Registration Based Super-Resolution Reconstruction for Lung 4D-CT

Xiuxiu Wu, Shan Xiao, Yu Zhang*

***Abstract*—Lung 4D-CT plays an important role in lung cancer radiotherapy for tumor localization and treatment planning. In lung 4D-CT data, the resolution in the slice direction is often much lower than the in-plane resolution. For multi-plane display, isotropic resolution is necessary, but the commonly used interpolation operation will blur the images. In this paper, we present a registration based method for super resolution enhancement of the 4D-CT multi-plane images. Our working premise is that the low-resolution images of different phases at the corresponding position can be regarded as input "frames" to reconstruct high resolution images. First, we employ the Demons registration algorithm to estimate the motion field between different "frames". Then, the projections onto convex sets (POCS) approach is employed to reconstruction high-resolution lung images. We show that our method can get clearer lung images and enhance image structure, compared with the cubic spline interpolation and back projection method.**

***Key words:* lung 4D-CT; super-resolution reconstruction; Demons registration; POCS algorithm**

I. INTRODUCTION

Four dimensional computed tomography (4D-CT) is widely used for lung cancer radiotherapy today. The 4D-CT imaging technique can help capture respiratory motion information that is of curial for the target definition of radiation therapy. To acquire 4D-CT lung data, the prolong scanner time is inevitable, which leads to a considerably increased radiation dose [1, 2]. Due to dose limitation, CT slices are usually thick. This results in that resolution that is high in-plane and is low in the through-plane direction. Therefore, it would not provide isotropic 3D data set viewable in any oblique orientation. In order to achieve isotropic display of multi-plane images, e.g. coronal and sagittal images, the interpolation along the superior-inferior direction is necessary. The commonly used interpolation methods are nearest-neighbor interpolation and linear interpolation, due to the easy and fast. However, the interpolation operation will result in the image blur.

Super resolution (SR) techniques are effective approach to enhance image resolution. The basic idea behind SR is to combine the non-redundant information contained in multiple low-resolution frames to generate a high-resolution image [3]. Many SR techniques have been proposed over the last two decades [4]. These methods can be roughly divided into two categories: frequency domain and spatial domain methods. Frequency-domain methods explored shift and aliasing properties of the Fourier transform. However it suffers from two problems: difficulty to deal with noisy image and the limitations to only deal with degradation models with global movement. However, real problems are much more complicate. Researchers nowadays most commonly address the problem mainly in the spatial domain, for its flexibility to model all kinds of image degradations. Generally, the motion estimation and iterative reconstruction are the key steps for SR reconstruction. The spatial domain image observation model will be introduced in detail in Section II.

The main objective of this paper is to enhance the image quality for lung 4D-CT multi-plane display. Lung 4D-CT data provide respiratory synchronized low-resolution image sequences of the lung. Building on this character of the data, we regard the low-resolution images of different phases at the corresponding position as different "frames", and propose a registration based SR reconstruction method to improve the resolution of lung 4D-CT multi-plane images for display. First, we employ the Demons registration [5,14] to estimate the motion field between different "frames". Then, the projections onto convex sets (POCS) [6-8] approach is employed to reconstruction high-resolution lung images. Compared with conventional cubic spline interpolation methods and back projection (BP) [9] methods, we will show that our method yields superior performance both qualitatively and quantitatively.

We will present brief overview of SR imaging model in Section II. Motion field estimation and POCS SR approach will be presented in Section III. Experimental results of the proposed method will be provided in Section IV. We then give the conclusion in Section V.

II. IMAGING MODEL

Since SR reconstruction is an inverse problem, it requires an image degradation model to estimate the high resolution (HR) image underlying the low resolution (LR) images. Generally, the imaging model [10] can be expressed as:

$$g_k = DB_kM_kF + n_k, k = 1, 2, \ldots, N \tag{1}$$

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Where g_k is the k-th low-resolution image, F represents the original high-resolution image, M_k is the transformation matrix of g_k relative to F, B_k is optical blur matrix, D is down-sampling matrix, n_k represents the additive random noise in the k-th low-resolution observed image.

The SR approach aims at inversing the given model to restore the original HR image. To solve such an inverse problem, different optimization methods were proposed to estimate the best solution. Typically, iterative back-projection (IBP) [11], projection onto convex set algorithm (POCS) and posteriori (MAP) based algorithm [12, 13] are commonly used approaches. In this paper, we select POCS to SR reconstruct HR lung 4D-CT multi-plane images, since POCS algorithm is simple and effective, and can easily introduce priori constraints.

III. METHOD

A. Motion Estimation

The motion fields are obtained through the application of an elastic registration algorithm to the lung 4D-CT frames. We employ the Demons registration approach to estimate the warp matrices since the algorithm is able to deliver the accurate sub-pixel motion information [14].

Let us denote the individual frames as functions of sets of coordinates, $I_k(x,y)$, where $I_k(x,y)$ is the intensity of the k-th image at position (x,y). A displacement vector can be calculated as:

$$\vec{v}=\frac{(I_k(x,y)-I_1(x,y))\vec{\nabla}I_1(x,y)}{(\vec{\nabla}I_1(x,y))^2+(I_k(x,y)-I_1(x,y))^2} \tag{2}$$

It maps a position in frame k onto a position in frame 1. The deformation fields are calculated for every k on the lung 4D-CT images. They are calculated at each point (x,y) in order to create the warp matrices M_k, and applied to the HR images (see Equation (1)).

B. POCS Super-resolution reconstruction

The POCS method describes an alternative iterative approach to incorporating prior knowledge about the solution into the reconstruction process. With the estimates of registration parameters, this algorithm simultaneously solves the restoration and interpolation problem to estimate the SR image. POCS takes a priori knowledge as a constraint which is defined as a convex set containing ideal high-resolution images. An arbitrary point in the intersection of all convex sets can be regarded as a reconstruction result. Actually, POCS refers to a process that a point F in imaging space iteratively projects to and locates on the intersection of convex sets.

POCS is an iterative super-resolution method and the process can be represented as:

$$F_{n+1}=P_mP_{m-1}\cdots P_1F_n \tag{3}$$

Where, P_i denotes projection operator corresponding to convex set ψ_i. F_n is the result after n iterations.

A convex constraint is defined based on a priori knowledge of the noise:

$$\psi_1=\{F|R^{(i)}(a,b)\le\eta^{(i)}(a,b)\},\ i=1,2,\cdots,L \tag{4}$$

Where $\eta^{(i)}(a,b)$ is a determined threshold, $R^{(i)}(a,b)$ is the residual, which can be defined as:

$$R^{(i)}(a,b)=L^{(i)}(a,b)-\sum_{x=c-2}^{x=c+2}\sum_{y=d-2}^{y=d+2}F(x,y)H'(x,y;a',b'),\ i=1,2,\cdots,L \tag{5}$$

$L^{(i)}(a,b)$ denotes the gray value at (a,b) of the i-th low-resolution image. $H'(x,y;a',b')$ is the normalized form of the point spread function. Where (a',b'), (c,d) are corresponding points of the current estimation F relation to (a,b) of the low-resolution image $L^{(i)}$.

Let P_1 be the convex projection operator corresponding to the convex set ψ_1. The current estimate F can be projected as following formula:

$$F_{n+1}(x,y)=P_1F_n(x,y)$$
$$=F_n(x,y)+\begin{cases}\dfrac{(R^{(i)}(a,b)-\eta^{(i)}(a,b))H'(x,y;a',b')}{\sum_{x=c-2}^{x=c+2}\sum_{y=d-2}^{y=d+2}H'(x,y;a',b')}, & R^{(i)}(a,b)>\eta^{(i)}(a,b);\\ 0, & -\eta^{(i)}(a,b)\le R^{(i)}(a,b)\le\eta^{(i)}(a,b);\\ \dfrac{(R^{(i)}(a,b)+\eta^{(i)}(a,b))H'(x,y;a',b')}{\sum_{x=c-2}^{x=c+2}\sum_{y=d-2}^{y=d+2}H'(x,y;a',b')}, & R^{(i)}(a,b)<-\eta^{(i)}(a,b);\end{cases} \tag{6}$$

IV. RESULTS

To evaluate the performance of the proposed method, we apply our approach to enhance the resolution of lung 4D-CT data. The 4D-CT data includes 10 phases, and its inter-slice resolution is $2.5mm$, in-plane resolution is $0.97mm\times0.97mm$ respectively. We present both visual and quantitative results to demonstrate the performance of the proposed method, with comparison to cubic-spline interpolation and BP method.

Fig.1 shows the example results of motion estimation between two coronal images of different phases using Demons registration method. Fig. 1(a) is the coronal image of one phase; Fig. 1 (b) is the corresponding image from the other phase. Fig. 1 (d) is the motion field between these two images. Fig.1(c) is the corrected image of Fig.1(a) based on the motion field (Fig. 1 (d)). The different map of Fig.1(b) and Fig.1(a) is shown in Fig.1(e). Fig.1(f) shows the different map of Fig.1(b)

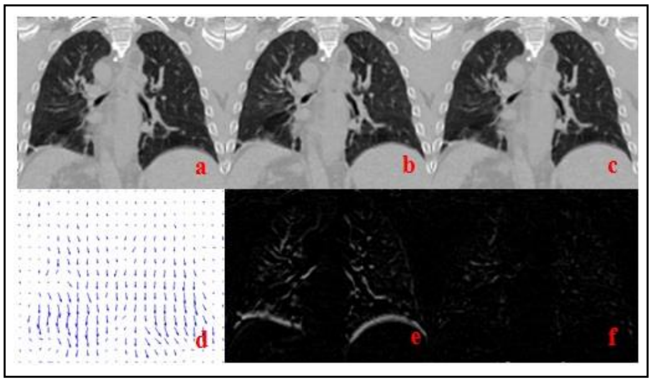

Fig.1. The example of motion estimation. (a) the coronal image of one phase; (b) coronal image of another phases; (c) corrected image of (a) based on the motion field (d); (d) motion field between (a) and (b); (e) different map of (b) and (a); (f) different map of (b) and (c).

and Fig.1(c). The results show the registration ability to accurately estimate the lung deformation.

Fig.2 shows typical coronal and sagittal reconstruction results. From left to right, the results given by cubic spline linear interpolation, BP reconstruction, and our method are shown respectively. For better visual comparison, the enlarged views of the area marked by squares in the first and the third row are shown in the second and the fourth row. Compared with the results given by cubic spline interpolation and BP, our method yields more clear images with improved structure and enhanced edges and details.

In addition to visual evaluation of the output images, quantitative measures of resolution is computed and used to evaluate the performance of the proposed method.

We use the edge width to measure resolution improvement. As defined in [15], the edge width is calculated as:

$$width = \frac{4.4}{a} \tag{7}$$

Where a is inversely proportional to the width, and belongs to a sigmoid function of $q(u) = \dfrac{1}{1+\exp(-a(u-c))}$ [15].

A sample of edge width with five edges from one coronal image is summarized in Tab.1. Several points may be learned from Tab. 1. A clear improvement is presented in the edge-width of the SR result, in comparison to the cubic-spline interpolation. In comparison to BP, the edge width is also improvement. The results indicate a successful augmentation of the image resolution via the SR procedure.

Tab.1. The Edge Width Of Different Approaches

	Cubic –spline interpolation	**BP**	**Proposed method**
edge1	3.5080	3.2658	**2.4641**
edge2	3.1953	2.6701	**2.6607**
edge3	3.4114	2.8221	**2.4942**
edge4	3.0922	2.4437	**2.2266**
edge5	5.0855	3.4517	**2.4509**
mean	3.6585	2.9307	**2.4593**

V. CONCLUSION

In this paper, we propose a new method to enhance lung 4D-CT image multi-plane display resolution. We regard the images of different phases as different "frames". Then, the SR approach can be employed to reconstruct the HR lung images. Consequently, we employ the Demons elastic registration approach to obtain the motion field of low resolution images. The POCS super-resolution algorithm is used to reconstruct a clear HR image. Experimental results show that the proposed algorithm is superior to conventional cubic spline interpolation method and the back-projection algorithm in visual evaluation and quantitative assessment.

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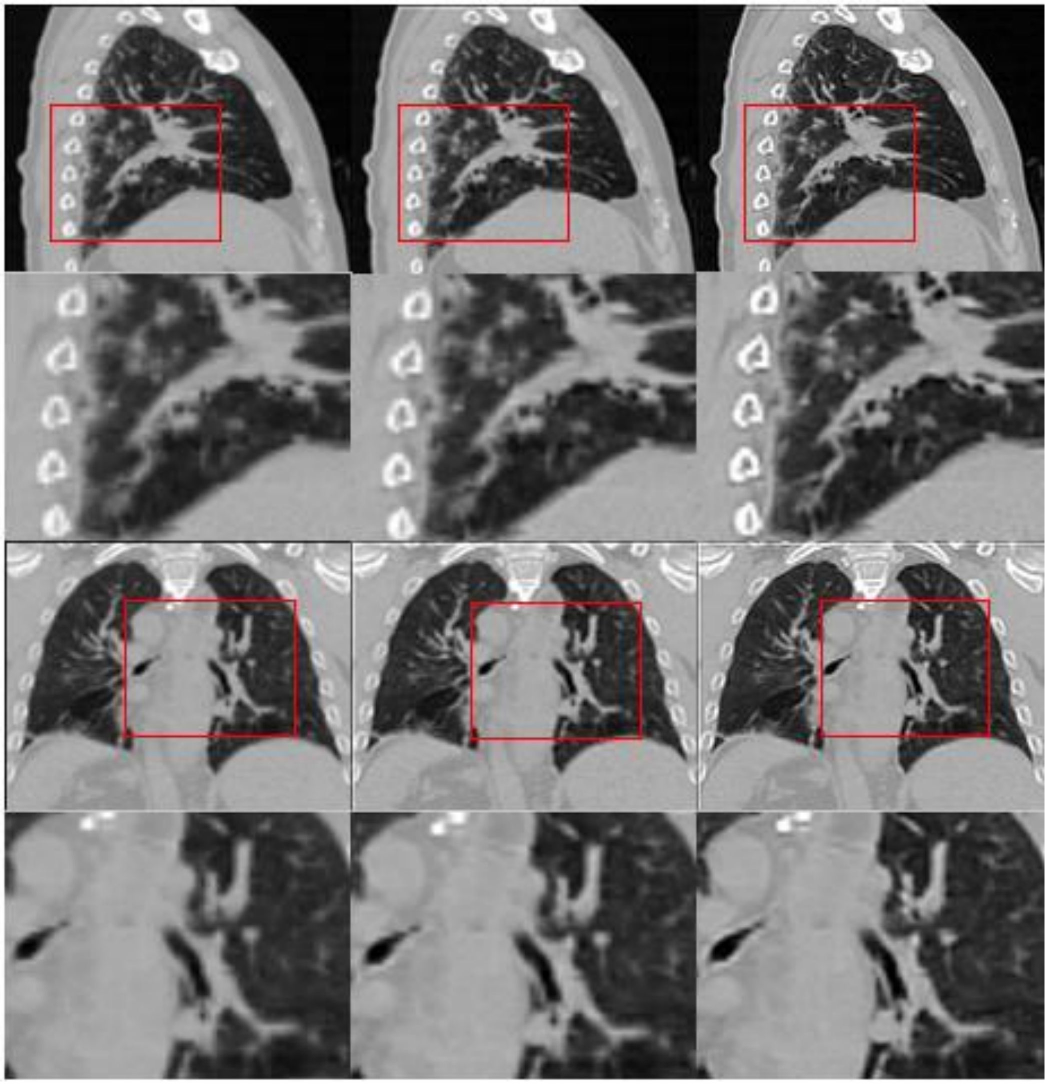

Fig. 2. Results of multi-plane image super-resolution reconstruction. From left to right, the results given by cubic spline linear interpolation, BP reconstruction, and proposed method are shown respectively.

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