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Trimmer sequencing time minimization during dynamically collimated proton therapy using a colony of cooperating agents

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Abstract

The dynamic collimation system (DCS) can be combined with pencil beam scanning proton therapy to deliver highly conformal treatment plans with unique collimation at each energy layer. This energy layer-specific collimation is accomplished through the synchronized motion of four trimmer blades that intercept the proton beam near the target boundary in the beam's eye view. However, the corresponding treatment deliveries come at the cost of additional treatment time since the translational speed of the trimmer is slower than the scanning speed of the proton pencil beam. In an attempt to minimize the additional trimmer sequencing time of each field while still maintaining a high degree of conformity, a novel process utilizing ant colony optimization (ACO) methods was created to determine the most efficient route of trimmer sequencing and beamlet scanning patterns for a collective set of collimated proton beamlets. The ACO process was integrated within an in-house treatment planning system optimizer to determine the beam scanning and DCS trimmer sequencing patterns and compared against an analytical approximation of the trimmer sequencing time should a contour-like scanning approach be assumed instead. Due to the stochastic nature of ACO, parameters were determined so that they could ensure good convergence and an efficient optimization of trimmer sequencing that was faster than an analytical contour-like trimmer sequencing. The optimization process was tested using a set of three intracranial treatment plans which were planned using a custom research treatment planning system and were successfully optimized to reduce the additional trimmer sequencing time to approximately 60 s per treatment field while maintaining a high degree of target conformity. Thus, the novel use of ACO techniques within a treatment planning algorithm has been demonstrated to effectively determine collimation sequencing patterns for a DCS in order to minimize the additional treatment time required for trimmer movement during treatment.

Keywords

protons; optimization; collimation

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1. Introduction

Pencil beam scanning (PBS) enables the delivery of intensity modulated proton therapy (IMPT) treatments (Chu *et al* 1985, Pedroni *et al* 1991, Chu *et al* 1993). Similar to intensity modulated x-ray therapies (IMXT), IMPT uses several non-uniform treatment fields to achieve a desired dose distribution around the target (Paganetti *et al* 2005a, Pedroni *et al* 2005) while also increasing the target conformity and healthy tissue sparing relative to single-field uniform dose treatment methods (Glimelius *et al* 1999, Lomax *et al* 1999, 2004, Paganetti *et al* 2005a, Flynn *et al* 2007, 2008, Bolsi *et al* 2008, Merchant *et al* 2008). Additional healthy tissue sparing and an increase in target conformity are achievable through the use of collimation, especially for low-energy treatments where the lateral proton beamlet penumbra increases due to the larger nominal spot size (Chu *et al* 1993, Gustafsson *et al* 1994, Bues *et al* 2005, Paganetti *et al* 2005a, Daartz *et al* 2009, Charlwood *et al* 2016, Moteabbed *et al* 2016, Winterhalter *et al* 2018a). While the use of collimators, such as apertures, provide some benefit, further improvements can be achieved with energy layer-specific collimation through the sequenced motion of four trimmer blades (Hyer *et al* 2014a, 2014b, Wang *et al* 2014, Smith *et al* 2016), referred to hereafter as dynamically collimated proton therapy (DCPT). In comparison to other collimators, such as a multi-leaf collimator which could effectively serve in a similar capacity, the DCS retains a smaller footprint which allows the device to be placed close to the patient thereby minimizing the amount of scatter and divergence between the patient and last collimating component. An additional benefit of the DCS over contemporary collimators is the projected reduction in secondary neutron production as the collimators are constructed from nickel (Smith *et al* 2018), a material which has a lower secondary neutron production rate than brass or tungsten (Brenner *et al* 2009). While benefits have been reported from the idealized treatment planning studies of Moignier *et al* (2015, 2016a, 2016b) and Smith *et al* (2016), the dosimetric improvements come at the cost of an increased treatment time. The goal of this work is to develop a method to reduce the trimmer sequencing time while maintaining a high degree of target conformity achieved in the idealized DCPT treatment plan.

The proposed DCS prototype has a maximum trimmer acceleration of 19.6 m s^{-2} and velocity of 2.5 m s^{-1} , although a safe, 'all-day' operating speed was reported as 0.35 m s^{-1} (Hyer *et al* 2014a). Even with this capacity of rapid movement, the progression of trimmer positions for each collimated beamlet would still appear to be slower than the proton beam scanning speed. While the exact scanning speed of a proton therapy system varies among vendors and relies on multiple variables, studies have published scanning speeds ranging from 5.0 m s^{-1} and 10.0 m s^{-1} (Marchand *et al* 2000, Paganetti *et al* 2005b, Shimizu *et al* 2014). This is inefficient since the beam would be paused until the trimmers mechanically transition to their next set of positions. While individually collimating every proton beamlet separately may result in an idealized plan with a greater healthy tissue sparing and target conformity, the large time penalty associated with the movement of trimmers would limit the treatment capacity of the clinic and possibly allow for greater intrafraction patient motion. An initial solution to reduce the time penalty of DCPT treatments was presented in the work of Hyer *et al* (2014b). In this work, it was proposed to deliver DCPT treatments within a fixed grid of beam spots over the target while dividing each row across the center to allow

contiguous sets of double half-rows to be delivered while sharing the same orientation of trimmer positions (Hyer *et al* 2014a, 2014b). However, this may not be the optimal solution and has potential for further improvement. The delivery style was used during the treatment planning studies of Moignier *et al* (2015, 2016a, 2016b) who approximated the delivery time to be within 32 s per treatment field but used a maximum trimmer velocity for all movements and did not consider trimmer acceleration. Additionally, this method groups beam spots deterministically based on physical location relative to a raster-style scanning pattern and forces a common orientation of trimmers which may not provide optimal collimation for all beam spots within the group. This method also limits the positioning of beam spots to a fixed grid prohibiting the applications of contour scanning to DCPT with a DCS as additional healthy tissue sparing benefits have been demonstrated (Meier *et al* 2017, Winterhalter *et al* 2018b). Therefore, a more robust method of trimmer sequencing is necessary to fully exploit the dosimetric advantages associated with DCPT using a DCS while also providing an expedient delivery.

For most external beam radiation therapy patients, the duration of a treatment fraction is governed by patient and treatment set-up, image registration and review, required beam energy changes for the case of proton therapy, and the total prescribed monitor units. This usually results in a total treatment time of around 15–30 min depending on the treatment but can be on the order of five minutes for some advanced forms of x-ray beam therapy such as VMAT. In the case of step-and-shoot IMXT, additional time is necessary for changes in collimation while the beam is turned on and off during movements (Sanghani and Mignano 2006). Methods to minimize leaf motion and number of apertures per treatment field have been proposed in order to minimize the total treatment time for step-and-shoot and dynamic IMXT with an MLC using Norm-minimization and simulated annealing algorithms (Alber and Nusslin 2001, Crooks *et al* 2002). However, these techniques are not directly applicable to the unique case of DCPT with a DCS since the delivery of a treatment field is accomplished with energy-specific, aperture-like sequences of four trimmers. With a DCS, each collimated beam spot may have an idealized trimmer orientation which is unique from all other beam spots at the same energy layer. The task at hand is then to optimize the sequence of trimmer positions so that the energy layer is delivered as quickly as possible while minimizing how much these idealized trimmer positions are compromised. This problem is very similar to that of the *traveling mailman* problem: a mathematical thought experiment in which one tries to determine the quickest route that a mailman should take to visit all houses in a neighborhood in the least amount of time possible. There does not exist a generalized, analytical solution to this problem, but the methods of ant colony optimization (ACO) have been shown to successfully and rapidly solve this problem (Dorigo *et al* 1996).

2. Methods

2.1. Ant colony optimization

ACO is a heuristic, swarm-intelligence method that can solve optimization problems stochastically via a colony of cooperating agents (Dorigo *et al* 1996). It has been employed to solve a variety of optimization problems in CT reconstruction (Papenhausen *et al* 2013), split inventory routing (Wong and HasnahMoin 2017), and much more such as air traffic

control (Haldenbilen *et al* 2013). The approach can be described with an anecdotal example of ants from an ant colony trying to locate the most food nearest to their ant hill. Assume the ant colony has some disposable members that can search for food. Before the i th ant ventures out, there is an initial desirability, $\eta_{m,n}$ that may influence the direction the ant begins to wander from point $\vec{x}_m$ to $\vec{x}_n$. In addition to this initial desirability, there is also the past proficiency from the previous ants, $\tau_{m,n}^i$. As the ants emit pheromones, the past proficiency is updated by $\Delta\tau_{m,n}$ each time an ant travels from $\vec{x}_m$ to $\vec{x}_n$. However, the pheromones of the previous ants evaporate at an evaporation rate, ρ , lessening the influence that the past proficiency has upon the system by forgetting the routes taken by older ant iterations. The past proficiency and initial desirability then influence the route the ant will search for food by modifying the probability that a transition will take place, $p_{m,n}^i$. This can be represented mathematically as Dorigo *et al* (1996),

$$p_{m,n}^i = \frac{(\tau_{m,n}^i)^\alpha (\eta_{m,n})^\beta}{\sum_{\zeta \in N} (\tau_{m,\zeta}^i)^\alpha (\eta_{m,\zeta})^\beta}, \quad (1)$$

where,

$$\tau_{m,n}^{i+1} \leftarrow (1 - \rho)\tau_{m,n}^i + \Delta\tau_{m,n}. \quad (2)$$

Equation (1) illustrates how the probability distribution is normalized to describe the probability that a transition from point m to point n will occur given all possible points that the i th ant could travel to from point m for which $n = 1, \dots, N$. Equation (2) describes how this probability map will change for the next ant iteration given the route taken by the current ant. The element increases by $\tau_{m,n}$ if the ant visits the point $\Delta\tau_{m,n}$ while all the point's probability uniformly diminishes by a factor of $1 - \rho$. The specific parameters used for equations (1) and (2) are listed in table 1. The variables α and β are constant, arbitrary scaling factors which are defined to ensure efficient convergence of the optimization process.

2.2. Algorithm integration within DCPT treatments using a DCS

Several assumptions are made to facilitate the optimization process:

1. Only beam spots nominally placed outside the target are initially collimated.
2. The algorithm is implemented as a final step once the trimmer positions and beam spot positions are chosen similar to the direct aperture optimization method of Shepard *et al* (2002). Individual beamlet distributions are calculated followed by a re-optimization of beamlet weights.
3. During the ACO process, the individual proton beamlets are initially treated independently from one another where each beam spot's relative trimmer positions are optimized uniquely to that beam spot.

4. A spot group is defined as a collection of beamlets that share a common set of trimmer positions.
5. A trimmer position is considered floating if it is set at least 2.5 cm from its nominal spot position as this distance does not influence the beamlet distribution for the IBA UN model (Gelover *et al* 2015). Therefore, the trimmer is assumed to coincide with the respective trimmer position of the next beam spot when evaluating the necessary time to move between beam spots.
6. Uncollimated beam spots are included in any collimated group of beam spots so long as the trimmers are at least 0.5 cm from the beam spot's position. Any beam spots which are left are grouped together as an additional group.
7. The algorithm presented applies to 'step-and-shoot' spot scanning delivery such that the beam is gated on and off as the trimmers move between each configuration.

The ACO process was extended and incorporated into the DCPT treatment optimization by first considering each energy layer as a set of independent beam spot groups, where each beam spot group shares a unique trimmer orientation as shown in figure 1. In general, a spot group can be composed of more than one beam spot. During the course of optimization, the trimmer positions are defined by $S \equiv \{X1, X2, Y1, Y2\}$, that describe the position in space the trimmer resides on its respective axis of motion. Since each of the four trimmers in the DCS can move independently from one another, only the furthest distance between corresponding trimmer positions is used to describe the required transition distance between the two sets of trimmer positions, d . The principle task of this optimization problem is to minimize the total distance the trimmers translate as they progress through the entire treatment plan which can be described by the following objective function,

$$L = \sum_{\phi=1}^{N-1} d(l_{\phi}), \quad (3)$$

where L is the total path length to deliver the energy layer based upon the trimmer transition distances. Each trimmer sequence step, ϕ , is a transition between the trimmer configurations stored in S . Completion of the minimization process will provide the set of trimmer transitions to navigate S for the lowest value of L .

The initial desirability matrix, η , should reflect the required distance to transition the trimmers between beam spots within a given energy layer, as this is primary quantity we wish to minimize. To accomplish this, an initial desirability matrix is calculated based upon the magnitude of the required change in trimmer positioning to transition between sets of trimmer positions, $m \rightarrow n$, where there are N potential trimmer sets. The pair-wise differences between all possible transitions in an energy layer are converted to a sampleable, normalized 2D *a priori* desirability matrix, η , by,

$$\eta_{m,n} = \begin{cases} \frac{1}{\sum_j^N \sum_k^N \frac{d_{m,n}}{d_{j,k}}}, & \text{if } m \neq n \\ 0 & \text{if } m = n \end{cases}. \quad (4)$$

Equation (4) therefore describes the relative speed of transitions in the evaluated energy layer. The quickest transitions between trimmer orientations have a higher probability than the slower transitions, which have a greater $d_{m,n}$ value. This matrix can also be conceptualized as a ‘road map’ which can be navigated to find an efficient route to sequence the trimmer blades during treatment. A single optimization iteration, i , is considered as an ‘ant’ in the anecdotal example which determines a route that the trimmer blades could use to deliver the energy layer efficiently. During a single optimization iteration, i , an inversion sampling method is used to navigate a potential delivery route for the energy layer in several steps, ϕ , that the trimmer blades make between sets of trimmer blade orientations. The history of trimmer transitions between groups of beam spots for the i th optimization iteration at the ϕ th step is recorded in h . This binary matrix is used both to normalize transition probabilities during each step and update the past proficiency after each optimization iteration to describe which routes are more desirable,

$$h_{m,n}^\phi = \begin{cases} 1 & \text{if transition } d_{n,m} \text{ has occurred before or at transition } \phi \\ 0 & \text{if transition } d_{n,m} \text{ has not occurred} \end{cases}. \quad (5)$$

A total of $N - 1$ transitions must occur for a single optimization iteration to determine a route in which all trimmer orientations are delivered in the given energy layer. Upon completion of a single optimization iteration, the past proficiency is updated by,

$$\Delta\tau_{m,n}^{i,\phi=N-1} = \kappa_\tau \cdot h_{m,n}^{\phi=N-1}, \quad (6)$$

where κ_τ is the past-proficiency update factor, and

$$\tau_{m,n}^{i+1} = (1 - \rho) \cdot \tau_{m,n}^i + \Delta\tau_{m,n}^{i,\phi=N-1}. \quad (7)$$

The process is repeated with a new iteration $i + 1$ until all optimization iterations have been simulated. The time it takes for a route to be completed is then calculated from the sum of each trimmer displacement along the optimal ant path.

The completion of all optimization iterations provides a population of potential trimmer sequencing routes. The route corresponding to the minimum time value is chosen as the solution. If this value is larger than the maximum allowable time penalty allotted for a treatment field, the beam spots undergo a grouping scheme redefining how the beam spots in each energy layer are grouped as a member in a new set with a larger grouping size, S' . Beam spots are grouped together in a way to preserve their idealized trimmer positions by searching for other beam spots in the same energy layer which require the least amount of

trimmer movement to transition between them. Subsequent beam spot grouping is performed until the time constraint is met; further grouping may result in less conformal treatment plans as a larger number of beam spots are forced to share a common orientation of trimmer blades. The primary benefit of beam spot grouping is that after each grouping of beam spots, the effective number of trimmer transitions required to deliver the energy layer reduces approximately by the same factor of beam spots grouped.

2.3. Algorithm parameter optimization and testing

ACO has several desirable qualities including its versatility and robust design that makes use of a population-based approach which can be applied to solve many different problems. Since the probability density function of possible routes changes after each ant iteration, a proof of parameter optimality is challenging and beyond the scope of this work. However, tests can be performed by perturbing the number of optimization iterations, a , the convergence coefficients, α and β , the past-proficiency update factor, κ_p , and the evaporation factor, ρ , while investigating their impact upon the entire system. Additionally, since ACO is stochastic, adjacent simulations using identical parameters may yield different end results. This optimization algorithm was coded and implemented within a research-based treatment planning system, RDX, written in MATLAB® (R2017b and R2018a). An initial efficiency testing and parameter optimization was performed for use during treatment plan delivery time minimization of DCPT. Several sets of optimizations were initially performed on a single intracranial treatment plan previously studied (Moignier *et al* 2015, 2016a, 2016b, Smith *et al* 2016). Once these ACO parameters were optimized, the algorithm was applied to two other treatment planning data sets which together included a dual-field chordoma, ependymoma, and low-grade glioma treatment plan. These plans are a subset of a larger collection of intracranial treatments which have been used among multiple treatment planning studies (Moignier *et al* 2015, 2016a, 2016b, Smith *et al* 2016, Smith *et al* 2019) of a dynamic collimation system for which the specific information regarding the planning characteristics are summarized in table 2.

2.4. Comparison to a contouring scanning approach

In addition to the ACO-treatment planning deliveries, a separate analytical calculation was also carried out to compare the expected trimmer sequencing time associated with a contour-like scanning approach applied to each of the three treatment plans studied in this work. Like ACO, each energy layer was assumed to be delivered independently. All uncollimated beam spots in an energy layer were assumed to be delivered first before the trimmers were positioned for a collimated beam spot. The sequencing of trimmers was assumed to follow the scanning of the beam to the nearest beam spot until all spots were delivered in an energy layer. This initial comparison did not consider grouped sets of beam spots.

2.5. Treatment planning optimization

The three patient datasets with brain tumors used in this study were previously studied in the work of Moignier *et al* (2015, 2016a, 2016b) and Smith *et al* (2016). Baseline plans were created without collimation using a model of the IBA Universal Nozzle (Moignier *et al* 2015). A direct parameter optimization (DPO) algorithm was designed to further improve the quality of the dose distributions in terms of target conformity, healthy tissue sparing, and

trimmer sequencing time minimization by simultaneously optimizing the trimmer position, beam spot placement, and delivery sequence of collimated beamlets cohesively during dynamically collimated proton therapy treatments delivered with the DCS. A detailed summary and discussion of this optimization algorithm can be found in the work of Smith *et al* (2019) but is summarized here for completeness. The initial treatment plan was determined from beam spots placed in a fixed grid with a lateral and distal spot spacing of 4 mm and 5 mm, respectively. Gradients were then calculated with respect to an objective function based off of dose-volume histogram goals that iteratively changed the trimmer and spot position for all collimated beam spots until a solution was found which maximized the target conformity while still maintaining adequate target coverage. The resulting treatment plans were taken as the set of nominal plan for which the rest of this work utilized.

ACO parameter optimization was initially performed using the chordoma treatment plan as a surrogate test plan. The treatment was initially optimized without any time constraints: the beam spot positions and trimmer positions for each beam spot in the 90° field of the idealized treatment plan were then used to optimize individual ACO parameters. The nominal values for the convergence factors, α and β , the past proficiency update factor, κ_p , and the evaporation factor, ρ , were set to 1.01, 0.1, 1.01, and 0.0001, respectively. An illustration of the optimization process is shown in figure 2. During the process, the trimmer sequencing time is minimized by grouping sets of beam spots together based on whether they share similar trimmer positions and then optimizing the sequenced movement of the trimmers throughout the treatment using the modified ACO method described in section 2.2.

3. Results

3.1. Ant colony parameter optimization

Figure 3 shows the box plots representing the spread in the minimum trimmer sequencing time determined from 20 separate ACO iterations with 300 ants each. The optimal ACO parameters determined from this specific treatment planning case were 1.01, 0.1, 1.01, and 0.0001 for α , β , κ_p , and ρ , respectively. Little difference was noticed in the optimized ACO parameters should the order or parameter optimization change. The exception to this were the learning parameter, κ_p , and the evaporation coefficient, ρ . A dependence on the number of ant histories was found for the learning parameter, κ_p ; enough iteration histories are required for the learning parameter to influence the sampled probability distribution, p . Additionally, the evaporation coefficient, ρ had a dependence on the learning parameter; the learning parameter had to be much larger than the evaporation coefficient to avoid random walking behavior as illustrated in the bottom-left plot of figure 3. Convergence of this ACO algorithm is shown in the bottom-right plot in figure 3 for the minimum trimmer sequencing time determined with increasing number of simulated ant histories, a , and compared to the trimmer sequencing time estimated for the same treatment field delivered using an analytically determined contour-like scanning approach resulting in a trimmer sequencing time of 250.7 s. The remaining time estimates for trimmer sequencing are listed in table 3 for the other treatment planning fields.

3.2. Treatment planning investigations

The three treatment plans summarized in table 2 were optimized using the custom research algorithm in RDX. Two maximum trimmer speeds were used during the plan optimization to investigate the effects of spot grouping and trimmer sharing on the entire treatment plan. Each plan was optimized to be delivered within 60 ± 10 s per treatment field with a trimmer acceleration of 19.6 m s^{-2} and maximum trimmer velocities of either 2.50 m s^{-1} or 0.35 m s^{-1} . The optimized treatment planning coverages are summarized in the DVH plots in figure 4 with further details of the plan beamlet grouping and total trimmer sequencing time listed in table 4.

4. Discussion

Dynamic collimation with the DCS provides significant advantages with regard to target conformity and healthy tissue sparing relative to un-collimated treatments (Moignier *et al* 2015, 2016a, 2016b, Smith *et al* 2016). However, there is a trade off between dosimetric improvements and trimmer sequencing time. While different techniques have been previously proposed to reduce trimmer sequencing time when using the DCS, they limit the delivery of spots to within a fixed grid and force large amounts of beam spots to share collimation positions that may not be optimal. Thus, to fully exploit the benefits from the delivery of a dynamically collimated treatment using the DCS requires a treatment delivery modality and plan optimization scheme to reflect this technology. Optimizing the delivery of a DCPT treatment can be transformed into the mathematical *traveling salesman* problem for which swarm intelligence optimization methods have been shown to solve rapidly and sufficiently. Integrating ACO methods is also modular in the proposed design. Any arrangement of beam spots organized by energy layer and specified with their unique set of trimmer positions and beam spot positions can be expressed in this formalism.

4.1. ACO parameter optimization

It is important to determine an adequate set of optimization parameters for the ACO system. The differences shown when evaluating the past proficiency update factor, κ_p , in figure 3 indicate that poor selection of parameters could result in trimmer sequencing times more than doubled in length of the most optimal routes. Even with an adequate set of ACO parameters chosen, the algorithm could still result in finding severely less optimal routes resulting in a larger trimmer sequencing time should not enough optimization iterations be used. This is due to the immense amount of possible solutions available for even a single energy layer; an energy layer with 100 collimated beam spots will have nearly $E128$ potential delivery routes. Consequently, the past proficiency convergence parameter, α , appears to have the largest impact upon the convergence of the system as this variable scales the initial desirability matrix highlighting the quickest transitions of trimmers among beam spots. The past proficiency update factor, κ_p , had the second largest influence on the system's convergence as it depicts the past proficiency of a route which updates the initial desirability matrix after each ant iteration. This can be negatively affected should the evaporation coefficient, ρ , be too large and erase the progress of the past proficiency iterations.

4.2. ACO for time minimization during DCPT

Two trimmer translational speeds were investigated to quantify the change in healthy tissue sparing achievable as the algorithm groups more beam spots together to share a common set of trimmer positions. The maximum velocity of 2.50 m s^{-1} was reported as the fastest obtainable speed predicted for the DCS prototype while 0.35 m s^{-1} has been referred to as the acceptable ‘all-day’ operating speed. Reducing the allowed trimmer speed during treatment requires a larger grouping size to ensure that the same treatment timing constraints are satisfied. A similar realization is found for reducing the existing trimmer sequencing time for the same maximum allowed trimmer speed; the magnitude of which can be estimated by the ratio of beam spots in a collimation group between the compared treatment plans. For the low-grade glioma treatment planning case presented in this work, decreasing the maximum allowed trimmer speed from 2.50 m s^{-1} to 0.35 m s^{-1} resulted in a spot grouping size increase from 3 to 7 or 9 spots sharing the same orientation of trimmer positions. The increase in beamlet grouping had a small impact upon the target coverage. A small increase in the dose to the 10 mm ring of healthy tissue surrounding the target was observed indicating that the OAR sparing was slightly compromised as the trimmer velocity decreased which resulted in an increase to the spot grouping size. Specifically, an increase of 1.29 Gy, 1.46 Gy, and 1.29 Gy to the median surrounding healthy tissue for the chordoma, ependymoma, and low-grade glioma treatment plans, respectively, was found between the treatments planned with a maximum collimation velocity reduced from 2.50 m s^{-1} to 0.35 m s^{-1} . However, while target conformity and healthy tissue sparing are less than the idealized scenario, they still present as a significant reduction with respect to the un-collimated treatment plan and are deliverable at a cost of approximately a minute of additional trimmer sequencing time per field.

4.3. Additional applications of the extended ACO algorithm

While the focus of the proposed optimization design is specific to the minimization of trimmer sequencing time during dynamically collimated proton therapy using a DCS, the aforementioned methods may be applied to other instances of time minimization in radiation therapy. One example is with the transition of different MLC field shapes for a static photon, proton, or neutron treatment fields. Additionally, a similar time-minimization benefit may also be obtained by applying these ACO methods to optimize the transition of multiple non-coplanar treatment angles during SRS and SBRT treatments delivered with the Cyberknife technology.

5. Conclusion

The ability to provide field- and energy-specific collimation during pencil beam scanning proton therapy allows the DCS to provide superior dose distributions in comparison to un-collimated and aperture-based collimated proton therapies. However, the benefits of dynamic collimation must be weighed against the additional time required to deliver a treatment; providing unique collimation for each beamlet may not be feasible. To resolve this problem, a novel application of ant colony optimization was implemented to determine an optimal trimmer translation sequencing pattern to deliver a DCPT treatment while minimizing the required trimmer sequencing time. While this technique alone was shown to determine

collimation scanning routes on the order of a few minutes for an idealized treatment plan, further reduction in the overall trimmer sequencing time was achieved by grouping sets of collimated beamlets which shared similar trimmer positions. This technique was shown to successfully modify a set of intracranial treatment plans to be deliverable within about a minute per treatment field while still maintaining a high degree of target conformity and healthy tissue sparing the DCS technology offers.

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Figure 1.

Sample of collimated beam spots and trimmer transitions for the case where each beam spot is uniquely collimated (left column) and beam spots are grouped in sets of threes to share a common orientation of trimmer positions in order to minimize the number of required trimmer movements (right column). Higher-order beam spot grouping would thus follow a similar trend. The green spots highlight the beamlets undergoing collimation at each frame.

Figure 2.

Example distribution sequence of beam spots and collimation positions for a three-spot group (left column) and a six-spot group (right column). A normalized beamlet dose distribution is also shown at each energy layer to illustrate dose coverage with respect to the radiological projection of the target at the Bragg Peak depth (green). Diagonally oriented beam spots are initially favored when organizing groups since they tend to easily share common trimmer positions. However, spot groups may also include diagonally oriented trimmed beam spots with beam spots that are primarily trimmed by only a single trimmer, especially as the group size increases.

Figure 3.

Optimization of ACO parameters. Each box plot represents the distribution of the minimum trimmer sequencing time of 20 ant colony optimizations runs. Unless noted otherwise, each ant colony optimization run utilized 300 ants and had their κ_r , ρ , α , and β parameters set to 1, 0, 1, and 1, respectively. The bottom row shows a set of trimmer sequencing time minimizations where no previous histories were used to influence the search paths (left, denoted as random walking) and where the κ_r , ρ , α , and β parameters were set to their optimized values of 1.01, 0.0001, 1.01, and 0.1, respectively (right). The dotted line in the optimized search plot is the estimated trimmer sequencing time for a contour scanning trimmer sequencing.

Figure 4.

The resulting dose-volume histograms for the treatment plan coverage of the target and surrounding ROIs are plotted for separate optimizations in which the maximum trimmer velocity was set to 2.50 m s^{-1} and 0.35 m s^{-1} to investigate the effects that fixing trimmers for groups of beam spots has upon the entire treatment planning dose distribution (bottom row).

Table 1.

Coefficients used for heuristic ant-colony optimization methods described in equations (1) and (2). Additional variables are summarized for the remainder of the this work within the extension below.

Variable	Description
$p_{m,n}^i$	Probability of transition from trimmer configuration m to n
$\eta_{m,n}$	Attractiveness or <i>a priori</i> desirability
$\tau_{m,n}$	Trial level/past proficiency (<i>pheromone</i> level)
ρ	Pheromone evaporation coefficient
κ_τ	Past-proficiency update factor
s_m	The m th set of trimmer positions for the m th group of beam spots
$d_{m,n}$	Matrix of pairwise distance difference values between sets m and n of trimmer positions
$h_{m,n}^\phi$	Binary history matrix indicating if the transition $m \rightarrow n$ occurred prior to step ϕ
L	Total of the maximum between the four trimmer displacements to deliver an entire energy layer

Table 2.

List of treatment plans investigated including each plan's planning target volume, radiological depth of each beam, prescribed dose, and beam orientations used during treatment planning. The CT planning geometry and target for each plan are illustrated in figure 2.

Plan	Diagnosis	PTV (cm ³)	Energy range (MeV)	Prescribed dose (Gy)	Beam orientations
P1	Chordoma	42	143–182	50	Apex (0°)
			111–159		Right lateral (90°)
P2	Ependymoma	150	98–158	54	Apex (0°)
			98–157		Left superior oblique (225°)
P3	Low-Grade glioma	92	98–159	54	Left lateral (270°)
			98–166		Left superior oblique (225°)

Table 3.

List of times (in seconds) required for trimmer sequencing throughout each treatment planning field. The sequencing of trimmer blades were determined for the s^0 case using a contour-like scanning method and ACO.

	Chordoma		Ependymoma		Glioma	
Method	RLAT (90°)	APEX (0°)	APEX (0°)	LSO (225°)	LLAT (270°)	LSO (225°)
Contour	250.7	220.1	426.9	390.8	327.4	355.7
ACO	135.5	121.6	283.4	254.7	190.6	207.2

Table 4.

A summary of the beam spot grouping required to achieve trimmer sequencing times less than 60 s per treatment field for the three treatment plans in figure 4. The sequencing of trimmer blades were determined for the s^0 case using a contour-like scanning method and ACO. Two cases were investigated for each treatment plan where the maximum trimmer velocity was set from 0.35 m s^{-1} to 2.50 m s^{-1} . The 10 mm ring of healthy tissue around the PTV is shown for each optimized plan evaluated from the DVHs in figure 4.

Treatment plan	Treatment fields	$V_{\max}$ (m s^{-1})	NT Ring $D_{50\%}$ (Gy)	Spots per group	Total time (s)
Chordoma	APEX(0°) RLAT(90°)	—	35.94	1/1	—
Chordoma		2.50	35.94	2/2	50.7/54.1
Chordoma		0.35	37.23	4/5	62.1/57.3
			Contour-like scanning approach		250.7/220.1
Ependymoma	APEX(0°) LSO(225°)	—	40.65	1/1	—
Ependymoma		2.50	40.95	4/4	55.3/50.6
Ependymoma		0.35	42.41	11/10	60.0/61.7
			Contour-like scanning approach		426.9/390.8
Glioma	LLAT(270°) LSO(225°)	—	36.00	1/1	—
Glioma		2.50	36.74	3/3	59.0/60.8
Glioma		0.35	38.03	7/9	52.5/55.4
			Contour-like scanning approach		327.4/355.7