A fast and robust level set motion-assisted deformable registration method for surgical platform: Comparison with conventional methods

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ABSTRACT

A level set motion assisted deformable registration method for diagnostic computed tomography (CT) and preoperative CT images were proposed and its accuracy and speed were compared with those of other conventional methods. Fifteen 3D CT images obtained from lung biopsy patients were scanned. Each scan consisted of diagnostic and preoperative CT images. Each deformable registration method was initially evaluated with a landmark-based affine registration algorithm. Various deformable registration methods such as level set motion, demons, diffeomorphic demons, and b-spline were compared. Visual assessment by two expert thoracic radiologists using five scales showed an average visual score of 3.2 for level set motion deformable registration, whereas scores were below 3 for other deformable registration methods. In the qualitative assessment, the level set motion algorithm showed better results than those obtained with other deformable registration methods. A level set motion based deformable registration algorithm was effective for registering diagnostic and preoperative volumetric CT images for image-guided lung intervention.

Keywords

Deformable registration, Surgical platform, 3D CT image, Level set motion, Lung intervention, visual scoring.

1. INTRODUCTION

Image-guided intervention is a medical procedure that was developed as an alternative to the traditional surgical process. Image-guided procedures have a lower risk of complications than traditional procedures because of the short operating times and small incisions. A fast patient recovery is another advantage of image-guided intervention.

Image registration is performed using either rigid registration or deformable registration algorithms [1]. Various rigid image registration algorithms have been described [2-5], and several deformable image registration techniques have been developed for use in medicine as rigid registration algorithms were implemented. Medical imaging applications based on these registration techniques are undergoing wide-scale development for specific purposes and in different medical environments. The use of the appropriate deformable registration technique in each case may improve the results of image-guided intervention.

The purpose of the present study was to suggest appropriate image registration procedures and suitable deformable registration methods for image-guided intervention in the lung. We used a level set motion method and compared it with other deformable image registration techniques such as the demons, diffeomorphic demons, and b-spline algorithms. The initial rigid registration was computed using an affine transformation approach, and level set motion registration was used for preoperative image registration.

2. METHOD

In general, the image-guided intervention in the lung requires the registration of images of different respiratory states of the same patient, thus establishing a correspondence between the same lung structures in both images. There are two main approaches towards image registration. The overall procedure for a proposed registration method for robotic intervention consists of the following two main steps as out-lined in Figure 1: 1) computing geometric transformation that aligns the planning CT image and preoperative CT images given a set of pair landmarks and 2) matching of the lung structure with the deformable registration method.

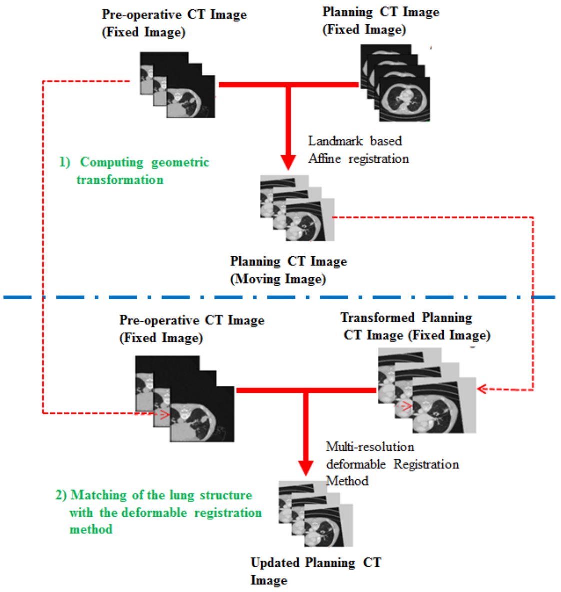

Figure 1. Workflow of the deformable image registration algorithm for robotic intervention.

Figure 2 shows preoperative (fixed) CT and planning CT (moving) images for the application of landmark-based transformation algorithms.

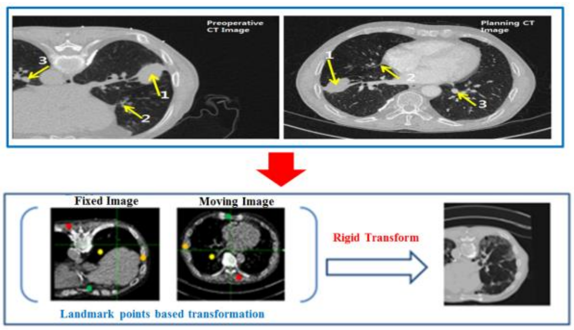

Figure 2. Initial landmarks on preoperative CT and planning CT images: three point landmarks are selected by clinical experts.

In this case, the planning CT scans were performed with the patient in the supine position, whereas the pre-operative CT images were acquired in the prone position because of the intervention procedures. To align the positions, the clinical experts extracted three landmark points from consolidations, lung anatomy or nodules on these images. The following sequence of steps is typical for the extraction of landmarks using preoperative and planning images: 1.Planning and preoperative CT images are acquired; 2.The clinical experts check the position of the patient (supine or prone); 3.The clinical experts search for anatomical landmarks such as lesions, consolidations, or vessels in the planning and preoperative CT images; 4.The clinical experts use the computer system to extract the center point of the anatomical landmarks on display; 5.CT images with a set of point landmarks are obtained upon procedure completion.

After extracting landmarks, the planning and preoperative CT image is aligned by the affine transformation algorithm [6,7]. The initial part of the algorithm looks at defining similar landmarks between two different images, and solving the equations based off of said landmarks to obtain an affine transformation between the source image and the target image. Due to the fact that an affine transformation is defined by six parameters, it is necessary to have at least three landmarks defined in each image. Second step is to compare four automatic methods to perform the deformable registration of image-guided lung intervention; 1) Demons and 2) diffeomorphic demons registration widely used deformable image registration algorithms. 3) Level set motion registration using level set theory. 4) The deformable registration model based on B-splines.

In this study, we focused on validation of level set deformable registration for the image-guided lung intervention. Level set methods measures intensity difference between the two image whereas demons registration method calculates gradients of the moving image on a smoothed image. As shown in Figure 2, the quality of planning and preoperative CT images differed in this study. CT image quality is related to radiation dose, with increased radiation dose resulting in better image quality [8]. As with other diagnostic-type CT images, the quality of a planning CT image is important for a confident diagnosis and to design intervention plans. However, in this case, the quality of preoperative CT images is low, and the reduction in the radiation dose to the patient results in noise.

Deformable registration based on Level set motion

The level set framework for image registration was proposed by Vemuri [9]. The equation was derived from the optical flow equation. The main idea of the level set motion framework is to register iteratively image I1(x) along its gradient direction until it deforms to the target image I2(x).

The equation for motion is similar to those of the original demons registration.

To transform the level-sets of the intensity function of the source image into the level-sets of the intensity function of the target image, the formulation of the registration is as follows:

$$I_t(X,t) = I_2(X) - I(X,t)\|\nabla I(X,t)\|, \quad \text{with } I(X,0) = I_1(X) \qquad (1)$$

where $I_2(X)$-$I(X,t)$ is the speed of evolution.

Using the above equation, we can derive geometric transformation explicitly be-tween the source and the target images for image morphing. The equation is ex-pressed as follows:

$$\vec{V}_t = [I_2(X) - I_1(\vec{V}(X))]\frac{\nabla I_1(\vec{V}(X))}{\|\nabla I_1(\vec{V}(X))\|}, \quad \text{with } \vec{V}(X,0) = \vec{0} \qquad (2)$$

where $\vec{V} = (u, v, w)^T$ is the displacement vector at in the 3D case and the operator is $V(X) = (x-u, y-v, z-w)^T$.

For additional mathematical details, we refer the reader to Vemuri et al. 2000 and 2003 [8,9]. As in most image-based registration methods, a multi-resolution approach is applied to registration algorithms to improve the robustness and convergence speed of the algorithm.

3. MATERIALS

The images were selected from clinical data sets obtained from 15 patients. All data sets were resampled to a resolution of 512×512×30 voxels to compare the registration performance and computation time. All experiments were performed using a 64 bit Intel Processor (2.4 GHz and 16 GB of RAM) running Windows because algorithms tend to use a large amount of system memory.

4. RESULTS

The registration techniques can be evaluated using various methods. In the present study, several quantitative assessment and visual scoring systems were used by clinical experts to evaluate the deformable registration methods.

Visual scoring by clinical experts

Two clinical experts independently scored the visual alignment of the lung for each registered CT image obtained using four techniques (level set motion, demon, diffeomorphic demons, and b-spline) and compared it with the corresponding fixed image. All deformable registration algorithms for the 15 patient data sets were assessed according to three criteria: lung anatomy, soft tissues, and lesions. The alignment of lung anatomy between the registered and reference images was considered only within the boundaries of the lung structure.

The visual scores ranged from 1 to 5, with 1 being the worst and 5 the best. Table 1 shows the assessment criteria for the scoring system, which were provided to each expert.

Rating score	Indicated quality	Definition
5	Excellent	Perfect registration (lung structure, soft tissue, and lesion)
4	Good	Almost completely registered with very minor mis registration
3	Adequate	Well registered with some mis-registration
2	Poor	Not well registered
1	Very poor	Not registered in entire images

Table 1. Definition of the 5-point rating score.

The mean (± standard deviation (SD)) of scores for the three assessment criteria were 3.12 (0.49), 2.18 (0.59), 2.74 (0.67) and 2.26 (0.69) for level set motion, demons, diffeomorphic demons, and b-spline, respectively. These were the average scores derived from 60 registration results (15 CT patient data sets, each with four registered images), obtained by two clinical experts using three assessment criteria, totaling 360 visual scores. The summary results of the visual scores for the four registration algorithms are presented graphically in Figure 3.

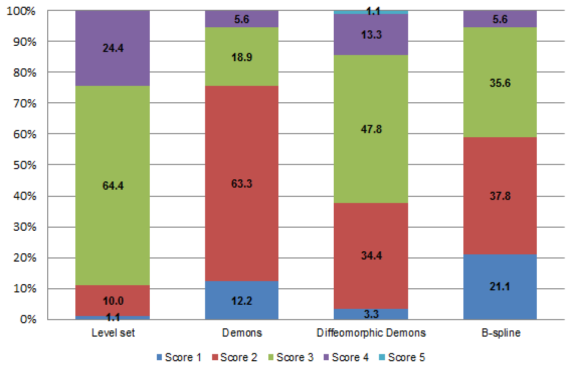

Figure 3. Summary of the visual scoring for each of the four registration techniques.

The results of comparisons performed using the paired t-test showed significant differences in the visual scores (Table 2).

Algorithms	T test	P value
Level set vs. Demons	9.23	0.000
Level set vs. Diffeomorphic demons	3.79	0.001
Level set vs. B-spline	6.95	0.000

Table 2. Paired t-test results for comparison of visual scores between level set motion and other image registration techniques.

Comparisons among all assessment criteria indicated that the level set motion deformable registration algorithm was significantly superior to the demons deformable registration, diffeomorphic demons registration, and b-spline deformable registration ($p<0.05$) with respect to all assessment criteria.

Registration assessment

To evaluate the accuracy of each registration method, we calculated the root mean square error (RMSE), median absolute deviation (MAD), and entropy. These measures are estimates of the quality and accuracy of registered images [10]. The mean and SD of the RMSE, MAD, and entropy are shown in Table 3.

	Mean (Standard Deviation)		
	RMSE	MAD	Entropy
Level set	18.67 (7.84)	5.27 (3.88)	8.98 (0.76)
Demons	24.21 (7.39)	6.73 (5.08)	9.20 (0.85)
Diff. Demons	21.31(6.89)	5.93 (4.23)	9.38 (1.01)
B-Spline	26.79 (6.70)	6.73 (4.85)	9.18 (0.84)

Table 3. Quantitative assessments of root mean squared error of intensity difference and median absolute deviation of intensity difference.

The RMSE, MAD, and entropy of the level set motion registration were lower than those of the other registration methods.

4. DISCUSSION

In the present study, the proposed level set motion registration technique achieved significantly better lung alignment than other deformable registration techniques for robotic intervention. Although a comparative analysis of level set motion registration and other deformable registration approaches has been made [10,11], previous studies provided a limited validation of the alignments achieved and the procedures were tested using images of similar quality that were acquired from patients.

Unlike previous studies, the present study assessed a level set motion deformable registration algorithm for robotic intervention. Such comparisons are important to define a simple and fast intervention procedure that might be required by a deformable registration algorithm. Although the overall best results were obtained using the level set registration, the diffeomorphic demon algorithm also achieved good results. No significant differences in visual scoring and qualitative assessment were observed between the level set motion and diffeomorphic demons algorithms. However, we showed that the level set motion registration technique yielded improved alignment results compared with other deformable registration techniques with regard to the robotic intervention. Moreover, the level set motion technique provides additional opportunities to recover misalignments beyond those of other deformable registration techniques during intervention procedures.

5. CONCLUSION

Overall, the level set motion technique showed good performance for the registration of diagnostic CT images versus preoperative CT images. Based on the visual and quantitative assessments, the level set motion technique showed good results regarding image registration for image-guided intervention in the lung. The evaluation revealed differences between the four registration techniques (Table 3 and Figure 3).

The results of the present study suggest that the proposed deformable registration technique can achieve a significantly superior alignment to that obtained with the currently available deformable registration techniques.

Future work should include upgrading of the framework of image guided intervention. First, a set of point landmarks should be selected automatically during the initial registration procedure. Second, the level set motion registration should be improved to reduce registration error and achieve faster computation times. Improved level set motion registration algorithms could be combined with other deformable registration algorithms

6. ACKNOWLEDGMENTS

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