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Abstract. Current four-dimensional computed tomography (4-D CT) lung image reconstruction methods rely on respiratory gating, such as surrogate, to sort the large number of axial images captured during multiple breathing cycles into serial three-dimensional CT images of different respiratory phases. Such sorting methods may be subject to external surrogate signal noises due to poor reproducibility of breathing cycles. New image-matching-based reconstruction algorithms refine the 4-D CT reconstruction by matching neighboring image slices, and they generally work better for the cine mode of 4-D CT acquisition than the helical mode due to different table positions of axial images in the helical mode. We propose a Bayesian model (BM) based automated 4-D CT lung image reconstruction for helical mode scans. BM allows for applying new spatial and temporal anatomical constraints in the optimization procedure. Using an iterative optimization procedure, each axial image is assigned to a respiratory phase to make sure the anatomical structures are spatially and temporally smooth based on the BM framework. In experiments, we visually and quantitatively compared the results of the proposed BM-based 4-D CT reconstruction with the respiratory surrogate and the normalized cross-correlation based image matching method using both simulated and actual 4-D patient scans. The results indicated that the proposed algorithm yielded more accurate reconstruction and fewer artifacts in the 4-D CT image series. © 2015 Society of Photo-Optical Instrumentation Engineers (SPIE) [DOI: [10.1117/1.JMI.2.2.024004](https://doi.org/10.1117/1.JMI.2.2.024004)]

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1 Introduction

Four-dimensional computed tomography (4-D CT) captures a large number of axial images of the lung in multiple respiratory cycles and reconstructs them into a series of three-dimensional (3-D) CT images at different breathing phases. It has been widely used in diagnosis and image-guided treatments (such as image-guided biopsy and radiation therapy) for lung cancer. In radiation therapy, 4-D CT helps precisely plan and optimize the orientation, shape, and dose of radiation beams and guides the delivery of radiation beams toward the tumor in the presence of respiratory motion.^{1,2} Recently, 4-D cone beam CT has also been used for radiotherapy planning.^{3–5} Because 4-D CT data are acquired prior to the treatment, they may not reflect the real-time anatomy and updated tumor position; thus, motion compensation methods can be used for motion compensation during treatment.^{6–9} In particular, the clinical target volume (CTV) and planning target volume (PTV) can be manipulated in 4-D CT to ensure that the radiation dose covers the entire CTV, is within the PTV, and does not damage neighboring critical tissues during respiratory cycles.^{1,2} Successful implementation of 4-D CT scanning not only provides breathing dynamics,

but also minimizes motion artifacts for imaging diagnosis and image-guided procedures. In addition to developing fast scanning devices, respiratory gating and retrospective image reconstruction are the major techniques for improving 4-D CT imaging quality.

Different from 3-D CT scanning, 4-D CT is acquired by slowly moving the couch so that we can capture multiple scans for the same position for different respiratory phases. The axial images obtained at one position are sorted into multiple CT volumes corresponding to their different respiratory states, thereby generating series of 3-D CT images. The scan can be achieved in either cine or helical modes.¹⁰ In cine mode, the CT scanner continuously captures multiple axial images (dependent on the number of multislice detectors) at one couch position for a certain period of time. Then the x-ray beam is automatically turned off and the table is moved to the next position. The CT scanner begins another round of continuous scan at the new couch position. This process is repeated until a predetermined portion of the body is fully covered. The helical scan acquires image data continuously while the table moves at a constantly slow speed, programmed by a pitch factor, i.e., the ratio between the distance the table translates in one gantry rotation and the width of the x-ray collimation. The difference between the cine and helical

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modes is that the slice locations of all slices in helical mode are different. In both modes, a large number of axial images are captured during multiple breathing cycles, and the goal of 4-D CT reconstruction is to sort these axial images into a series of 3-D CT images based on their breathing phases and slice positions.¹⁰ Figure 1 illustrates the acquisition of 4-D CT in the helical mode. The scanned axial images are first assigned to corresponding respiratory phases based on the surrogate signals and then serial 3-D images are reconstructed according to their table positions.

Current 4-D CT reconstruction methods can be divided into two categories: (1) using respiratory signals and (2) using image computing tools with/without respiratory signals. In the first category, surrogate signals from a respiratory belt, a chest height marker, a strain gauge, or a spirometer can be used to record the respiratory phase of each synchronized axial image.¹¹ Then by dividing the magnitude of respiratory signal into different breathing phases, these axial images can be grouped accordingly. However, because of the poor reproducibility of breathing cycles, such breathing signals appear to not be exactly periodical and may misgroup some axial images, resulting in discontinuity of anatomical structures in the serial 3-D images.^{12–14}

In the second category, researchers attempted to reconstruct 4-D CT using image matching methods (after sorting with surrogate signals). In Ref. 15, Pan et al. defined a region of interest (ROI, e.g., in diaphragm area) on CT images and counted the number of diaphragm pixels in ROI, which gives respiratory phase signals because the diaphragm usually has large motion during breathing. However, such an ROI-based method may be difficult to determine the breathing for the upper lung field. In Ref. 16, Lu et al. extracted the lung fields and counted the segmented lung volumes. 4-D CT images were reconstructed according to the lung field volumes. This is more robust than the surrogate method because it corrects some misgrouped axial images because of the lower effect of upper lung axial images on lung field volumes. Wu et al.¹ proposed a patient breath pattern learning model based on 4-D CT images, and Hinkel et al.¹⁷ presented a diffeomorphic motion model for reconstruction. But the accuracy of such methods relies on the similarity of

breathing patterns between the trained model and the images on the fly. Anatomical image features^{18–23} were also proposed for accurate image matching. In the normalized cross-correlation (NCC) model proposed by Eck et al.²⁴ and Carnes et al.,²⁵ respiratory phases of the axial images are matched based on NCC. Alternatively, Li et al.²⁶ proposed to use spatial coherence instead of NCC. However, the spatial coherence based method depends on the overlapping of multiple CT scans, which may increase the radiation dose to patients. Finally, due to continuous moving of the table, each axial slice has a different table location in the helical mode. As more helical 4-D scans are being used in radiotherapy planning, it is highly desirable to study the methods for its image reconstruction and the nonuniform table position should be considered in the reconstruction.

This paper proposes a 4-D CT reconstruction algorithm for helical scanning based on the Bayesian model (BM) framework, referred to as BM 4-D CT reconstruction.²⁷ Our rationale is that the reconstructed images should preserve the topology features of anatomical structures at each time-point, and at the same time, the image sequence should reflect underlying respiratory motion. Therefore, despite whether the image slices have uniform locations or not, the surfaces of the anatomical structures at each phase should reflect such constraints: ideally the chest surface should be continuous and smooth in both spatial and temporal domains. Hence, in the BM 4-D CT reconstruction algorithm, image sorting (resultant serial 3-D CT) is jointly estimated with an underlying ideal image series whose surface's spatial-temporal properties are subject to such smoothness constraints. The optimization is achieved by iteratively assigning each axial image to their best phase while enforcing spatial-temporal surface smoothness constraints. Finally, due to the nature of helical 4-D scanning, the image and surface matching also takes into account the unequal interslice distances of axial images in each respiratory phase, and the final reconstructed images are generated using a cubic B-spline-based interpolation.

Two sets of experiments were performed to evaluate the performance of the proposed algorithm using simulated and real data, respectively. For simulation, we generated helical mode axial images by using the temporal deformations obtained from real 4-D CT images, so the exact respiratory phase for each image can be used as the ground truth. Our BM 4-D CT reconstruction algorithm was then applied for reconstruction, and the resultant images were compared with the ground truth of the simulated scans. The NCC-based image matching method was also compared.²⁵

On the other hand, we used the images from 40 lung cancer patients undergoing radiotherapy planning at the Department of Radiation Therapy to validate the algorithm. Both the external surrogate reconstruction and the NCC-based image matching method²⁵ were used for comparison. Because the ground truth for sorting the axial images into 4-D CT was not available, the spatial and temporal smoothness of the chest and lung field surfaces extracted from all the reconstructed images are computed and compared. In addition, the quality of the reconstructed images was also visually assessed by counting the number of slices with abrupt bumps and artifacts in the reconstructed images. The results for both simulated and real scanning data indicated that our method outperformed NCC-based image matching methods.

In the remainder of this paper, Sec. 2 introduces the proposed reconstruction algorithm in detail, Sec. 3 provides the experimental results and comparison analysis for both simulated

Fig. 1 Acquisition of helical mode four-dimensional computed tomography (4-D CT).

and real patient datasets, and Sec. 4 presents the conclusion of this study.

2 BM 4-D CT Reconstruction Method

2.1 Algorithm Formulation

During helical mode scanning, axial images are captured continuously while the table slowly moves. The moving speed is determined so that the axial images captured within each small longitudinal range can cover an entire respiratory cycle, dependent on the slice thickness, the number of simultaneous slices the scanner can capture (e.g., multiple row detector CT), and the time period of a breathing cycle. Using the synchronized surrogate respiratory signals, the axial images can be initially sorted to different respiratory phases, and the axial images for each phase form a 3-D image according to their table positions. However, because of the lack of reproducibility of breathing cycles and surrogate noises, misgrouped axial images could generate artifacts in the reconstructed serial 3-D images, e.g., there might be sudden boundary jumps between neighboring slices.

The objective of this paper is to assess such assignments and to correct the misgrouped ones so that the 3-D images at each phase preserve topological features of anatomical structures, and at the same time, the serial 3-D data reflect respiratory motion well. Thus, a BM-based 4-D CT reconstruction algorithm is proposed to enforce the spatial and temporal smoothness of the chest surfaces. The advantage of using the chest surface smoothness constraints is that the chest surface can be easily captured using stereo video cameras and can be obtained in real time; thus, in the future, it is possible to extend the algorithm to use a computer vision based method to track the chest surface motion and estimate the lung motion from chest surface to reconstruct 4-D CT images in real time.

Suppose all the axial images are captured and sorted to a series of K (the number of respiratory phases in one breathing cycle) 3-D images using respiratory belt signals, denoted as $D = \{D_1, D_2, \dots, D_K\}$, and there exists an ideal series of 3-D images, denoted as $I = \{I_1, I_2, \dots, I_K\}$, with corresponding chest surfaces $R = \{R_1, R_2, \dots, R_K\}$; the goal of our reconstruction algorithm is to come up with a series of newly reconstructed images, $S = \{S_1, S_2, \dots, S_K\}$, so that the respiratory phases of S match those of D , and the anatomical properties of S (spatial and temporal smoothness) match those of I and R . This estimation can be done by maximizing the following joint posterior distribution of S and R :

$$P(S, R|D) = \frac{P(D|S)P(S, R)}{P(D)} = \frac{P(D|S)P(S|R)P(R)}{P(D)}, \quad (1)$$

where R and D are assumed to be independent. Because image set D is known (i.e., $P(D) = 1$), S and R can be estimated by

$$(S^*, R^*) = \operatorname{argmax}\{P(S, R|D)\} \\ = \operatorname{argmax}\{P(D|S)P(S|R)P(R)\}. \quad (2)$$

When the probabilities in Eq. (2) are estimated using the Gibbs distribution, the maximization of the joint posterior distribution is equivalent to minimizing the energy function.

$$E(S, R) = E(D|S) + \alpha E(S|R) + \beta E(R), \quad (3)$$

where α and β are the weighting factors. The first term $E(D|S)$ denotes the degree of matching between the resultant image sequence S and the observed data D , and it can be calculated by the NCC between the two image sequences.

$$E(D|S) = \frac{1}{K} \sum_{k=1}^K -NCC(D_k, S_k). \quad (4)$$

The second term of Eq. (3), $E(S|R)$, stands for the degree of matching between the result S and the chest surfaces R of the underlying ideal image sequence (I). Here, $E(S|R)$ is defined by the distance between the ideal surface R and the surface extracted from S .

$$E(S|R) = \sum_{k=1}^K H_R[G(S_k), R_k], \quad (5)$$

where $G(S_k)$ represents the chest surface extracted from image S_k . The distance between the surfaces R and $G(S_k)$ is defined by the Hausdorff-Chebyshev metric.²⁸ First, we calculate the maximum minimal distance $h_R[R, G(S_k)] = \max_{g \in G} \{\min_{r \in R} d(r, g)\}$, where $d(\cdot)$ represents the Euclidean distance between two surfaces. Then the symmetric Hausdorff-Chebyshev metric is defined by

$$H_R[R, G(S_k)] = \max\{h_R[R, G(S_k)], h_R[G(S_k), R]\}. \quad (6)$$

Since the Hausdorff metric calculation is computationally expensive, we use the parallel computation presented in Ref. 29.

The third term of Eq. (3) represents the prior shape constraint of R , and it consists of the spatial and temporal smoothness constraints of the serial chest surfaces. Because it is not necessary to constrain the surface within each axial plane, we only need to consider the spatial smoothness in the z direction (between neighboring slices) as well as the temporal smoothness in the time-domain (between neighboring phases). Thus, $E(R)$ is calculated as

$$E(R) = \frac{1}{K} \sum_{k=1}^K \frac{1}{|\Omega|} \sum_{\mathbf{v}} \left[\frac{\partial R_k(\mathbf{v})}{\partial z} \right]^2 \\ + \lambda \frac{1}{K-1} \sum_{k=1}^{K-1} \frac{1}{|\Omega|} \sum_{\mathbf{v}} \{\mathbf{f}_{k+1}[\mathbf{v} + \mathbf{f}_k(\mathbf{v})] - \mathbf{f}_k(\mathbf{v})\}^2, \quad (7)$$

where the first term is the average of the squared surface gradients along the z direction by considering the unequal slice distances, and the second term calculates the average of the temporal smoothness of the deformation field $\mathbf{f}_k$, $k = 1, \dots, K-1$ across the image sequence. $\mathbf{v}$ is a lung field surface voxel in phase k , which forms the surface point domain Ω . $|\Omega|$ represents the number of voxels. λ is the tradeoff between the spatial and temporal constraints. The temporal surface motion deformation field $\mathbf{f}_k$ is calculated by using surface-based image registration for R .

Compared to the standard maximizing a posteriori equation, which only maximizes the posteriori $P(S|D) = P(D|S)P(S)/P(D)$, the major difference of the proposed BM estimation is that an ideal surface R is jointly estimated together with S . This allows for applying the additional spatial and temporal anatomical constraints to the reconstructed 4-D CT images, but they

are not directly applied to S . Thus, the equation can tolerate the shape differences between the final results and the intermediate images. By minimizing the energy function defined in Eq. (3), we can choose the optimal phase to which each axial image is assigned.

After reconstruction, we obtain a new image series $S = \{S_1, S_2, \dots, S_K\}$ from the original CT volumes' D . However, the slice locations are not uniform. The nonuniform cubic B-spline-based interpolation is then used to resample the images to equal slice distances. Nonuniform cubic B-spline interpolation provides an ideal trade-off between performance and computation efficiency in the spline family. Most recent results have shown that the local support property of nonuniform cubic B-spline has more efficiency with the computation than other interpolation methods, such as linear interpolation, the thin-plate or elastic-body splines interpolation, etc.^{30–32}

Specifically, suppose that the dimension of S_k is $X \times Y \times Z$; the goal for interpolation is to recalculate the image intensity at $\{s_k(x, y, z) | 1 \leq x \leq X, 1 \leq y \leq Y, 1 \leq z \leq Z\}$, where z is defined uniformly. Given the current position $z \in [1, Z]$, C neighboring slices $[S_{k,i}(x, y), i = 1, \dots, C]$ are used for interpolation. The intensity $s_k(x, y, z)$ is calculated by

$$s_k(x, y, z) = \frac{\sum_{i=1}^C B_{i,n} S_{k,i}(x, y)}{\sum_{i=1}^C B_{i,n}}, \quad x \in [1, X], \quad (8)$$

$$y \in [1, Y],$$

where $B_{i,n}$ is the n -order B-spline basis function, and for cubic B-spline, $n = 3$ and $C = 5$. The n -order B-spline basis function can be calculated recursively from $(n - 1)$ -order basis function.

$$B_{i,n} = \frac{z - t_i}{t_{i+n} - t_i} B_{i,n-1} + \frac{t_{i+n} - z}{t_{i+n} - t_i} B_{i+1,n-1}, \quad (9)$$

where t_i , $i = 1, 2, \dots, C$ is the slice position of image $S_{k,i}(x, y)$. The initial basis equation $B_{i,1}$ is given by

$$B_{i,1} = \begin{cases} \frac{z-t_1}{t_2-t_1}, & t_1 \leq z < t_2 \\ \frac{t_3-z}{t_3-t_2}, & t_2 \leq z < t_3 \\ 0, & \text{otherwise} \end{cases} \quad (10)$$

2.2 Algorithm Implementation

The optimization of the energy function in Eq. (3) can be implemented by iteratively calculating R and S . Given a series of N axial images (for lung imaging, N is >1000), we can first sort them into K (typically 10) phases based on the surrogate signals, which gives the current data observation $D = \{D_1, \dots, D_K\}$. We use D as the initialization of S and iteratively perform the following two steps:

Step 1: Optimize the ideal serial surfaces R by fixing S . By extracting the surfaces from the serial images S and performing longitudinal surface registration, we obtain the initial surface series R and their longitudinal deformations $\mathbf{f}_k$, $k = 1, \dots, K - 1$. Then R can be optimized using the finite gradient descent method.

$$R \leftarrow R - \xi \partial E(S, R) / \partial R, \quad (11)$$

where ξ is the updating step.

Fig. 2 The framework of the Bayesian model (BM) based 4-D CT reconstruction algorithm.

Step 2: Optimize the image sequences S by fixing R . Once a new ideal chest surface series is obtained, we iterate all the N axial images and reassign each to the k 'th phase that gives the minimal energy equation.

$$k^* = \operatorname{argmin}_k [E(S, R)] = \operatorname{argmin}_k [E(D|S) + \alpha E(S|R)]. \quad (12)$$

Notice that because of the nature of helical mode scanning, the distances between neighboring slices within each 3-D CT image S_k are different. The surface registration method we use can register two surfaces with different meshes, thus, it can handle this issue. The optimization algorithm stops until the number of phase reassignment is smaller than a prescribed number (5 in our case), and the algorithm generally stops after three to four iterations. Figure 2 summarizes the process of the algorithm.

To obtain the longitudinal deformation of the surface series R , we adopt the spherical demons' fast surface registration method.³³ This registration method contains two interactive steps. The first step aims to optimize the change of longitudinal deformations as follows:

$$\mathbf{u}^n = \operatorname{argmin}_{\mathbf{u}^n} \{ \|R_{k+1} - [R_k \circ \mathbf{f}_k^n \circ \exp(\mathbf{u}^n)]\|^2 + \|\mathbf{u}^n\|^2 \}, \quad (13)$$

where $\mathbf{u}^n$ denotes the change of longitudinal deformations $\mathbf{f}_k^n$, $k = 1, \dots, K - 1$ after n iterations. The circle operator in Eq. (13) means deforming a surface using a deformation field. Thus, $R_k \circ \mathbf{f}_k^n \circ \exp(\mathbf{u}^n)$ indicates the operation to deform R_k first by field $\mathbf{f}_k^n$ and then by $\exp(\mathbf{u}^n)$. Based on the first step, the update of $\mathbf{f}_k$ is

$$\mathbf{f}_k^{n+1} = \operatorname{argmin}_{\mathbf{f}_k^n} \{ \|\mathbf{u}^n\|^2 + \|\nabla \mathbf{f}_k^n\|^2 \}. \quad (14)$$

The optimization of longitudinal deformations can be implemented by interactively calculating $\mathbf{u}^n$ and $\mathbf{f}_k^{n+1}$.

3 Experimentation Results

The proposed BM-based 4-D CT reconstruction algorithm was evaluated using both simulated and real helical mode lung CT datasets. First, lung 4-D CT volumes were simulated by registering real patient 4-D CT data and then deforming the first phase CT using the deformation fields;³⁴ then, each newly

generated 4-D CT was rearranged into a series of helical mode axial scans by considering the table motion and inserting surrogate signal noises. In this way, the underlying deformation and the phase assignment of each axial image are known. The surrogate-based, NCC-based, and the proposed BM-based 4-D CT reconstruction algorithms were applied to reconstruct the serial 3-D images. The numbers of incorrect axial image assignments were compared for different algorithms. Second, real helical mode lung CT datasets were used in the validation. Because the ground truth was not available for the real dataset, we used lung field smoothness and chest surface smoothness on the reconstructed 4-D CT dataset as quantitative measures. In addition, visual examination was performed by counting the number of artifact axial images to provide the qualitative evaluation.

3.1 Validation Using Simulated Images

Ten real 4-D CT volumes were used to generate the simulated helical mode scanning sequences with prescribed table motion and simulated surrogate signal noises. Because the ground truth of each axial image belonging to each respiratory phase is known, the simulation allows for quantitative evaluation of the reconstruction accuracy among the surrogate-based, NCC-based, and the proposed BM-based 4-D CT reconstruction algorithms.

3.1.1 Simulate 4-D CT

First, the longitudinal image registration algorithm³⁵ was applied to the surrogate-based reconstructed 4-D CT data of each patient. Then using the first exhale 3-D CT as the baseline, a new 4-D CT dataset of 10 phases was simulated by using the temporal deformation fields to deform the baseline image. We also visually inspected the images to ensure each baseline image was well constructed and had no obvious artifacts. Image slice based matching was used to pick the axial images if there was

any artifact. Then the simulated 4-D CT images were used to simulate helical mode 4-D scans as described below. In our experiments, the number of slices per 3-D CT image is 136. The dimension of each slice is 256 pixel $\times$ 256 pixel. Slice thickness is 3.0 mm and the pixel spacing in the X and Y directions is 1.96 mm $\times$ 1.96 mm.

3.1.2 Simulate helical mode image sequence

Assuming the table moving speed as V (table moving distance in mm per second) and the respiratory frequency as F (number of respiratory cycles per second), the slice thickness as vs , and m axial images are captured per second, the i 'th axial image $I_i(x, y)$ is then selected from the simulated 4-D CT volumes $D = \{D_1, D_2, \dots, D_K, D_{K+1}, \dots, D_{K+m}\}$ that cover one entire respiratory cycle.

$$I_i(x, y) = D_{\left[\frac{(i-1)(2K+2)F}{m}\right]} \left\{ x, y, \left[\frac{(i-1)V}{vs \cdot m} \right] \right\}, \quad (15)$$

$$i = 1, \dots, N.$$

3.1.3 Surrogate-based reconstruction

Because respiratory signals are not available for the simulated image sequences, they are simulated by measuring the motion of the chest surface point on the simulated CT volumes. We selected four chest surface points and calculated the average y -location and assigned these values to each axial image in the helical mode image sequence. White Gaussian noise (SNR = 3) was then added into the respiratory signal, and the axial images were rearranged accordingly to new CT volumes, as shown in Fig. 3. Due to the surrogate signal noises, some slices may be rearranged to incorrect phase CT volumes, thereby producing reconstruction artifacts.

Fig. 3 Simulated 4-D scanning data, breathing signals, and reconstruction using the surrogate-based method.

3.1.4 Reconstruction using the BM-based reconstruction

The proposed BM-based 4-D CT reconstruction algorithm was applied to reconstruct the images. A workstation running Microsoft Windows 7 professional with an Intel Core i7-2820QM CPU (2.30 GHz) and 8.00 GB of RAM was used. α and β were selected as 0.5 divided by the mean value of the corresponding energy functions. λ was selected so that the weight for temporal smoothness is half that of the spatial smoothness. Figure 4 shows the results of one simulated CT volumes set. Figure 4(a) shows the simulated volumes as the ground truth; Fig. 4(b) gives the corresponding reconstructed volumes using surrogate-based reconstruction; and Fig. 4(c) shows the reconstructed volumes using the proposed Bayesian method. It can be seen that the artifacts (marked by red arrows) due to surrogate signals are now corrected using BM-based reconstruction.

We also applied the NCC-based image matching²⁵ for comparison. The Carnes algorithm first manually arranges several axial images into different respiratory phases and then uses slice-by-slice image matching to sort the rest of the axial images. In this experiment, based on surrogate signals, axial images were first classified to different phases that each contained 20 axial images on the lower part of the body. Then an image-based matching method was applied to rearrange all the other slices.

Figure 5 shows more examples using surrogate-based, NCC-based, and BM-based reconstruction. Figure 5(a) shows the simulated volumes; Fig. 5(b) shows the results using surrogate-based method; Fig. 5(c) shows the results by the Carnes algorithm, and Fig. 5(d) plots the results of the proposed algorithm. It can be seen that the proposed BM-based 4-D CT reconstruction performs better than the Carnes algorithm in terms of eliminating most of the artifacts (marked by red arrows), particularly in the region close to the diaphragm.

To quantitatively evaluate the reconstruction performance, we compared the reconstructed images with the simulated ground truth by counting the number of correctly sorted axial images in each reconstructed 4-D CT image series. Therefore, for each time-point of a subject, the reconstruction error is

defined by the percentage of incorrectly sorted axial slices over the total number of slices. Then the mean and standard deviation (std) of the reconstruction errors can be computed for all the respiratory phases of that subject.

Table 1 lists the mean and std values for 10 simulated subject image series. Bigger errors indicate that there are more misgrouped axial images. It can be seen that the proposed BM-based 4-D CT reconstruction algorithm yields fewer reconstruction errors than other methods. Figure 6 gives the box plots of these errors. The BM-based method improved the performance compared with the surrogate-based method (with median values of 0.8 and 3.6%) and Carnes method (with median values of 0.8 and 1.6%). The Fisher's exact test shows that the improvement of the BM-based reconstruction over the other two methods is significant (p value < 0.0001).

3.2 Experiments on Real Data

In the second experiment, original 4-D CT scans of 40 patients were used to evaluate the performance of image reconstruction. The data were collected using the Philips big bore CT in helical mode at Houston Methodist Hospital Department of Radiation Oncology as part of the ongoing institutional review board approved study "Image guided therapy and interventional treatment of cancer" (IRB0608-0097). The average number of slices per scan is 1330 (± 50). Slice thickness is 3.0 mm and pixel spacing in the X and Y directions is 1.17 mm $\times$ 1.17 mm. An elastic belt was used for monitoring respiratory motion. Initial respiratory-gated 4-D CT reconstruction was performed on the big bore CT, which was used as the initialization of our algorithm. The proposed BM-based 4-D CT reconstruction algorithm was then applied to generate the final 4-D CT serial images.

Similar to the previous experiment, the reconstruction results using the big bore CT and the Carnes algorithm were compared quantitatively and qualitatively. For the Carnes algorithm, the first 20 axial images of each phase generated from the big bore CT were used as the initialization. The parameters α , β , and λ are the same as those in the previous experiment.

Fig. 4 Examples of the reconstruction results: (a) the simulated volumes; (b) surrogate-based reconstruction; and (c) the results using BM-based reconstruction algorithm.

Fig. 5 Visual comparison of the reconstruction results: (a) ground truth; (b) surrogate-based method; (c) Carnes algorithm; and (d) the proposed BM-based 4-D CT reconstruction.

All the data were first visually assessed after reconstruction. Figure 7 illustrates example results from three different subjects. Figures 7(a1), 7(b1), and 7(c1) show the results of the surrogate-based reconstruction method, Figs. 7(a2), 7(b2), and 7(c2) are those of the Carnes algorithm, and Figs. 7(a3), 7(b3), and 7(c3) give the reconstruction results of the proposed algorithm. Artifacts are highlighted by red arrows. For the surrogate method, the artifacts of misassignment appeared more frequently in

the areas close to the diaphragm, and there are also some artifacts for the Carnes algorithm. Overall, the proposed BM-based 4-D CT reconstruction preserved the anatomical structure in each 3-D CT image much better. Because the areas close to the diaphragm are subject to larger motion, we can notice the artifacts easily for the methods compared, and such motion artifacts had been corrected using the Bayesian 4-D CT reconstruction.

Table 1 The average and standard deviation (std) of reconstruction errors for 10 simulated subjects.

Patient index	Surrogate-based reconstruction		Carnes method		Bayesian model based reconstruction	
	Average (%)	Std (%)	Average (%)	Std (%)	Average (%)	Std (%)
Pat. 1	3.8	0.4	1.7	0.3	0.9	0.3
Pat. 2	3.7	0.3	1.5	0.2	0.8	0.3
Pat. 3	4.0	0.4	1.4	0.3	0.6	0.3
Pat. 4	3.8	0.3	1.4	0.2	0.6	0.2
Pat. 5	3.4	0.4	1.4	0.2	0.7	0.2
Pat. 6	3.9	0.5	1.6	0.2	0.8	0.2
Pat. 7	4.2	0.4	1.9	0.2	1.0	0.2
Pat. 8	3.8	0.3	1.7	0.2	0.9	0.2
Pat. 9	3.8	0.4	1.7	0.3	0.9	0.3
Pat. 10	3.8	0.4	1.6	0.2	0.9	0.3

Fig. 6 Box plots of reconstruction errors.

For quantitative comparison, we calculated the spatial and temporal smoothness about the chest surfaces and the lung field surfaces extracted from the resultant CT images using Ref. 36. The spatial smoothness M_{spt} of each subject is defined by the average absolute values of the surface gradients along the z direction.

$$M_{\text{spt}} = \frac{1}{K} \sum_{k=1}^K \frac{1}{|\Omega|} \sum_{\mathbf{v} \in \Omega} |\partial R_k(\mathbf{v}) / \partial z|. \quad (16)$$

The temporal smoothness M_{tmp} is calculated from the longitudinal deformation fields of the serial surfaces extracted.

$$M_{\text{tmp}} = \frac{1}{K-1} \sum_{k=1}^{K-1} \frac{1}{|\Omega|} \sum_{\mathbf{v} \in \Omega} |\{\mathbf{f}_{k+1}[\mathbf{v} + \mathbf{f}_k(\mathbf{v})]\} - \mathbf{f}_k(\mathbf{v})|. \quad (17)$$

Figure 8 is the box plot of the spatial and temporal smoothness of the chest surfaces for all 40 subjects in the experimental dataset. It can be seen that the proposed BM-based 4-D CT reconstruction algorithm yielded much spatially and temporally smoother chest surfaces. Because we did not change the original axial images (only cubic B-spline interpolation was used), a larger average smoothness value may indicate that there are more slices with artifacts in the reconstructed data. Therefore, the quantitative results indicate that there are fewer sudden jumps of the surfaces or fewer artifacts as compared to other methods. We also calculated the spatial and temporal smoothness of the lung fields extracted from the experimental results, and a similar conclusion can be drawn from the box plot shown in Fig. 9. It is worth noting that the spatial smoothness for the lung field is bigger than that of the chest surface. This may indicate that the chest surface is smoother and is suitable for applying the smoothness constraints.

It might be biased to use the chest surface smoothness as a quantitative measure to evaluate the results, since the smoothness measure is also used in the energy function. In order to provide an objective comparison, the spatial and temporal smoothness metrics for the lung field surfaces extracted from the reconstructed images would be more appropriate. Due to the lack of ground truth of the 4-D reconstructed patient data, it is difficult to conceive other relevant quantitative metrics at this point. Therefore, we used simulated image datasets in the first experiment where the ground truth is known.

Fig. 7 Examples of 4-D CT reconstruction: (a1), (b1), and (c1) surrogate method; (a2), (b2), and (c2) Carnes algorithm; and (a3), (b3), and (c3) the proposed BM-based 4-D CT reconstruction.

We also plotted the bone segmentation results of the reconstructed images. Because bone structures and surfaces are very stable and smooth, the artifacts of the reconstructed images can be easily visible from 3-D rendering pictures. Figure 10 shows one example of the segmentation results, including the results using surrogate-based, image-matching-based, and the proposed methods. Artifacts are highlighted in red circles. Notice that the proposed method did not generate any obvious bone structure artifacts in the reconstructed image. From visual and

Fig. 8 (a) Spatial (M_{spt}) and (b) temporal (M_{tmp}) smoothness of chest surfaces.

Fig. 9 (a) Spatial (M_{spt}) and (b) temporal (M_{tmp}) smoothness of lung field surfaces.

quantitative comparison, it can be concluded that fewer sudden jumps of anatomical structures were found using our method as compared to other methods based on the clinical datasets.

To further validate the results, all the reconstructed images were visually evaluated. Each image was visually assessed and the number of slices with artifacts (namely those with noticeable sudden anatomical jumps) was counted. In our experiments, the maximum number of slices with artifacts in one CT volume using the surrogate method is six. Eighty-six volumes from the 40 4-D CT dataset have six slices with artifacts. By using the Carnes method, the maximum number is also six. But only 17 volumes from the 40 4-D CT datasets have six slices with artifacts. When we used the BM method, the maximum number of slices with artifacts is four, and only 22 volumes from the 40 4-D CT dataset have four slices with artifacts. Figure 11 illustrates the box plots of the average number of

slices with artifacts for each subject. The average number of slices with artifacts of the BM method is 1.4, 32% of that using the surrogate method and 43% of that using Carnes method.

In summary, the proposed method yielded fewer artifacts in reconstructed images as compared to the surrogate-based method and the Carnes algorithm. However, it requires image segmentation and registration prior to applying the Bayesian framework to resort the image slices into different respiratory phases. As for validation, we used both simulated and real 4-D CT scans and calculated the spatial and temporal smoothness as well as the number of slices with artifacts to compare the performance of the algorithm. Future works include further improving the computational speed of the proposed algorithm and performing radiotherapy planning and guidance trials using the reconstructed 4-D CT images to investigate its performance in clinical settings.

Fig. 10 Visualization of bones after reconstruction: (a) surrogate-based method; (b) Carnes algorithm; and (c) the proposed algorithm.

Fig. 11 Statistical results of evaluated artifact slices of 40 subjects.

4 Conclusions

This paper presents a BM-based 4-D CT reconstruction algorithm for helical mode lung scanning. A joint Bayesian estimation is designed to ensure spatial and temporal smoothness of surfaces of anatomical structures in the reconstructed 4-D CT images. Using clinical datasets for patients undergoing radiotherapy planning, we visually and quantitatively compared the performance of the proposed algorithm with the surrogate and image-matching-based methods. Both the simulation and real data results showed that the proposed algorithm yielded many fewer artifacts. Future works include adding the smoothness information of inner organs and vessels into the reconstruction and incorporating vision-based chest surface monitoring devices in the framework for real-time 4-D CT reconstruction.

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