceptable computation time.
Keywords: *Beam selection, Objective function, Optimization, Radiotherapy, Termination, Tumor, Water can.*

1. Introduction

The objective of IMRT is to enhance the therapeutic ratio by employing intensity-modulated beams that produce highly conformal dose distributions for target volumes while maintaining normal tissues within dosage limitations. Beam angles are chosen at the outset of IMRT treatment planning, and afterward, beam intensity maps are developed via inverse optimization techniques guided by an OF [1]. Decisions about beam angles are now primarily based on the planner's prior experience. Several repetitions of trial and error are usually required. This may result in realistic therapeutic techniques, although they are not always perfect [2]. In IMRT, where highly conformal dose distributions in all three dimensions are a goal, ABAS assumes even more significance. Although it is most effective for plans with a small count of beams (≤5) [3], it has also been shown to be clinically significant for plans with a big count of beams (≥9) in some challenging circumstances if the tumor volume covers a major organ or multiple vital organs [4]. Compared to plans with a greater number of less-optimized beams, those with fewer well-optimized beams were proven to be just as good, if not better. Recent research has focused on ABAS for IMRT [5,6]. Despite positive results, developments are still insufficient, notably in optimization efficiency, due to the drawback of intensive calculation in IMRT optimization. There will always be a need to strike a balance between how quickly and accurately an optimization can be accomplished. Previously, researchers employed compromise tactics to increase IMRT dose and define the most desired beam orientations to address the optimization challenge. More investigation into how these approximations affect optimization outcomes is needed. Many natural algorithms have been

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published for application in radiation planning optimization issues, which take their lead from biological intelligence and inherit a global search mechanism [7].

The author [8] suggests beam optimization by employing an initial set of isotropic beams. The approach optimizes the cross-sectional area of the target at every beam's position by guiding each beam to the best position determined by the overlap of the critical structure with the target from the beam's eye view (BEV) with the BEV margin. In the final, optimal beam configurations, beams are kept far apart while passing safely around obstructions. You should be able to construct adequate plans for radiosurgery patients if you use evenly weighted beams in the necessary orientations (single fraction, prescription isodose 60%-80%). User-added wedge optimization is commonly used in radiation therapy treatment plans (multiple fractions, prescription isodose 90%-98%). By sacrificing dose conformance or dose gradient, this optimization strategy enhances the important structure-sparing qualities of a previously unoptimized isotropic beam structure, as demonstrated by a sample radiosurgery scheme. This optimization procedure is thought to provide a straightforward method for developing conformally structured beam radiation therapy protocols for the treatment of intracranial lesions. Article [9] investigates the optimum way to pair photons and particles. They present an approach for optimizing treatment regimens that use many types of radiation at the same time for three separate uses. 1) Combinations of electrons and photons are presented for treating a surface tumor, with the possibility that the electrons will lower the total normal tissue dosage. Because both modalities are supplied during each fraction, joint optimization must account for accumulated physical dosage. 2) It is demonstrated that protons are utilized by providing more dosage to tumor areas in a hepatic stereotactic body radiation treatment employing a combination of photons and protons, with a total of 5 fractions administered. In such combinations, biologically effective dosage cumulative optimization allows for fractionation; and 3) integration of carbon ion and photon have been demonstrated to be successful against glioblastoma, with the former capable of distributing a higher dosage to the radioresistant gross tumor volume and the latter is superior at protecting healthy tissue while still achieving the clinically-required volume through the use of fractionation. Finally, the benefits of multimodality therapy over single-modality therapies can be realized by maximizing it all at once, making use of the unique qualities of many different forms of radiation.

Multiple gradient-based optimization strategies may get caught in a local minimum while trying to address the radiotherapy inverse optimization issue. The research [10] provides a novel gEUD–based optimization method to overcome these constraints. In the new optimization approach, different penalties are applied depending on whether the administered dose is inside or outside of the recommended range. To assess its performance, a TG119 phantom and two types of clinical scenarios (prostate and neck cancer) were used. The initial gEUD-based optimization model, as well as the improved version, were both assessed. In addition, they compared the proposed gEUD-based linear optimization technique to an earlier optimization model. They employed the gradient-based optimization approach for this purpose. And created a novel optimization model to improve OARS sparing while maintaining planning tumour volume (PTV) coverage. The optimization model's parameters must be adjusted by hand, but in theory, DV-based optimization should accomplish the same outcome. Genetic algorithms (GA) are proposed by researchers [11] as a new optimization approach for choosing beam weights and directions in radiotherapy. The next generation, containing plenty of chromosomes, will be better because of genetic operators. A heuristic approach termed "sudden death" was developed to hasten convergence. With the help of a case study, they show how evolutionary methods can be used in 3D RTP. The researchers [12] intended to test if simulated annealing (SA) might be utilized for beam selection to improve a noncoplanar VMAT. They were able to develop a set of globally ideal beams to utilize as anchors during therapy by combining SA with direct leaf trajectory optimization. The TG119 standard and two clinical studies were utilized to evaluate the efficacy of the proposed approach. Lastly, coplanar and noncoplanar beam choosing were used as benchmarks to evaluate SA's beam selection approach. The finding demonstrates that the prescribed dose was successfully administered to the defined volume of tumor in every case. In terms of OAR sparing, the noncoplanar SA strategy beat the coplanar greedy method and the noncoplanar greedy method, although not on all organs. In some patient settings, the suggested SA methodology could prove more clinically attractive than the coplanar approach since it can produce appropriate noncoplanar beam orientations, as demonstrated in this research.

In the article [13], a neural network is trained for a sample of patients utilizing medically sound recommendations for beam orientations and other treatment parameters. After training, the neural network can generate efficient treatment suggestions from CT scan data in a timely and reliable manner. When a neural network is built via an evolutionary strategy, for example, its ability to generalize is considerably boosted. Successful hospital trials have demonstrated that the system is generally well-liked and even capable of making more effective treatment suggestions than human radiologists. The recommended approach [14] automatically generates accurate beam angles by combining beam intensity profiles and thereby considering the effective delivered dosage. To verify the accuracy of the dosage distribution system, they evaluated it to a commercial device using the same beam setup and then generated beam patterns and Dosage Volume Histogram (DVH). Next, put the optimization process to the test using real-world clinical scenarios, both simple and complex. Both the doctor and the simulation, which used an identical commercial system, discovered excellent results after applying the right therapy, proving the efficacy of the technology. In article [15], the suggested beam orientation selection procedure is broken down into two components. The Scatter Search and global optimization method are used to estimate the gantry angles. The intensity profile is then estimated for each beam configuration using the CG technique, which assigns a weighted value to the numerous beam angle possibilities. The proposed method was tested using a phantom example with easily identifiable perfect beam angles. A DVH and dosage distribution for clinical studies (TG-119 and prostate) were generated and studied to determine the algorithm's performance. To evaluate the effectiveness of the suggested approach, a clinical design with the enhanced beam arrangement has been compared with a conventional equiangular plan. In contrast to equispaced coplanar beams, DVHs, and dosage patterns were significantly enhanced when BAO configurations were implemented. The proposed technique can efficiently choose the beam direction for IMRT inverse planning for a variety of tumor sites. As far as we know, there is still an opportunity for improvement in the existing situation. In this paper, we suggest a unique optimization for maximizing the beam angle in IMRT planning.

2. Beam-Angle Optimization Issues

A beam is the collection of radiation rays that travels from the gantry head, where the radiation is produced, to the individual's body, where the target (tumor) is located. When operating in a static isocenter setting, the gantry head rotates to follow the patient. The goal is to shield normal tissues from radiation as much as possible while yet delivering the appropriate dose to the target utilizing a fixed number of beams pointing in a fixed number of directions. By dividing beams and adjusting their weights with a variety of inverse computation methods, IMRT can employ intensity-modulated beams to generate the necessary doses.

Following the beam selection and direction, either manually or with the assistance of a computer, the beams are collimated into smaller pieces called beamlets, which typically measure 0.5 cm * 0.5 cm at the isocenter plane. It is preferable to optimize the ray weights. (intensities). If the optimal intensity maps are found, the doses received by organs can be estimated. Radiation therapy can then be guided through these optimized intensity maps if the calculated dosages are within clinical tolerance.

The essential principle underlying BAO is that a specific number of beams must be chosen from a pool of beam candidates, resulting in a combinational optimization problem. Beam incidence directions for coplanar radiation can be any angle within a 360-degree gantry rotation. When a BAO is implemented, the full 360 degrees of gantry angles are typically broken up into smaller, evenly distributed increments of 5 or 10 degrees. Researchers frequently employ such increments, and it was giving the increment of 5 degrees is sufficiently small for BAO, whereas very tiny changes in beam orientation don't have a significant effect on the final dosage distribution, apart from enhancing computational expenses because of the larger beam angle [16]. When attempting to solve BAO, the enormous multiverse of solutions in ABAS is a significant computing challenge. Another difficult inverse problem is beaming intensity mapping for a specific set of beams. Beam intensity maps in IMRT are associated with specific beam arrangements, demanding optimization of these maps for every beam configuration that is part of the BAO. As a result, the intensity map of a beam that is part of many beam combinations (and thus plans) will change greatly from that of a beam that is part of a single beam combination (and so a single plan), necessitating optimization of all beams in the new plan. Because of the interaction of variables, the computation becomes so complex that typical optimization methods are inefficient when applied to the BAO problem [17-19].

3. Materials and Methods

The methodology and other theoretical concepts are detailed in this section.

3.1. Objective Function

Tumors are exposed to radiation from a variety of angles in IMRT. The goal of the beam orientation is to minimize damage to healthy tissues and organs at risk (OARs) by creating highly conformal dosage dispersion to the targets in 3D. To decrease the gap between the expected and target dosage dispersion, the beam angles are quantitatively modified with the help of an OF. The study's primary objective is as described below:

$$F_{obj}\left(\vec{x}^{(k)}\right) = \alpha . F_{OAR}\left(\vec{x}^{(k)}\right) + \beta . F_{PTV}\left(\vec{x}^{(k)}\right) \quad [1]$$

$$F_{OAR}\left(\vec{x}^{(k)}\right) = \sum_{i=1}^{N_{OAR}} \sum_{j=1}^{NT_i} \delta . \omega_j . \left(d_j\left(\vec{x}^{(k)}\right) - p_j\right)^2 \quad [2]$$

$$F_{PTV}\left(\vec{x}^{(k)}\right) = \gamma . \sum_{i=1}^{NT_{PTV}} \delta . \omega_j . \left(d_j\left(\vec{x}^{(k)}\right) - p_j\right)^2 - \eta . \sum_{i=1}^{NT_{PTV}} \delta . \omega_j . \left(d_j\left(\vec{x}^{(k)}\right) - p_j - d_j\left(\vec{x}^{(k)}\right) . log\left(\frac{d_j\left(\vec{x}^{(k)}\right)}{p_j}\right)\right) \quad [3]$$

$$d_j\left(\vec{x}^{(k)}\right) = \sum_{m=1}^{N_{ray}} a_{jm} . \vec{x}_m^{(k)} \quad [4]$$

Here

$F_{OAR}\left(\vec{x}^{(k)}\right)$ → part linked with all the OARs,
$F_{PTV}\left(\vec{x}^{(k)}\right)$ → part linked with the target,
N_{OAR} → total OARs,
NT_i → point number in the ith OAR,
NT_{PTV} → point number in the target
ω_j → weight
d_j → calculated dose
p_j → prescribed dose
a, β → regularizing parameters
γ, η → importance factors
N_{ray} → total rays
$\vec{x}_m^{(k)}$ → intensity.

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The second half of equation (3) uses the target's entropy information to compute the homogeneity of the dose distribution. Optimizing for maximum entropy, according to information theory, entails reducing system information or improving dose homogeneity. Our OF considers both dosage and dose-volume constraints. All doses to the target must be larger than D_{Dmax} and less than D_{Dmin}, with no doses lower than D_{DVmin} absorbing more than V_{min}% of the target volume. All OAR doses must be less than the maximum permitted dosage, or D_{Dmax}, and no more than the maximum allowable dose per volume, or D_{DVmax}, can be absorbed by any given volume. After sorting the doses in ascending or decreasing order, the penalty for points exceeding V_{max}% or V_{min}% is calculated, revealing the dose-volume constraints. To simplify the calculation, the portion of the OF relevant to entropy measurement is neglected during beam-angle optimization, as are the associated dose-volume limits. Dose-based quadratic OF like this one is quite common and straightforward. The CG method improves the final intensity maps at the best possible angles by making use of the whole OF.

3.2. Beam Angle Selection Using Modified ABC

- ABC: In 2005, Karaboga [20] presented the ABC Algorithm for optimization, which was influenced by beehive swarm behavior. Employed Bee (EB), onlooker Bee (OB), and scout bees (SB) are three kinds of population bees that work together to find new places to store food. Each EB searches for new food sources by engaging with other bees. If a better location is located, the EB will remember it rather than the old one. OBs determine the food sources to examine by employing the information gathered by EB. If there is a significant improvement, the OB will remember the new position. The EB changes into a SB and is given a new starting point for the subsequent search cycle if the food supply is no more. The ABC algorithm works in the following way:

1. Initialization: Food for the i^th bee is initially generated as $x_i = (x_{i,1}, x_{i,2} \dots x_{i,D})$

$$x_{i,j} = L_j + \varphi_{ij}(U_j - L_j) \quad [5]$$

for $i = 1,2,\dots,NP$ and $j = 1,2,\dots,D$, where NP → Total bees, D → Total variables or dimensions, φ_{ij} → random number between $(0,1)$, and L_j → lower bounds at j^th dimension, U_j → upper bounds at j^th dimension.

2. EB stage: By utilizing the below equation, the i^th bee communicates with the k^th bee and together they create a new food supply denoted by v_i.

$$v_{i,j} = \begin{cases} x_{i,j} + \varphi_{ij}\left(x_{i,j} - x_{k,j}\right); j = j^* \\ x_{i,j}; \quad j \neq j^* \end{cases}$$

where k → random number in [1 to NP], $k \neq i, j^*$ → arbitrary value in [1 to D], and φ_{ij} → arbitrary value in $[-1, 1]$. Keep in mind that thej^{*th} the component is the sole place where v_i and x_i diverge. The new position value v_i is determined concerning the past one x_i. Replace x_i with v_i if and only if $f(v_i) < f(x_i)$; otherwise, keep x_i and $set\ trial(i) = trial(i) + 1$, where $trial$ → total trials.

3. Onlooker bee stage: The OB utilize the probability values $p(i)$, they compute to select food sources based on quality.

$$p(i) = \frac{fit(x_i)}{\sum_{j=1}^{NP} fit(x_j)} \quad [7]$$

Where

$$fit(x_i) = \begin{cases} \frac{1}{1+f(x_i)}; \ f(x_i) \geq 0, \\ 1 + |f(x_i)|; Otherwise \end{cases} \quad [8]$$

Create a new v_i using the same equation (6) as before if $rand(0, 1) < p(i)$. Swap out x_i for v_i if and only if $f(v_i) < f(x_i)$, otherwise, keep $x_i$and $set\ trial(i) = trial(i) + 1$

4. Scout bee stage: Generate a new location for $x_i$using if the quality of the food source x_i cannot be increased within the allowed number of trails $(limit)$ in equation (5).
5. Determine the optimal x_{best} location and f_{best} value.
6. Steps 2 to 5 should be continued till the termination requirement is met.

- Firefly Algorithm: In this section, we highlight Yang's 2008 [21] introduction of the concept of the firefly algorithm method employed in the MABC algorithm's SB phase. FA is influenced by the activity of fireflies, which alter based on the brightness and attractiveness of the surrounding light. If two fireflies are present in the same region, the one with lesser luminosity will be drawn to the one with higher luminance. In contrast, the attraction is inversely proportional to the two fireflies' distance, where the Euclidean norm determines the distance between any two fireflies x_i and x_j.

$$r_{ij} = \left(\sum_{k=1}^{D}(x_{ik} - x_{jk})^2\right)^{1/2} \quad [10]$$

To calculate the attractiveness β_i, we use

$$\beta_i = \beta_0 e^{-\gamma r_{ij}^2}$$

where γ is the light absorption coefficient and β_0 is the light attractiveness at $r = 0$. In most cases, 1 is utilized for both β_0 and γ. The flight of firefly x_i to a more appealing firefly x_j yields a new position, as follows:

$$x_i = x_i + \beta_{ij}(x_j - x_i) + \alpha(rand(0,1) - 0.5) \quad [11]$$

where $rand(0,1)$ and α are arbitrary values ranging from 0 to 1.

- MABC optimization: For the MABC algorithm's construction, all ABC steps are calculated. The journal [22] proposed a method termed search space division (SSD) to form the population from the start. We gradually leverage the optimal solution information to quicken the search for the EB phase, hence enhancing the ABC search equation. During the OB stage, 25% of EB are picked at random for additional search moves. If multiple best solutions for multimodal functions are discovered, the poorest 5% of locations are replaced with new positions built with the knowledge of the current and the total best solutions (M) while dealing with long-distance relocations, as a scaling factor. The new position is built during the SB phase utilizing the Firefly algorithm technique, which entails changing an old, out-of-date position to a more advantageous one based on its distance from the current one. This is a MABC algorithm suggestion.

1. Initialization: Create the ith food source x_i utilizing the SSD to produce high-quality initial solutions.

$$x_{i,j} = L_j + \frac{(\phi_{ij}+2i-1)(U_j-L_j)}{2NP} \quad [12]$$

for $i = 1, 2, 3, .., NP$ and $j = 1,2,3, \dots D$, where ϕ_{ij} = random value between $[-1, 1]$.

2. Employed bee stage: The optimal position x_{best} is employed by the following calculation to construct a new food source v_i:

$$v_{i,j} = \begin{cases} x_{i,j} + \varphi_{ij}(x_{i,j} - x_{k,j}); & j = j^* \\ x_{i,j}; & j \neq j^* \end{cases}$$

where $k \rightarrow$ arbitrary value belongs to 1 - NP, $k \neq i, j^* \rightarrow$ arbitrary value belongs to 1 - D, and $\varphi_{ij} \rightarrow$an arbitrary value ranging from -1 to 1. Remember that the j^{*th} the component is the only point where v_i and x_i diverge. The new position v_i value is decided concerning the previous one x_i. If and only if $f(v_i) < f(x_i)$, replace x_i with v_i; otherwise, keep x_i and $set\ trial(i) = trial(i) + 1$, where $trial$ represents the total trials.

3. Onlooker bee stage: The above-mentioned equation can be utilized to construct a new position v_i if the probability score utilized by OB to make judgments are held constant at $p(i) = 0.25$ if $rand(0,1) < p(i)$.
4. If the OB's probability values are fixed, then they will always make the same decisions, $p(i) = 0.25$, if $rand(0,1) < p(i)$, and the above equation is used to generate a new position v_i. Replace x_i with v_i if and only if $f(v_i) < f(x_i)$, otherwise maintain x_i and $set\ trial(i) = trial(i) + 1$. Furthermore, the equation is used to replace the worst spots with new ones.

$$x_{z_t} = \mathrm{M}\left[x_{best} + \phi_t\left(x_{z_t} - x_{r_1}\right) + \omega_t\left(x_{best} - x_{r_2}\right)\right] \quad [14]$$

Where $z_t, t = 1,2,..,[0.05NP]$, are the indices of the 5% worst positions, r_1 and r_2 are randomly picked indices from 1 to NP such that $r_1 \neq r_2 \neq z_t$ for all t, ϕ_t and ω_t random values in the range $[-1,1]$, and M represents the total best locations from the previous generation.

5. Scout bee stage: Use the following Firefly algorithmic tactic to generate a new scout-bee position in place of the out-of-date x_i.

$$x_\mathrm{i} = x_\mathrm{i} + e^{-r_{iq}^2}\left(x_\mathrm{q} - x_\mathrm{i}\right) + (rand(0,1) - 0.5) \quad [15]$$

where q → First index, $f(x_q) < f(x_i)$.

3.3. Beam Intensity Optimization Maps Using the CG Technique

Using the recorded beam angles, a personalized intensity map can be created. The optimization is quickly done with the help of a CG technique with a few modified iterations to quicken the calculation process. The final value of the OF can be used to determine a person's fitness. Although they are fast, gradient-based algorithms might become stuck in local minima [23]. A gradient-based method is adopted here due to the need to minimize processing time. A CG technique could be represented as

$$\vec{x}^{(k+1)}(\lambda) = \vec{x}^{(k)} + \lambda.\vec{h}^{(k+1)} \quad [5]$$

$$\vec{h}^{(k+1)} = -\nabla F_{obj}\left(\vec{x}^{(k+1)}\right) + \frac{\left[\nabla F_{obj}\left(\vec{x}^{(k+1)}\right) - \nabla F_{obj}\left(\vec{x}^{(k)}\right)\right].\nabla F_{obj}\left(\vec{x}^{(k+1)}\right)}{\nabla F_{obj}\left(\vec{x}^{(k)}\right).\nabla F_{obj}\left(\vec{x}^{(k)}\right)}.\vec{h}^{(k)} \quad [6]$$

Here,

k → iteration number,

$\vec{x}^{(k)}$ → beam profile vector at kth iteration,

$\nabla F_{obj}\left(\vec{x}^{(k)}\right)$ → gradient of the OF at the point $\vec{x}^{(k)}$,

λ → step size

Equation (6) is started with $\vec{h}^{(1)} = -\nabla F_{obj}\left(\vec{x}^{(1)}\right)$.

During the intensity maps optimization, negative-weighted rays (i.e., beamlets) will emerge in the mathematics, but they are not possible in practice. One popular practice involves resetting all negative ray values to 0 at the end of each iteration. It is no longer guaranteed that this procedure will yield an ideal response. To overcome this problem, this work employs an approach similar to that provided in the article [24]. Ray Weight non-negativity is regarded as a stringent criterion that must always be met. If the constraint excludes the method from performing the step λ that will minimize the OF through the direction $\vec{h}$, the solution is to resume the recurrence relationship of equations (5) and (6) at the present location.

After k^th iteration, if $\frac{[F_{obj}(\vec{x}^{(k)})-F_{obj}(\vec{x}^{(k-1)})]}{F_{obj}(\vec{x}^{(k)})}$ is less than a reasonable little value (0.001 in our study), the intensity map optimization is accomplished.

3.4. Dose Calculation

To account for tissue heterogeneity correction and scatter effects in the dosage computation, we used a 3D-FSC technique based on a pencil beam in our research. The dose deposition matrices, which represent the total dosage supplied to each volume by each discrete angle candidate, are generated before optimization. If MABC decides to optimize utilizing a subset of beam angles, the matching matrices for those beam angles are used. There are two main ways for reducing calculation time:

(1) We only take into consideration the dosages from pencil beams that fall within the BEV of the target (referred to as effective rays) and
(2) Due to their sparse nature, deposition matrices have indexes such that only a small fraction of dosages above the threshold level are considered in the dosage calculation.

The non-indexed deposition matrix is used for the total dosage computation after the best beam angles are determined and introduced to the intensity map.

4. Result and Discussion

The suggested ABAS technique is tested by first selecting two test cases A and B with extremely clear ideal beam angles to determine if ABAS can indeed locate these angles. Then, the effectiveness of ABAS is evaluated using a more complex phantom example (test case C) designed to represent a prostate tumor.

4.1. Cases A and B

Figure 1 displays two hypothetical scenarios used to test the efficacy of ABAS. In scenario A, the best angles for three beams are 30, 150, and 270, or 90, 210, and 330 degrees; in case B, the best angles for four beams are 0, 90, 180, and 270 degrees. It is important to note that we do not provide equispaced initial angles, but instead arbitrarily initialize the first-generation population in order to thoroughly test ABAS. Using a discrete angle step of 5, we sample the complete 2 gantry angle without imposing any more beam angle restrictions. As a result, there are 72 possible choices in terms of angle.

As stated, determining the appropriate angles in these two instances takes lower than 5 minutes. The optimal beam angles and dosage distributions are illustrated in Figure 2. The optimal beam angles in scenario A are 30 degrees, 150 degrees, and 270 degrees, while in scenario B, they are 0 degrees, 90 degrees, 180 degrees, and 270 degrees, which are the same as the previously stated values.

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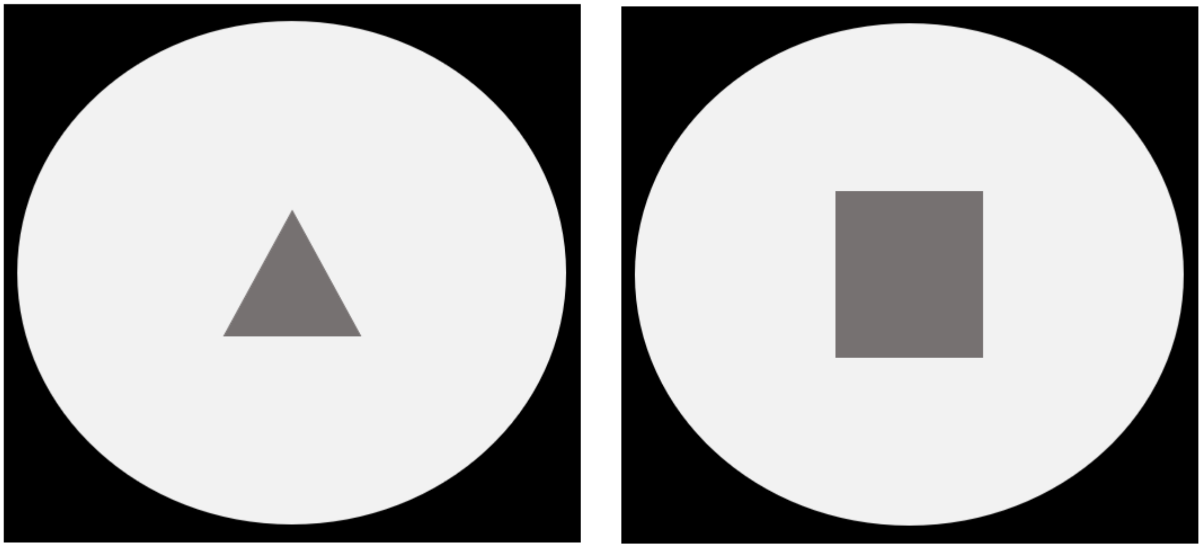
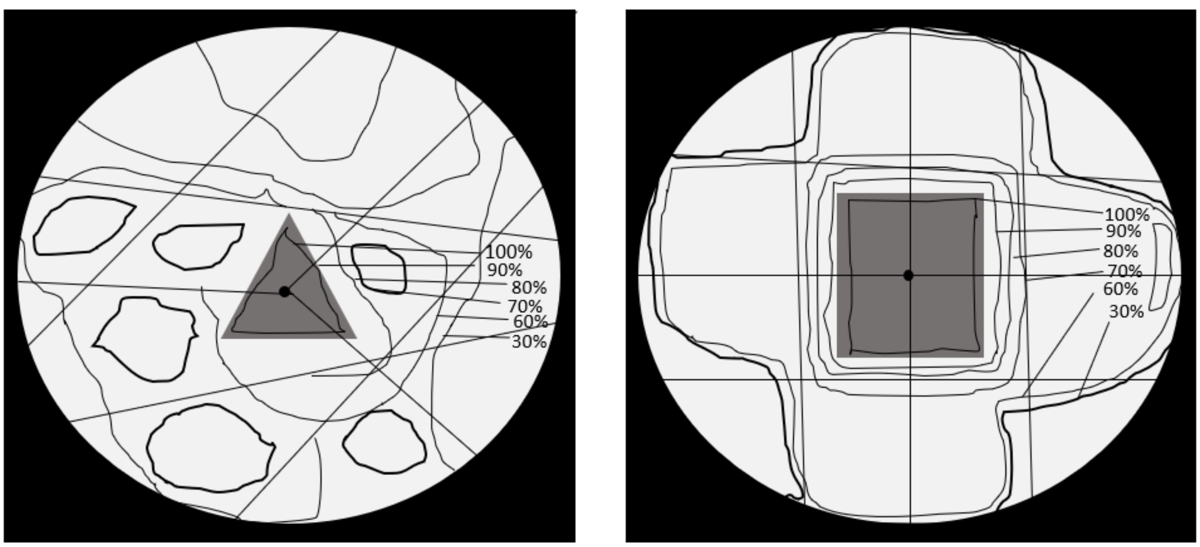


a) Case A b) Case B

Figure 1.
Simulated cases with known optimum beam angles.



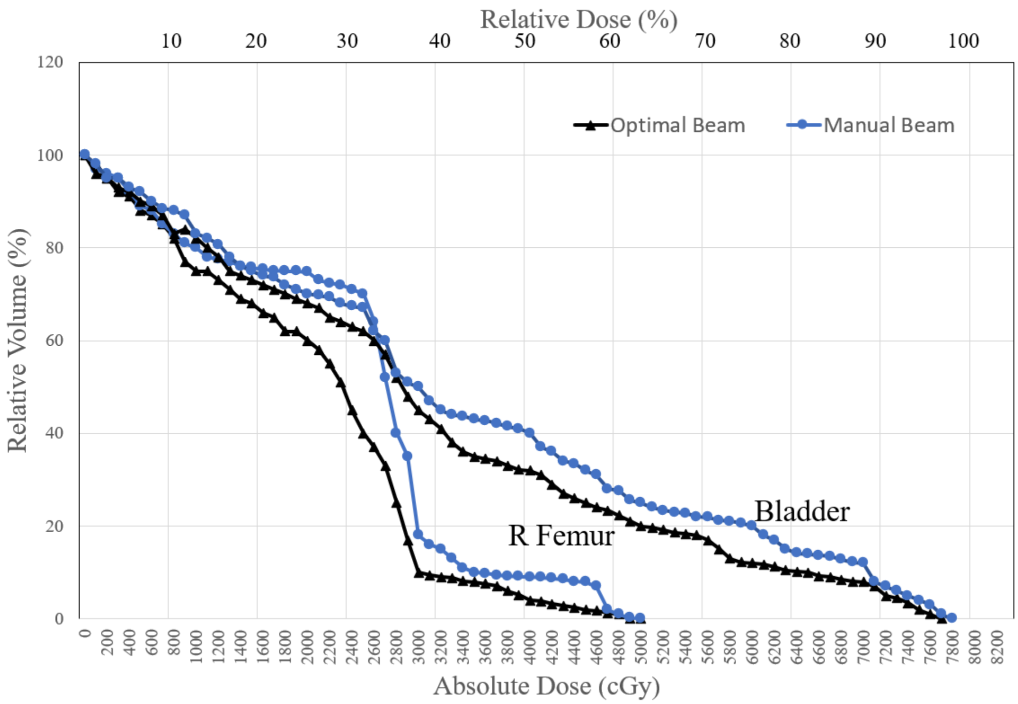
a) Case A b) Case B

Figure 2.
ABAS and dose distributions.

4.2. Test cases C

A more sophisticated case is used to test ABAS's performance, simulating the progression of a prostate tumor. The simulated model includes an OAR, bladder, and rectum, as well as a concave prostate. The volumes in this phantom example fill 10 CT slices and have consistent forms across all of the slices. A dose of 73 Gy is prescribed for the PTV, which is equivalent to a 100% dose. CT slices are separated by 0.5 cm, and voxel volumes are all 0.5 cm. The pencil beam is 0.5 in the isocenter plane. The PTV is exposed to five coplanar photon beams, each with a maximum power of 6 MV. In this case, both manually designed, equally spaced beams and automatically selected beams created by ABAS are used to achieve optimal performance.

Figure 3 shows the superior outcomes of beam angle tuning via DVH comparisons. Although the beam directions in the two schemes are comparable, the dosage distributions generated by the optimization technique are much superior. This is mostly due to the complexities of the anatomical components involved, and the major impact of intensity-modulated beams on overall dosage.



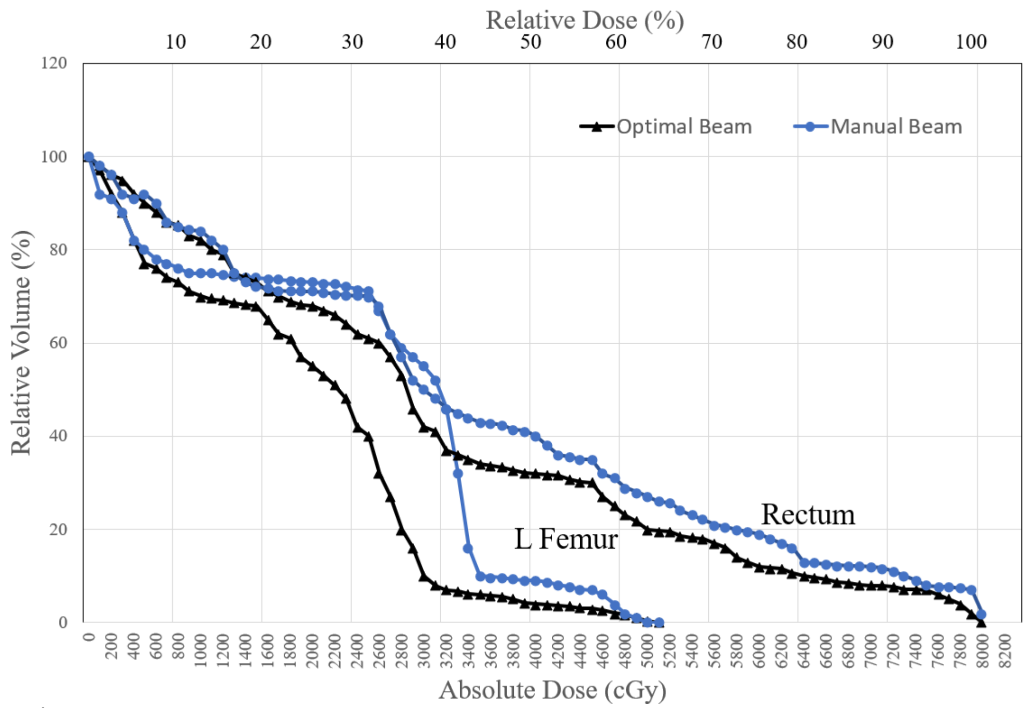


Figure 3.
DVH comparisons of the manual versus optimal plan for prostate cancer.

Table 1 displays statistics on the two optimization techniques (ABC and MABC). The table indicates that the MABC-based algorithm outperforms the ABC-based method. The computation time is lowered from 23 minutes 52 seconds to 18 minutes 34 seconds.

Table 1.
Performance comparisons of the optimization model.

Optimization	Run time	Computation time	Success rate
ABC	22	23 min 52 sec	1.0
MABC	22	18 min 34 sec	1.0

5. Conclusion

Planning for radiation therapy is crucial. The success of a patient's therapy depends heavily on the excellence of the plan used to provide that care. Recent decades have seen the invention of powerful dose calculation and optimization algorithms for IMRT. However, in the context of modern healthcare, treatment planning remains generally ineffective and labor-intensive. In this paper, we create an effective IMRT tool that selects beam angle planning autonomously. The choice of beam angles and the optimization of intensity maps are handled as independent operations in our ABAS algorithm. The optimal beam angles are selected with the help of a MABC approach, and the intensity maps for every beam combination are quickly optimized with the help of the CG approach using a dose based. The dose is determined using a 3D-FSC based on a pencil beam. Some unique strategies are utilized to boost the optimization effectiveness, allowing the beam angle to be implemented in a clinically acceptable computational time. There are three main ways in which MABC is superior to previous methods: (1) the OF simplifies during BAS, and the entire complex function is only employed for the intensity maps optimization (2) an immunity operation is added into MABC; and (3) a helpful fitness-scaling technique is done to advance the process. Many clinical cases will be used in the future to verify the validity of the suggested MABC algorithm. To further enhance the effectiveness of the optimization process, we are currently working on developing a flexible framework.

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