The Aperture Shape Optimization Based on Fuzzy Enhancement

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ABSTRACT The aperture shape optimization (ASO) is a critical step in the direct aperture optimization (DAO) method. During ASO, the gradient of objective function is calculated with respect to the beamlet weight. These gradient components are directly utilized to generate the new aperture shape. In this way, the beamlet of the large positive gradient value may be grouped into the generated aperture shape. The treatment quality may be deteriorated by adding this aperture into the treatment plan. In order to overcome this drawback, a novel method based on the fuzzy enhancement was proposed to generate the aperture shape. We apply the fuzzy enhancement method to enhance the gradient map that is composed of the gradients of objective function in a beam. The enhanced gradient map was then employed to form a network flow, which was solved to generate the new aperture shape. The optimal aperture shape was generated by removing the beamlet of the large positive gradient value from the new generated aperture shape. To verify the effectiveness, the proposed method was compared with the conventional column generation (CG) method on a prostate cancer case and on a head-and-neck cancer case. Experimental results demonstrate that the new algorithm has a better performance than the CG algorithm. The proposed method can further reduce the dose delivered to the critical structures, when the similar dose coverage is delivered on the targets.

INDEX TERMS Optimization, intensity modulated radiation therapy, fuzzy enhancement, aperture shape optimization.

I. INTRODUCTION

At present, intensity modulated radiation therapy (IMRT) is widely used in the clinical treatment of tumors. To achieve IMRT, there are two methods for realizing the static intensity-modulated mode, namely the two-step approach and the direct aperture optimization (DAO) approach [1]–[3]. For the former one, in the first stage, the (beamlet-based) fluence map optimization (FMO) problem is solved to find an optimal intensity profile or fluence map for each beam; in the second stage, the fluence maps are sequenced into a manageable number of apertures that are deliverable using a multileaf collimator system. However, it is a strongly NP-hard problem for sequencing a fluence map into the minimum number of apertures [4], and the sequencing step may cause a potential degradation of the treatment plan quality [5], the DAO approach integrates the beamlet-based FMO problem and leaf-sequencing problems into a single optimization model. Compared to the two-step approach, DAO approach improves the IMRT plan quality dramatically [6]–[8]. The DAO approach iterates two steps: the aperture shape optimization (ASO) and the aperture weight optimization. In ASO, the deliverable aperture that promises the largest improvement to the objective function is identified and is then added to the treatment plan. In the aperture weight optimization, the aperture weights are regenerated for the new set of apertures. The ASO plays an important role in DAO approach and determines the quality of the IMRT plan. Thus, in order to obtain the optimal apertures, many authors devote themselves to improving the ASO methods, which is grouped into three categories, namely the stochastic search methods [1], [9]–[12], the gradient-based methods [2], [5], and the network flow [3], [13]–[19].

Usually, each beam is typically modeled as a collection of hundreds of small beamlets, and the intensities of each of these beamlets are assumed to be controllable on an individual basis. With respect to the variables of the beamlet
The gradients of objective function in a beam are calculated and constitute a gradient map, which is utilized to search the optimal aperture shape [13]. Meeting any of the constraints imposed by the multileaf collimator, a change in leaf position is accepted if the value of objective function decreases. A change in leaf position is to open or to close the rays irradiated to the beamlets. The rays are opened for the beamlets whose gradients are smaller than zero. And the rays are closed for the beamlets whose gradients are larger than zero. The gradient value indicates the open or the close of the corresponding beamlet, namely the multileaf collimator leaf positions. In the works of Hardemark et al. [2] and Cassioli and Unkelbach [5], the aperture shapes are optimized with the deterministic search methods. For these methods, the local gradients with respect to the leaf position are applied to calculate the aperture shape. However, it is easy for these methods to fall into local minima. Stochastic search methods can escape from local minima by the use of a stochastic optimization approach. Shepard et al. [1] and Earl et al. [12] used the simulated annealing algorithm to optimize the aperture shapes, Cotrut and Xing [10] and Li et al. [11] used the genetic algorithm optimize the aperture shapes. Nonetheless, these methods cannot guarantee that all deliverable apertures are considered, and these search algorithms in general are inefficient.

The third approach involves column generation, which starts with an empty set of apertures and iteratively adds apertures to the treatment plan. In the generic column-generation (CG) approach described by Romeijn et al. [3], the gradients of objective function are employed to formulate a network flow, which can be solved as a shortest path problem. By solving this shortest path problem, an optimal aperture shape meeting machine specific requirements is generated. Carlsson [13] proved that the plan improvement rate is much higher with the adjustable aperture approach than with the fixed aperture approach early in the solution process. Peng et al. [16], [17] extended the CG approach to the case with constant gantry speed and dose rate (VMATc) using a heuristic framework. Moreover, to take advantages of GPU computing, effective parallel processing algorithm have been implemented [18]. Mahnam et al. [19] formed successive generations of apertures using graph algorithms for the sequencing and a gradient-based model with CG to optimize the intensities.

However, for the CG algorithm, there is a complex relationship between the aperture shape and the gradient component. Directly determining the leaf position by the gradients may result in a sub-optimal aperture shape. The objective function value is decreased by adding the new aperture shape in the IMRT plan. But, the positive value in the gradient map may be canceled out by the surround negative values. The beamlet of the positive gradient value may be grouped into the new generated aperture shape, especially for the beamlet of large positive gradient value. Adding this aperture shape into the treatment plan may decrease the treatment quality. Thus, in order to generate an optimal aperture shape, the beamlets of large positive gradient values should be excluded from the aperture shape as many as possible.

On the basis of the above comparison and considerations, a fuzzy enhancement algorithm [20] was proposed to enhance the gradient map, in order to improve the CG algorithm and reduce computation time. The enhanced gradient map was then applied to form a network flow, which was solved to generate the new aperture shape. The proposed method increased the large gradient that is far from zero and pressed the small gradient that is close to zero. The beamlet of the larger gradient gives the more contribution to decide the leaf position. On the opposite, it gives the less contribution. In this way, the new method avoids the cancel-out of the large positive gradient value by the surrounded small negative gradient values. The optimal aperture was obtained by removing the beamlet of the large positive gradient value from the new generated aperture shape. To test the effectiveness, the proposed method was compared with the CG algorithm on a prostate cancer case and on a head-and-neck cancer case. Experimental results show that the new algorithm has a better performance than the CG approach.

This paper is organized as follows: the first section is introduction, the second section is the methods for this paper, the third section is the specific settings and the results of the experiment, the experimental results is analyzed and discussed in the fourth section, and the fifth section is the conclusions.

II. METHODS
In this section, a new mathematical model is developed to solve the ASO problem. In section II.A, the dose is formulated as a function of aperture shapes and corresponding weights. Section II.B provides a solution process of the DAO algorithm. The new ASO algorithm based on the fuzzy enhancement is discussed in the section II.C.

A. DOSE CALCULATIONS
The structures in a phantom include both targets and critical structures, and are irradiated using a predetermined set of beams. Each beam \( m (m \in M) \) is decomposed into a rectangular grid of beamlets \( B_{im} \) with \( R \) rows and \( L \) columns. In this paper, a typical beamlet is of size \( 0.5 \times 0.5 \) cm\(^2\). The dose received by voxel \( j \) in the structure \( s \subseteq S \) from beamlet \( i \) of beam \( m \) at an unit intensity is marked as \( W_{ijms} \), which is deposition coefficient. Given the weight \( x_{im} \) for the beamlet \( i \) of beam \( m \), the dose \( D_{fs} \) received by voxel \( j \) \((j \subseteq J) \) in structure \( s \) as follow:

\[
D_{fs} = \sum_{m \in M} \sum_{i \in B_{im}} W_{ijms} x_{im}. \tag{1}
\]

The set of deliverable apertures is denoted as \( K \), and the corresponding weights of those apertures are marked as \( y_k \) \((k \in K)\). Let \( A_k \) denote the set of beamlets \( i \) \((i \in A_k)\) of beam \( m \) that are exposed in the aperture \( k \). Therefore, in the DAO algorithm, the weight \( x_{im} \) for beamlet \( i \) is calculated as
where formulated as:

$$x_{im} = \sum_{k \in K} \sum_{i \in A_k, j \in B_m} y_{ik}.$$  \hfill (2)

### B. THE DAO ALGORITHM

For the step and shoot IMRT, a plan optimization problem is formulated as:

$$\text{minimize } F(D) = \min \sum_{s=1}^{S} \sum_{n=1}^{N_s} J_s \sum_{j} F_{ns}(D_{js}).$$  \hfill (3)

where $F(D)$ is the objective function, $F_{ns}(D_{js})$ is the $n$th sub-objective function applied to the structure $s$. In order to control the dose delivered to the structure, $N_s$ sub-objective functions are applied to the structure $s$.

The DAO algorithm is implemented to solve this optimization problem, in order to generate the deliverable apertures, which include both aperture shapes and aperture weights. For DAO algorithm, there are two main steps in the loop of the solution process, namely ASO and the aperture weight optimization. In the first stage of the loop, a new aperture shape is generated by the ASO algorithm and is added to the treatment plan. Next, the aperture weight optimization is performed to recalculate the weights of new set of aperture shapes. After the aperture weight optimization, the previously added sub-optimal aperture may be deleted or be regenerated for the zero aperture weight. If the optimality conditions are satisfied or if the maximum number of loops is reached, the solution process is terminated. Otherwise, the next loop is entered.

The ASO takes an important role in the DAO algorithm and determines the quality of the IMRT plan. Many kinds of methods are proposed to improve the ASO \cite{1}–\cite{3}. Here, our aperture generation strategy follows the CG algorithm presented by Romeijn \textit{et al.} \cite{3}. Initially, a discretization of the cross-sections of the beams into beamlets is performed, as described in Section II.A. Next, with respect to the beamlet weight $x_{im}$, the gradient of the objective function $F(D)$ (equation 3) is calculated as follows:

$$\frac{\partial F(D)}{\partial x_{im}} = \sum_{s=1}^{S} \sum_{n=1}^{N_s} \sum_{j} \partial F_{ns}(D_{js}) \frac{\partial D_{js}}{\partial W_{ijns}}.$$  \hfill (4)

The gradients in a beam constitute a gradient map $G (g_{ij} \subset G).$ For the CG algorithm, the new aperture in a beam is then generated by combining beamlets into a feasible aperture, so that the sum of the gradient components of the included beamlets is as small as possible. The new generated apertures have to meet the user and machine specific requirements, such as connectivity, interdigitation, minimum gaps, and so on \cite{13}. In order to achieve this goal, the gradient map is applied to formulate the network flow, which can be solved as a shortest path problem \cite{3}. By solving this shortest path problem, an optimal aperture shape satisfying the conditions is generated. At last, the new aperture shape is added to the treatment plan.

### C. THE FUZZY ENHANCEMENT METHOD

A gradient map during the ASO is displayed in Figure 1. For the 3rd row, there are several feasible apertures which combine the different set of beamlets. As observed in Figure 1, the beamlets in the blue rectangle have the smallest value of the sum of the gradient component. Thus, the blue rectangle will be added to the plan. However, a beamlet of a large negative gradient value is enclosed in the new generated aperture shape. The optimal aperture shape is the one that has the sum of the gradient component of the enclosed beamlets is the smallest. However, there is a complex relationship between the aperture shape and the gradient component. This approach may not be optimal. It tends to generate a sub-optimal aperture shape, which may decrease the quality of the treatment plan at the later process of DAO. In order to avoid this drawback, a new method based on the fuzzy enhancement was proposed as follows.

During the ASO, the gradient value indicates the open or the close the corresponding beamlet. For the CG algorithm, the negative value of the gradient component indicates the reduction of the objective function value, when the corresponding beamlet is included into the new generated aperture shape. The optimal aperture shape is the one that the sum of the gradient component of the enclosed beamlets is the smallest. However, there is a complex relationship between the aperture shape and the gradient component. This approach may not be optimal. It tends to generate a sub-optimal aperture shape, which may decrease the quality of the treatment plan at the later process of DAO. In order to avoid this drawback, a new method based on the fuzzy enhancement was proposed as follows.

#### FIGURE 1. The gradient map of a beam during the plan optimization.

A gradient map during the ASO is displayed in Figure 1. For the 3rd row, there are several feasible apertures which combine the different set of beamlets. As observed in Figure 1, the beamlets in the blue rectangle have the smallest value of the sum of the gradient component. Thus, the blue rectangle will be added to the plan. However, a beamlet of a large positive gradient value is enclosed in the blue rectangle, because this positive value is canceled out by the surrounded negative values in the gradient map. Grouping the beamlet of the large positive gradient value into the new generated aperture shape may generate a sub-optimal aperture shape. There is a nonlinear causal relation between the leaf position and the gradient component. Because of this, sometimes, the beamlet of the large gradient value may play a more important role in calculating leaf positions than the sum of the surrounded beamlets of the small gradient values. Considering the problems above, the image enhancement step is...
necessary in order to make sure that the large positive value will not be canceled out by the surrounded negative values. In this paper, the fuzzy enhancement method was applied to enhance the gradient map.

The object of enhancement technique is to process the gradient map that the result is more robust than the original for generation of new aperture. The methods so far developed for image enhancement may be categorized in two broad classes, namely, frequency domain methods and spatial domain methods. The technique in the first category is based on modifying the Fourier transform of an image, whereas in spatial domain methods the direct manipulation of the pixel is adopted.

The technique used here is based on the modification of gradients in the fuzzy property plane of the gradient map. As fuzzy system is capable of representing diverse, non-exact, uncertain and inaccurate knowledge of information, fuzzy set is used in analyzing complex systems and decision processes [20]. The property domain is extracted from the spatial domain using fuzzifiers which play the role of creating different amounts of fuzzification in the plane. The fuzzy operator, contrast intensification, is taken as a tool for enhancement.

The original gradient map $G$ of size $R \times L$ has gradient levels $g_{rl}$ can be considered as a collection of fuzzy singletons in the fuzzy set notation.

$$C = \{\mu(g_{rl}), g_{rl}\} | r = 1, 2, \cdots, R; l = 1, 2, \cdots, L\}, \quad (5)$$

where $\mu(g_{rl})$ is the membership function that gradient map $G$ to the fuzzy domain $[0, 1]$. The value indicates the degree of the elements belong to the fuzzy set. Therefore, the membership $\mu(g_{rl})$ is 1 for those elements in the set $(c_{rl} \in C)$ and 0 for those out of the set $(c_{rl} \notin C)$. Larger values denote higher degrees of the memberships. From the aspect of mathematics, the major difference between the classical set and the fuzzy set is the value of membership function. The selection of membership function is dependent on the applications.

The membership function $\mu(g_{rl})$ has been adapted in this study to fuzzify the original gradient map $G$. The fuzzy feature can be explained as follows,

$$c_{rl} = \mu(g_{rl}) = \frac{1}{2} + \frac{g_{rl}}{2g_{\text{max}}}, \quad (6)$$

where $g_{\text{max}}$ is the absolute maximum of the gradient map $G$, $g_{rl}$ is the gradient level of the original gradient map. Equation (7) shows that when $g_{rl} \rightarrow g_{\text{max}}, c_{rl} \rightarrow 1$. When $g_{rl}$ decreases, $c_{rl}$ decreases correspondingly. Therefore, the calculated membership function transforms the gradient levels from the spatial domain to fuzzy domain. The original gradient map has been normalized in the range of $[0, 1]$. The threshold 0.5 divides the gradient levels into two regions, which are $[0, 0.5]$ for negative gradient region and $(0.5, 1]$ for positive gradient region. The plane composed by all $c_{rl}$, $(r = 1, 2, \cdots, R; l = 1, 2, \cdots, L)$ is called fuzzy feature plane.

If the contrast enhancement operator $\mu'(x)$ which is applied on the fuzzy feature plane $C$ can produce a new fuzzy set

$$\mu'(C) = C', \quad \text{its subjection function is expressed as:}$$

$$\mu'(c_{rl}) = \begin{cases} \frac{1}{2}[1 - (1 - 2c_{rl})^\beta] & c_{rl} \leq 0.5 \\ \frac{1}{2}[1 + (2c_{rl} - 1)^\beta] & c_{rl} > 0.5 \end{cases}, \quad (7)$$

where $\beta$ is the parameter which determine the shape of the $S$-function $\mu'(c_{rl})$. This operation increases the fuzzification of fuzzy set $C$, and decreases the value of $c_{rl}$ when it is more than 0.5, increases the value of $c_{rl}$ when it is less than 0.5.

The detailed of fuzzy enhancement algorithm in this paper can be described as,

1. Extract the fuzzy feature of the original gradient map, and constitute the fuzzy feature plane: $c_{rl} = \mu(g_{rl})$.
2. On the fuzzy feature plane, use contrast enhancement transformation $\mu'(c_{rl})$ to enhance fuzzy feature $c_{rl}$ and obtain the fuzzy enhanced $c'_{rl}$.
3. Apply inverse transformation on the new fuzzy feature plane to get the enhanced output gradient map $g'_{rl} = 2g_{\text{max}}(c'_{rl} - \frac{1}{2})$.

For the enhanced gradient map, the shape of the membership function used in this work is displayed in Figure 2. The curves in Figure 2 are the shape of the membership function (in equation 7) of the different parameter $\beta$. As parameter $\beta$ increases, the curve tends to be steeper for the variable that is far from $g_{rl} = 0.5$, which is mapped to the zero intensity in the gradient map. Thus, relatively to the gradient map $G$, the small gradient that is close to zero is pressed and the large gradient that is far from zero is increased in the enhanced gradient map. With the decrease of the parameter $\beta$, the situation is just on the contrary. For the parameter $\beta = 1$, there is no enhancement to the gradient map $G$, as the black dash line shown in Figure 2.

During the ASO, the large gradient may play a more important role in calculating leaf positions than the small gradient, especially for the large gradient of the positive value. Thus, in this work, a large parameter $\beta$ is selected to
increase the large gradient and to press the small gradient. Here, the parameter $\beta = 3$ is selected for equation (7). The gradient map in Figure 1 is enhanced by fuzzy enhancement and the results are shown in Figure 3. As observed in Figure 3, the optimal aperture shape for 3rd row is the blue rectangle. Compared with the results of the CG algorithm, the beamlet of the large positive gradient value is removed from the optimal aperture shape for the new method.

For the proposed method, the gradient map is enhanced by the fuzzy enhancement method. A large parameter $\beta$ is selected to increase the large gradient and to press the small gradient. The beamlet of the larger gradient gives the more contribution to decide the leaf position. On the contrary, it gives the less contribution. The enhanced gradient map is then utilized to generate the new aperture shape. In this manner, the cancel-out of the positive gradient value by the surrounded small negative values is avoided. And the optimal aperture shape is generated by removing the beamlet of large positive gradient value from the new generated aperture. Compared to the CG algorithm, it is no longer a linear relationship between the leaf position and the gradient component.

III. EXPERIMENTS AND RESULTS

To verify the effectiveness, the new method was tested on a 5-field prostate cancer case and on a 9-field head-and-neck cancer case. The dose matrix $W_{ijms}$ (in equation 1) was calculated by using the classical pencil beam algorithm [21] which was implemented on the software CERR [22]. In order to control the dose coverage on each structure, the different types of sub-objective function were applied, such as the minimum dose sub-objective function, the maximum dose sub-objective function, the uniform dose sub-objective function and the dose-volume based sub-objective function [23]. The proposed method was also compared with the CG algorithm [3], in which the same sub-objective functions were applied to the critical structures and the targets. The L-BFGS-B algorithm [24] was used to generate the weights of apertures. The shape of the membership function (equation 7) is determined by the parameter $\beta$. The membership function is applied to enhance the gradient map. Thus, the parameter $\beta$ plays an important role in the process of the fuzzy enhancement. Here, we used the parameter $\beta = 2$ for the prostate cancer case and the parameter $\beta = 3$ for the head-and-neck cancer case.

To assess the relative quality of each treatment plan, optimization results were evaluated according to practical clinical guidelines, as specified by Marks et al. [25]. The dose criteria in the inverse planning optimization for the two plans are shown in Table 1. The different optimization methods were compared in terms of the following parameters: mean dose, maximum dose, generalized equivalent uniform dose (gEUD) [26], aperture numbers, and computation time. The gEUD value was calculated according to the formula given by Niemierko [26]. The value of the parameter $a$ in gEUD was selected as $8$ for both the bladder wall and the rectum wall, and $1$ for the parotid gland [27].

### A. RESULTS FOR THE PROSTATE CANCER CASE

Our method was tested on a prostate cancer case. We used five coplanar 6 MV photon beams, with gantry angles of $36^\circ$, $100^\circ$, $180^\circ$, $260^\circ$, and $324^\circ$, respectively. And the beam’s source-axis distance was 100 cm. Our method was compared to the CG algorithm in this case. To that end, we used the same objective function for these two methods. In order to improve tumor control probability, one uniform dose sub-objective function and one minimum dose sub-objective function were
added to the planning target volume (PTV). The critical normal tissues considered here were the rectum wall and the bladder wall. To decrease the normal tissue complication probability, three dose-volume based sub-objective functions were applied to minimize the dose delivered to one critical structure. In order to make the dose outside of PTV drop sharply, a dose-volume based sub-objective function was added to the “tissue ring”, the outside of the area extending the PTV by 5cm.

Figure 4 displays the optimization results for the prostate cancer case. The CG algorithm and the proposed algorithm based on fuzzy enhancement are labeled as ‘CG’ and ‘FE’, respectively. As shown in Figure 4 (a) and (b), with the similar dose coverage on the target, there is a dose reduction in the critical organ for the proposed method. The behavior of the proposed model is also illustrated by showing the dose-volume histograms in Figure 4 (c). We computed the gEUD value for both the rectum wall and the bladder wall. For the CG approach, the gEUD values are 57.0 Gy and 62.4 Gy for the rectum wall and the bladder wall, respectively. And the results of the proposed method are 56.4 Gy and 61.9 Gy respectively for those two organs. In comparison with the CG algorithm, the proposed method has the advantage in terms of high-dose control for critical organs. In order to illustrate the performance of our method in more detail, Figure 4(d) shows the behavior of the objective function value as a function of the number of apertures generated.

B. RESULTS FOR THE HEAD-AND-NECK CANCER CASE

The proposed method was also tested on a head-and-neck cancer. Nine coplanar 6 MV photon beams were used to irradiate the target with the equal gantry angle interval. The gantry angles start from 0° and the beam’s source-axis distance was 100 cm. The proposed method was also compared with the CG algorithm in this case. The same objective function was applied for both the CG algorithm and the proposed method too. There were three PTVs for the head-and-neck cancer case. To guarantee the dose delivered to the targets, one mean dose sub-objective function and one minimum dose sub-objective function were added to a PTV. The critical structures considered here were the parotid gland, spine cord and brain stem. To control the dose delivered to the critical organ, a dose-volume based sub-objective function was applied to one parotid, and two maximum dose sub-objective functions were added to spine cord and brain stem, respectively. To make the dose outside of three PTVs drop sharply, a dose-volume based sub-objective function was also added to the “tissue ring”, the outside of the area extending the three PTVs by 5cm.
Figure 5 presents the optimization results for the head-and-neck cancer case. Compared to the CG approach, the proposed algorithm improves the conformity of the dose distribution, as observed in Figure 5 (a) and (b). The proposed method reduces the dose delivered to the critical structure obviously, when there is the similar dose coverage on the targets for two methods. The dose-volume histograms of the optimization results are shown in Figure 5 (c). We calculated the mean dose for parotid glands and the maximum dose for the spine cord and the brain stem. Relatively to the CG algorithm, the proposed method results in a gEUD decrease of 0.3 Gy and 0.5 Gy to the ipsilateral parotid gland and the contralateral parotid gland, respectively. For both the CG algorithm, the maximum dose is 48.9 Gy and 34.0 Gy for spine cord and brain stem, respectively. For the proposed algorithm, the maximum dose is 49.8 Gy and 30.4 Gy for spine cord and brain stem, respectively. Figure 5 (d) displays the behavior of the objective function value as a function of the number of apertures generated.

The performance of our method was illustrated in more detail. During the plan optimization, the aperture was added to treatment plan one by one. The numbers of apertures applied to the plan optimization are 60 and 90 for the prostate cancer case and the head-and-neck cancer case, respectively. After the process of DAO, the final apertures used in the treatment plan are obtained by removing the aperture of zero intensity from all applied apertures. Table 2 lists the computation time and the number of apertures.

IV. DISCUSSION

In this paper, we present an approach to solve the aperture shape optimization problem in IMRT treatment planning. The proposed algorithm falls into the category of optimizing leaf positions using the network flow. In the ASO, the gradient map was enhanced by the fuzzy enhancement. Then, the enhanced gradient map was utilized to generate the new aperture shape. To verify the effectiveness, the proposed
The result is not sensitive to parameter \( \beta \). And the parameter \( \beta \) is only need to be determined once for one kind of cancer case. The proposed method was tested on a prostate cancer case and on a head-and-neck cancer case. The results (Figure 4 and 5) proved that the proposed method was capable of generating clinically acceptable plans which meet the practical clinical guidelines [25].

For the CG algorithm [3], the gradient map is directly applied to generate the new aperture shape. The relationship between the leaf position and the gradient component is assumed as the linear relationship. In this way, the positive gradient value may be canceled out by the surrounded small negative gradient values in the gradient map. Thus, the sub-optimal aperture shape may be generated by enclosing the beamlet of the large positive gradient value into the new generated aperture shape. In this paper, the fuzzy enhancement method was implemented to enhance the gradient map. The large gradient was increased and the small gradient was presser. The effect to the leaf position is enlarged for the beamlet of the large gradient. On the other side, the effect to the leaf position is reduced. In this way, it avoids the cancel-out of the large positive gradient value by the surrounded small negative gradient values. So, the proposed method has ability to obtain the optimal aperture shape by removing the beamlet of large positive gradient value from the new generated aperture shape. There is a complex relationship between leaf position and the gradient component. The proposed fuzzy enhancement method cannot accurately describe this relationship. However, the proposed method can give an alternative to generate the aperture shape and to further improve the quality of the treatment plan, as shown in Figure 4 and 5.

We can change the enhancement result through adjusting the fuzzy parameter \( \beta \) that is obtained manually in a trial-and-error manner. Here, we used the parameter \( \beta = 2 \) for five prostate cancer cases and the parameter \( \beta = 3 \) for five head-and-neck cancer cases. The results proved that the proposed method was capable of generating clinically acceptable plans which meet the practical clinical guidelines. Therefore, for the same kind of cancer case, the optimization result is not sensitive to parameter \( \beta \). And the parameter \( \beta \) is only need to be determined once for one kind of cancer case.

The proposed method was also compared with the CG algorithm in detail. Experimental results showed the proposed algorithm has better performances than the CG algorithm for the head-and-neck cancer case, when there is the similar dose coverage on the targets. Relatively to the CG algorithm, the proposed method not only shortens the computation time, but also reduces the number of apertures, as displayed in Table 2.

TABLE 2. The computation time and the number of apertures used for both the CG algorithm and the proposed method.

<table>
<thead>
<tr>
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<th>Prostate</th>
<th>Head-and-neck</th>
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<td>Computation time (s)</td>
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<td>CG FE</td>
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V. CONCLUSION

We have developed a new aperture shape generation method based on fuzzy enhancement. In the ASO, the gradient map was enhanced by the fuzzy enhancement. Then, the enhanced gradient map was applied to generate the new aperture shape. In this manner, the optimal aperture was obtained by removing the beamlet of large positive gradient value from the new generated aperture shape. To verify the effectiveness, the proposed method was compared with the CG algorithm on a prostate cancer case and on a head-and-neck cancer case. Experimental results show that the proposed algorithm has better performances than the CG algorithm.

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