Source-detector trajectory optimization for customized CBCT field of view extension using simulated annealing algorithm

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Abstract

Cone Beam CT (CBCT) has become a routine clinical imaging modality in interventional radiology. Extended Field of View (FOV) CBCT is of great clinical importance for many medical applications, especially for cases where the Volume of Interest (VOI) is outside the standard FOV. In this study, we investigate FOV extension by optimizing customized source-detector CBCT trajectories using Simulated Annealing (SA) algorithm, a heuristic search optimization algorithm. The SA algorithm explores different elliptical trajectories within a given parameter space, attempting to optimize image quality in a given VOI. Kinematic constraints (e.g., due to collisions of the imager with the patient or other medical devices) are taken into account when designing the trajectories. For optimization process, a digital XCAT body phantom was used in which three lesions were placed at extreme positions in the phantom that could not be imaged with the standard circular trajectory. The volume around each lesion was considered as VOI. The geometry of Philips Allura Xper C-arm was considered for simulation. Tomographic Iterative GPU-based Reconstruction (TIGRE) and Universal Quality Index (UQI) were used for image reconstruction and image quality assessment, respectively. Our results showed that proposed trajectories could achieve a UQI of 0.9148, 0.9681, and 0.9632 at the respective three VOIs, which was significantly better image quality compared with circular trajectory (0.5960, 0.4892, and 0.4798 for the three VOIs). In addition, the FOV extension achieved for the three optimized source-detector trajectories was 28.75%, 23.57%, and 22.49%, respectively. Our experimental results have shown that our proposed customized trajectories can lead to an extended FOV and enable improved visualization of anatomical structures in extreme positions while taking into account the available kinematic constraints. This study offers a new approach to improve the diagnostic capabilities of CBCT imaging, thus providing valuable insight into improving patient care in CBCT imaging.

1 Description of purpose

In this study, we propose customized Cone Beam CT (CBCT) Field of View (FOV) extension by optimizing source-detector trajectories using Simulated Annealing (SA) algorithm. The proposed trajectories can extend the FOV and reconstruct Volumes of Interest (VOIs) at extreme locations that cannot be imaged with standard circular trajectories, taking into account kinematic constraints available in the surgery setup.

2 Methods

The SA is stochastic global search optimization algorithm which is commonly used to optimize a multi-parameter problem. It simulates the process of heating and then gradually lowering the temperature of a material. In reality, this is done to decrease defects and therefore, minimize the system energy. This algorithm can solve both unconstrained and bound-constrained optimization problems. A SA iteration begins with generating a new point on the available parameter space randomly. The distance of the new point from the current point follows a probability distribution which has a scale

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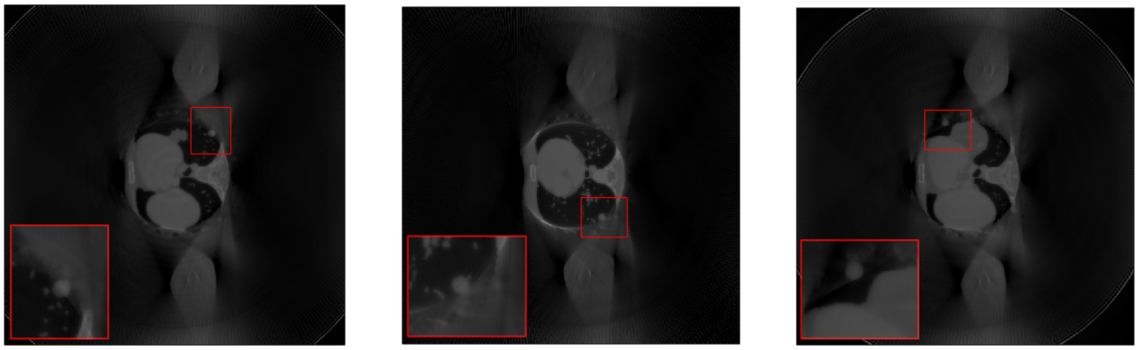
proportional to a variable called temperature. All new points which can lower a defined objective function, and also some which raise the objective function based on a certain probability are accepted by the algorithm. The latter avoids that the algorithm gets stuck in local minima in early iterations and enables searching for global optimum in a more efficient way. The temperature is controlled by the annealing schedule and is steadily decreased, while the best found point is stored. With decreasing temperature, the algorithms search reduces its extent. After a certain amount of points were accepted, reannealing takes place, meaning that the temperature is raised again and the process is repeated to potentially find a better solution this time. The algorithm stops after a stopping criterion is reached [1][2].

In this study, we use the geometry of a Philips Allura FD20 Xper C-arm for our experiments. The FD20 C-arm has 810 mm source-axis distance, 1195 mm source-detector distance, and a 38×38cm^2 detector with 0.7413 mm pixel pitch. For this study, we propose variations of elliptical trajectories to extend the FOV for particular VOIs. These elliptical trajectories have five parameters including ellipse long axis, ellipse short axis and isocenter x, y, z offsets from the origin (x, y and z correspond to right/left, front/back and cranial/caudal directions, respectively). These parameters form the parameter space which are then given to the SA algorithm for trajectory optimization process. To define these parameters, kinematic constraints e.g, collision to the patient table or patient body are taken into account. According to such kinematic constraints, defined on the geometry of the C-arm device similar to our previous publications [3][4][5], ellipse long and short axis can both have a range between 1 to 100 mm. In addition, the x, y and z origin shift can be a value between 0 to maximum 100 mm in each direction. If an elliptical trajectory was chosen that includes some unfeasible points (due to the collisions and constraints), the part which were not feasible were excluded (red marks in Figure 3).

For the simulations an XCAT digital body phantom was used [6]. We included three lesions at different positions in the phantom at thorax area. They were placed in phantom in extreme positions which would not be fully imaged with the standard circular trajectory. The goal was to reconstruct the regions around the lesion (defined as our VOI) optimally and to extend the FOV to include the particular VOI. For image reconstruction the Simultaneous Iterations Reconstruction Technique (SIRT) with 100 iterations from the Tomographic Iterative GPU-based Reconstruction (TIGRE) toolkit was employed [7]. The projection number was set to 360. The Universal Quality Index (UQI) was used as the objective function for SA optimization which was calculated at the defined VOI between the reconstructed images from the elliptical trajectory and the ground truth (digital phantom). The goal was to find an elliptical trajectory which minimizes the value of 1-UQI (in order to maximize UQI) for a given VOI. As a stopping criteria for SA, 1000 objective function evaluations (iterations) was chosen. For comparison, the UQI value between circular trajectory and the ground truth was also computed at three VOIs. To approximate the FOV extension, the 3D images from the circular and the optimized reconstruction were split into many small cubes with a length of 10 voxels. Then the UQI value is calculated for all of the cubes between the reconstructed images and corresponding cubes in the digital phantom. We considered the total number of cubes with an UQI value above a certain threshold as a measure for the FOV extension. The threshold was chosen 0.85 which showed a good compromise for image quality. This measure was computed for both circular and optimized trajectories and the difference was reported as the FOV extension measure. We should note that our proposed approach assumes a registered preoperative CT for trajectory optimization design (this can be done for example based on some initial projections and 2D/3D registration).

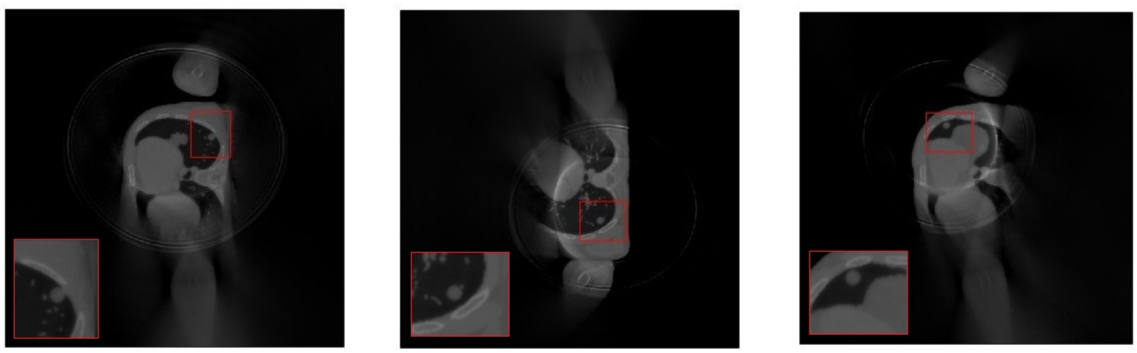
3 Results

Reconstructed images from circular and optimized trajectories at three lesion locations (VOIs 1-3) are shown in Figures 1 and 2. The isocenter offset corresponding to the source-detector trajectories for the three VOIs are shown in Figure 3 (the red assignment in Figure 3 represents the kinematic constraints which limited the offset). The optimization process and the best objective function value results (1-UQI) are shown in Figure 4 and Figure 5, respectively. The achieved UQI values for the three VOIs 1-3 for both circular and the optimized trajectories are reported in Table 1. In addition, the achieved FOV extension results for the three trajectories are given in Table 1 and are visualized in Figure 6.



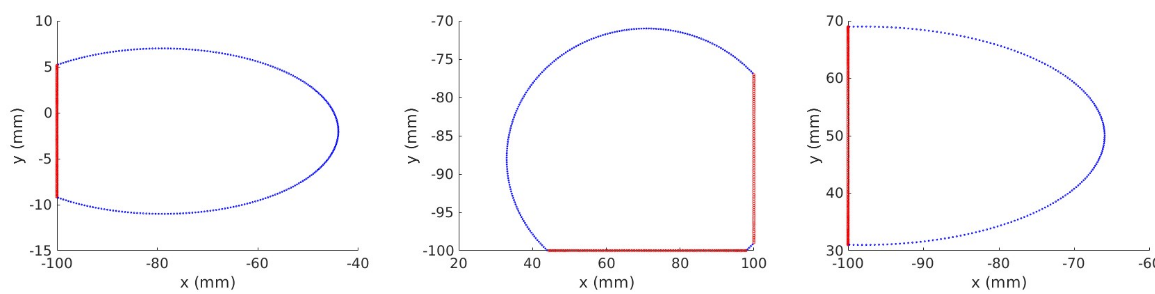
(a) (b) (c)

Figure 1: Reconstructed images from circular source-detector trajectory at three lesion locations (VOIs 1-3 from left to right).



(a) (b) (c)

Figure 2: Reconstructed images from optimized trajectories at three lesion locations (VOIs 1-3 from left to right).

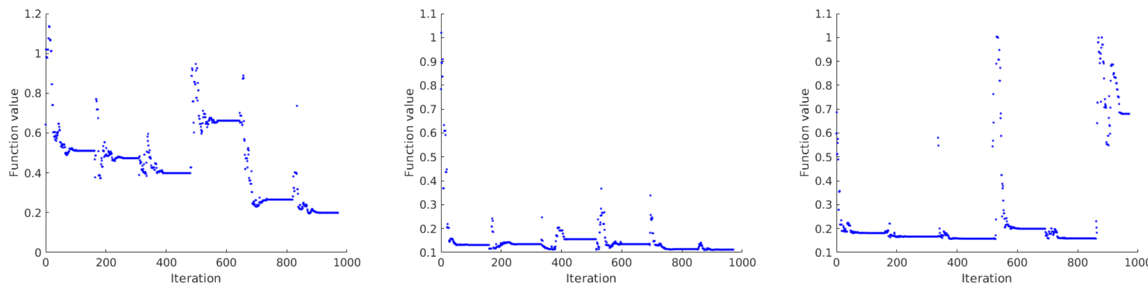


(a) (b) (c)

Figure 3: The isocenter offset in x and y directions corresponding to optimized source-detector trajectories for the three VOIs (VOIs 1-3 from left to right).

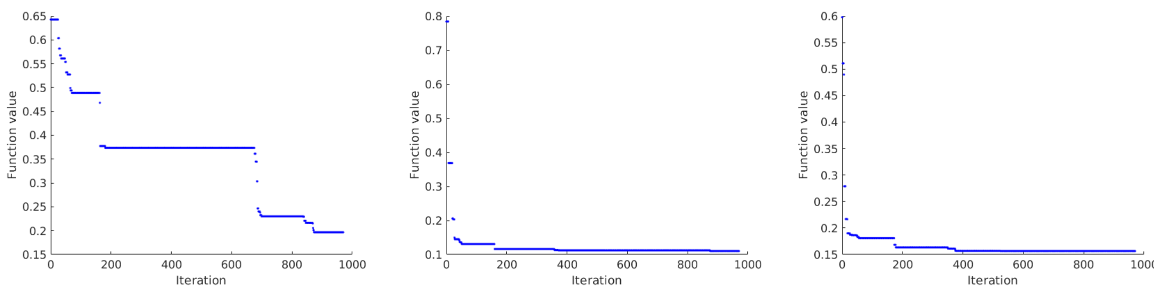
		VOI (a)	VOI (b)	VOI (c)
UQI	Circular trajectory	0.5960	0.4892	0.4798
	Optimized trajectory	0.9148	0.9681	0.9632
FOV extension		28.20%	23.57%	25.48%

Table 1: Results including UQI values achieved at three VOIs for both circular and optimized trajectories as well as FOV extension percentage.



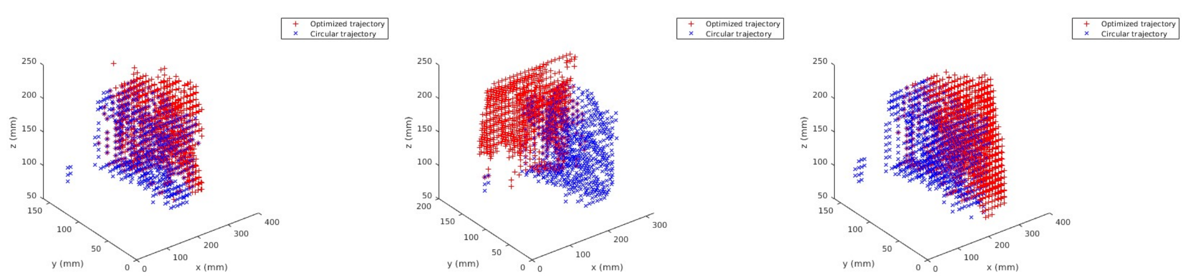
(a) (b) (c)

Figure 4: SA optimization processes to achieve the three optimized trajectories corresponding to VOIs 1-3 (from left to right). The objective function value (1-UQI) is plotted over the 1000 iterations.



(a) (b) (c)

Figure 5: Best achieved objective function value (1-UQI) is presented over the 1000 iterations for the three optimized trajectories corresponding to VOIs 1-3 (from left to right). The last point (point at iteration 1000) corresponds to the final UQI value.



(a) (b) (c)

Figure 6: Illustration of FOV extension results. The blue and red markers depict the location of cubes where an UQI value above 0.85 is reached for standard circular and optimized trajectories, respectively (for the three VOIs (VOIs 1-3 from left to right)).

4 Conclusion

This study shows that the SA algorithm can efficiently be used for optimizing source-detector trajectories for customized FOV extension in CBCT imaging. The achieved trajectories take into account the available kinematic constraints and enables CBCT imaging at extreme points which are not able to be reconstructed appropriately using standard circular trajectory.

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