A Pulmonary Deformation Registration Framework for Biplane X-ray and CT using Sparse Motion Composition

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***Abstract*— Lung cancer has the top fatality rate among all kinds of cancers. In clinical practice, CT guided nodule biopsy is an effective way to gain in vivo tissue samples for accurate diagnosis. However, the localization of lung lesions is very difficult due to severe lung respiration and tissues deformation. X-ray image benefits from less radiation and can be used to describe the deformation. In this paper, we propose a biplane X-ray images to pulmonary CT deformation registration framework, it uses Sparse Motion Composition (SMC) method to obtain an estimation of pulmonary motion which linearly combines the respiratory deformation vector field (DVF) of training samples, and then we use parametric control points on CT to refine the non-rigid pulmonary deformation. Finally, we get the accurate volumetric 3D registered image which is useful in intervention operations like image guided biopsy. The experimental results show that the proposed framework effectively uses the 2D X-ray images to accurately register the 3D pulmonary CT. The registration error is 2.83 (1.61) mm which is applicable for clinical practice.**

I. Introduction

Lung cancer is the leading cause of cancer deaths all over the world, according to "Lung cancer statistics" [1]. In clinical practice, early detection, diagnosis and treatment are quite important to improve the survival rate of lung cancer patients. Pulmonary nodule biopsy is an effective way to get in vivo tissue samples for accurate diagnosis and the challenge arises that how to target the lesions accurately. Image guided surgery (IGS) is widely used in clinic to assist surgeons do such intervention operations with a better visualization and lead to a much more precise result [2]. A common strategy for IGS is using a pre-operative Computed Tomography (CT) or Magnetic Resonance Imaging (MRI) of the specific patient to do a surgical planning, and using intra-operative images for slice or volumetric registration to present the intra-operative deformation [3].

Fiducials based registration method which often uses in surgical navigation system cannot be applied to pulmonary non-rigid deformation [4]. Intra-operative images such as fluoroscopy and X-ray contain relative less anatomy features, therefore feature based registration methods work not good. A widespread solution for pulmonary deformation registration is motion estimation from lung motion model. Approaches based on motion model have been proposed for motion tracking of coronary arteries [5], liver [6] and the lung [7]. However, most of them are based on 3D or 4D CT. Due to the large motion of lung and the relative lower quality of pulmonary X-ray, there are few works study the 2D X-ray registration to 3D CT for lung with motion model.

The goal of image registration methods is to estimate the DVF from which we can get the temporal or spatial motion of interesting regions. The problem we focus on here is a registration between 2D and 3D image which is an ill-problem in some way. Yixun Liu et al. [8] used a parametric sparse free form deformation (FFD) transform on 3D CT image, computed its projected 2D digitally reconstructed radiography (DRR) and maximize the Normalized Cross-Correlation (NCC) metric with intra-operative fluoroscopy images, optimized the sparse transform to get the deformed CT image. The computation cost much time and it did not use lung respiratory motion as prior knowledge. Ruijiang Li et al. [7] used *N* phases CT from 4D CT of one patient to build a PCA motion model. New DVFs could be generated by varying the PCA coefficients and then used similarity metric between the projected image and single X-ray to optimize the coefficients to compute the DVF, the deformed position of CT and tumor position could then be generated by inverted DVF. Using 4D CT of one specific patient means that the patient has to suffer from too much radiation, and PCA may lost some local motion details when discarding eigenvectors.

In this paper, we propose a framework that register 2D biplane pulmonary X-ray images to 3D CT to address the challenges that the radiation is high and the registration accuracy is low. The major contribution includes: (1) we used the registered 2D motion of landmarks from two orthogonal view to formulate their 3D motion, which was used to build a sparse 3D motion model. This was encouraged by our previous SMFP method [12] but here we used landmarks inside the lung rather than lung contours, which could estimate the inside pulmonary motion more accurately. (2) We applied SMC method to sparsely composite the training DVF so as to build the estimated DVF of specific patient with only one pre-operative CT.

II. Method

The goal of this paper is to estimate the respiration motion via the SMC method and refine the estimated deformation with parametric control points. The benefit behind the two-pass algorithm is that parametric control points based deformation can capture image intensity information of the

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This research is partially supported by 863 national research fund (2015AA043203) as well as the National Key research and development program (2016YFC0106200).

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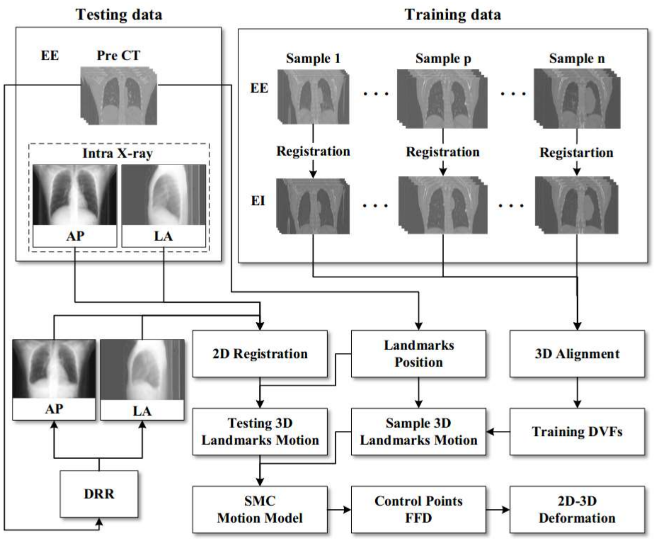

Figure 1. The framework of pulmonary deformation registration

X-ray image which is ignored in SMC. The framework is shown in Fig.1.

A. *Pre-process of data*

In our registration framework, the input data are the biplane X-ray images $I_{x,ap}$ and $I_{x,la}$ in anterior-posterior (AP) and lateral (LA) directions of a specific patient, and a pre-operative CT image I_{ct} is needed as well, we call them testing data. For the training image data, there are *N* subjects, each one contains two 3D CT images $I_{j,EE}$ and $I_{j,EI}$ at end-expiratory (EE) and end-inspiratory(EI) phases for *j*-th subject, respectively. A non-parametric discrete registration method with self-similarity context descriptor [9] is employed to get the DVF of each subject, we denote the *j*-th DVF as U_j which transform $I_{j,EE}$ to $I_{j,EI}$ as $I_{j,EI} = U_j * I_{j,EI}$.

For the consistent presentation of the training data and testing data, we use the EE phase as the reference phase for registration and the testing CT image is also in EE phase. We use semi-automatic segmentation method [10] to get the mask of the whole lung region I'_{ct} and $I'_{j,EE}$ of training and *j*-th testing CT respectively, and all the training EE phase CT data are affinely transformed to the testing CT as $I'_{ct} \approx A_j * I'_{j,EE}$, where A_j is the 4*4 affine matrix of *j*-th subject. Using A_j to align the training DVF as:

$$M_j = A_j * U_j, \tag{1}$$

where M_j is the aligned DVF used for estimating respiratory motion. Here the affine matrix A_j transform the position of DVF coordinates as well as their displacement vectors. The alignment process can make sure that the differences of anatomy or position can be eliminated as much as possible.

B. *Sparse motion model of pulmonary landmarks*

The sparse model for SMC is the 3D motion of landmarks in CT image. The landmarks are labeled in the testing CT image which can typically describe the respiratory motion. We denote the coordinate of *n* landmarks as $\{P_1, P_2 \dots, P_n\}$. The motion of these landmarks can be directly got from the corresponding coordinate position in M_i because we have aligned them. We denote the training landmarks motion of *j*-th subject to be $m_j = \{m_{j,1}, m_{j,2} \dots, m_{j,n}\}$, where $m_{j,i} = \{d^x_{j,i}, d^y_{j,i}, d^z_{j,i}\}$ concatenates the displacement motion of *x*, *y* and *z* directions for the *i*-th landmark. Therefore, we have built the landmarks sparse motion model as:

$$M_L = [m_1, m_2, \dots, m_n]^T. \tag{2}$$

The SMC method come from the SSC method [11] which can use a set of sparse coefficients to linearly combine the shape to represent a newly-input shape. Here we use the landmarks motion model rather than shape model and the SMFP method [12] using the motion of X-ray contours also proved the advantages of sparsely composition. But here the landmarks inside lung can better describe inside motion. The objective for recovering the sparse combination coefficients can be formulated as:

$$\underset{w}{\operatorname{argmin}} \|m_t - M_L w\|_2^2, \tag{3}$$

where the $w = [w_1, w_2, \dots, w_n]^T$ are the sparse coefficients for compositing landmarks motion and m_t is the target landmarks 3D motion in testing CT image which will be described in section C.

Taking into account the 3D landmarks motion error, a sparse vector *e* is explicitly added to reduce the error for the minimization step of Eq. (3). In addition, the convex relaxation of L0 norm to L1 norm makes the optimization problem computational effective. The Eq. (3) is reformulated as:

$$\underset{w,e}{\operatorname{argmin}} \|m_t - M_L w - e\|_2^2 + \alpha\|w\|_1 + \beta\|e\|_1, \tag{4}$$

where α and β are the regularization parameters for sparseness of *w* and *e* respectively [11]. Eq. (4) can be solved by homotopy-based method [13].

Because the landmarks motion linearly composited by *w* typically contain overall motion information of the lung, we can convert the problem of finding the best composited DVF for testing CT image to minimize the differences of landmarks motion between composited landmarks motion in training CT and their corresponding motion in testing CT image. Therefore, we can approximately obtain the DVF motion M_t of testing CT image by:

$$M_t = M_L w = \sum_{i=1}^{n} M_i w_i. \tag{5}$$

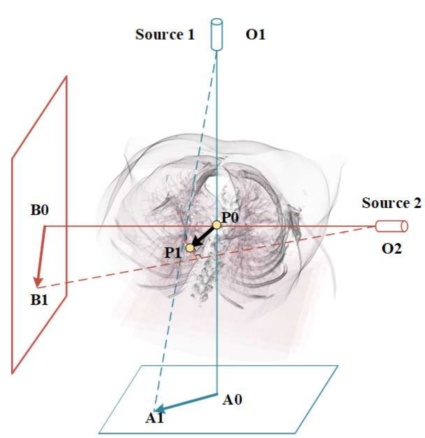

Figure 2. 3D motion compute from 2D motion

C. Pulmonary respiratory motion estimation

The pulmonary respiratory motion estimation problem is formulated as the minimization of Eq. (3). The difficulty of solving the minimization come from the 3D landmarks motion of testing image. We only have an EE phase 3D CT image and two orthogonal X-rays, the problem is how to find the 3D motion of landmarks from two orthogonal 2D images. Inspired by the projected motion estimation in bone surface reconstruction [14] and atlas-based volumetric micro-CT images registration [15] methods based on the epipolar constraint which is commonly used in stereo vision, we use the same way to find the 3D landmarks motion from projected 2D images as showed in Fig.2. The displacements in 2D X-ray are $\overrightarrow{A_0A_1}$ and $\overrightarrow{B_0B_1}$ which obtained from 2D b-spline registration with NCC similarity metric, the 3D estimated deformation vector is $\overrightarrow{P_0P_1}$ which is the shortest segment line from point P_0 to the line that is common perpendicular to $\overrightarrow{O_1A_1}$ and $\overrightarrow{O_2B_1}$. Finally, we got the 3D motion of landmarks from $\overrightarrow{P_0P_1}$ which is formulated as m_t in Eq. (3) and (4), solving w to get composited DVF.

D. Optimal adjustment by control points

After we get the respiratory DVF form SMC method, the respiratory motion can be solved, but there might exist some distortion caused by posture, position change or some other unexpected factors, therefore an optimization step is needed. In order to make use of the whole X-ray intensity information, b-spline based FFD registration [8] is adopted to refine its local deformation and use the similarity between DRR image of transformed CT image and its corresponding X-ray image. The refined transform can be obtained via the following equation:

$$\underset{U}{\operatorname{argmin}} \sum I_{xray} * P(CT * U) / \sqrt[2]{\sum P(CT * U)^2 * \sum I_{xray}^2}, \quad (6)$$

where U is the control point transform and $P(CT * U)$ is the CT projected image after transformed by U, I_{xray} is the X-ray image, the similarity metric is NCC which works well in the same modality registration. Here in our framework, the CT have been deformed by sparse composited DVF. This optimization step can converge fast due to the prior respiratory motion estimation by SMC method.

III. Results and Evaluation

We demonstrate the results of our proposed deformable registration framework here with 10 groups of CT images from *the 2nd Inpatient Department of FuZhou General Hospital*, using a SIEMENS SOMATOM spirit dual slice CT. Each group contains the EE and EI phases for the same patient at the same position on the CT bed and two X-rays at AP and LA directions scanned at EI phase. The spatial resolution of the reconstructed CT is $0.912 * 0.912 * 1.675$ mm^3 with $512 * 512 * 200$ voxels. Due to the limitation of the data, we set one of the group data to be testing data and the others to be training data alternatively. The coefficients were set to $\alpha = 1$ and $\beta = 40$ in Eq. (4) for a large sparseness for w and low for e.

Fig. 3 shows the CT slice views of our registration results where two of the testing data are included. The first and second rows are the absolute difference images of test data 6

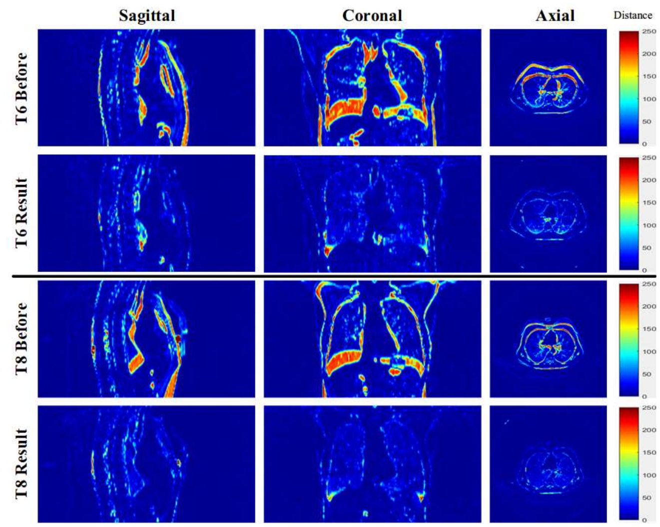

Figure 3. Registration results show in sagittal, coronal and axial views of the absolute difference images. Test data 6 and 8 are showed before and after registration with our proposed framework.

before and after registration. The third and fourth rows show the results of test data 8. The color mapping shows a lower absolute difference of two image in blue and higher in red. The first and third rows are the difference of EE and EI slice views and the second and fourth rows are the difference of EI and registration slice views. From Fig. 3, we can see that the framework can solve large deformation well (see the maximum displacement in z direction in Tab. 1). For the sagittal and coronal views, the registration works well for large deformation which can be obtained implicitly from LA and AP direction of X-rays in same way. For the axial view, because we have computed the 3D landmarks motion model for SMC, the registration also works well even though we do not have a short-axis X-ray.

In order to evaluate the results quantitatively, we used two common metrics, dice coefficient and target registration error (TRE). The dice coefficient can be formulated as

$$\text{Dice} = \frac{2*|R_A \cap R_B|}{|R_A| + |R_B|}, \quad (7)$$

where R_A and R_B are the registered region and target region. It

TABLE I. The maximum displaement in z direction (mm), dice coefficient and target registration error of registration for 8 testing data, TRE are expressed as mean (standard deviation)

Test data	Registration results			
	Max-displacement in z direction (mm)	*Dice coefficient*	*TRE 1 (mm)*	*TRE 2 (mm)*
1	60.3	0.894	3.2 (2.4)	3.1 (2.2)
2	36.6	0.926	2.9 (1.3)	2.9 (1.2)
3	35.7	0.935	3.0 (1.4)	2.8 (1.2)
4	46.2	0.938	3.1 (1.7)	3.0 (1.5)
5	41.3	0.914	3.2 (2.2)	3.2 (2.2)
6	33.0	0.955	2.7 (1.8)	2.6 (1.7)
7	39.6	0.976	2.8 (1.6)	2.7 (1.5)
8	16.75	0.983	2.4 (1.4)	2.4 (1.4)
Avg	38.68	0.940	2.91(1.72)	2.83(1.61)

indicates how much the two regions are overlapped. The TRE can be formulated as:

$$\mathrm{TRE} = \frac{1}{n}\sum_{i=1}^{n}\left|P_{i,reg} - P_{i,tar}\right|, \tag{8}$$

where $P_{i.reg}$ and $P_{i,tar}$ are the i-th landmark position in registered and target image, respectively. In order to compute the TRE metric, we labeled 10 landmarks in each EE phase, EI phase and the registered CT image, 2 of which located in the top area of lung with small deformation, 2 of which located in the middle area and the other 6 located in the bottom area with a relative larger deformation. These 10 landmarks were also used to build the SMC landmark motion model. We computed the maximum position displacement in z direction which can typically indicate the magnitude of respiratory motion, so as to find the influence from the varieties of respiratory amplitude.

As Tab. 1 shows above, the average dice coefficient is 0.94. '*TRE 1*' is the SMC deformation registration without control points optimization and '*TRE 2*' is the result after optimization. The average of '*TRE 1*' is 2.91 mm whose standard deviation is 1.72, and the '*TRE 2*' is 2.83 mm whose standard deviation is 1.61. The improvement from '*TRE 1*' to '*TRE 2*' shows that the parametric control points optimization can improve the registration. The TRE error of our registration framework is acceptable in clinical for interventional surgeries, such as lung nodule biopsy where they commonly focus on the lesions whose diameters are larger than 3 mm.

From these statistical result data, we know that the error is highly corresponding to the magnitude of respiratory motion and larger motion of lung is prone to cause larger registration error. Therefore, breathing smoothly and softly attach much significant to surgical success.

IV. DISCUSSION AND CONCLUSION

In this paper, we propose a framework that register 2D biplane pulmonary X-ray images to 3D CT which leads less radiation and preserves registration accuracy. In our framework, by using the SMC method, we simplify the complex problem for computing the composition of dense DVFs to composite the 3D typical landmarks motion. Only one pre-operative CT and two inter-operative X-ray images are needed which can reduce much radiation. The experiments of clinical data show that our registration framework can achieve good registration results.

For the future work, the pre-process method of data can be improved, notice that in Tab. 1, there exist a quite different CT image, test data 5, which is scanned from a child while the other test data are all adults. The size of his lung is much smaller than the others, so the affine transform of the CT anatomy here works not that good because of their large internal differences. In order to use this registration framework intra-operatively, GPU can be used to speed up the computation and try to achieve real-time registration from intra-operative biplane X-rays to pre-operative CT. For the purpose of good clinical application, the radiation from biplane X-rays are sought to be farther reduced such as trying to using only one side X-ray image.

CONFLICT OF INTEREST AND ETHICAL APPROVAL

The authors declare that there is no conflict of interest regarding the publication of this paper. The acquisition of CT scans has the approval of the ethics committee (certificate number FZGH20170406C01).

ACKNOWLEDGMENT

This research is partially supported by the National Key research and development program (2016YFC0106200) and 863 national research fund (2015AA043203) as well as the Chinese NSFC research fund (61190120, 61190124 and 61271318).

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