Automatic Non-rigid Lung Registration Method for the Visualization of Regional Air Trapping in Chest CT Scans

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Abstract. In this paper, we propose an automatic non-rigid lung registration method for the visualization of regional air trapping in full inspiration and expiration chest CT scans. To cope with intensity differences between CT scans, we segment the lung vessel and parenchyma in each scan. Then, we match them without referring any intensity information. We globally align two lung surfaces by affine transformation. Then, locally deformable transformation model is developed for the subsequent non-rigid registration. Subtracted quantification results are visualized by pre-defined color map. Experimental results show that proposed registration method is able to correctly align the full inspiration and expiration CT images in 10 patients. Our method can model the global and local deformation between full inspiration and expiration CT scans. Our non-rigid lung registration method may be useful for the assessment of regional air trapping by providing intuitive color-coded information of quantification results.

1 Introduction

Regional air trapping has been qualitatively assessed by comparing the intensity change of lung parenchyma during the respiration between full inspiration and expiration chest CT images. However, due to the change in body posture, the complex respiratory motion of lung, and heart beating, it is difficult for doctors to find correspondences manually between two CT data sets. Therefore, automatic lung registration methods, which align two images, and establish correspondences, are much helpful for radiologists to find areas of regional air trapping.

Several methods have been suggested for lung registration in temporal chest CT scans. Betke et al. [1] developed an automatic registration method of temporal chest CT images for the nodule registration. They detected the trachea, sternum and spine

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as anatomical landmarks using an attenuation-based template matching. The optimal rigid-body transformation that aligned the corresponding landmarks was found for the initial registration. Then, the initial surface alignment was refined step by step in an iterative closest-point process. However, the transformation model of this method assumed there was no local deformation between two scans so that this method cannot be applied to the registration between full inspiration and expiration scans. Fan et al. [2-3] proposed a volumetric lung registration method between CT images obtained at different stages of breathing. Both feature points and lung surfaces at consecutive frames were incorporated as a priori knowledge for 3D warping to derive an initial sparse comprehensive displacement field. This field was then interpolated over the entire volume in an iterative fashion governed by a model derived from continuum mechanics and 3D optical flow. However, their method was only validated for data sets, which had small volumetric differences. Dougherty et al. [4-5], and Torigian et al. [6] proposed an optical flow-based method to register images and visualize changes between temporal CT scans. Their method was applied to lung nodule assessment, evaluation of pulmonary enhancement, and functional changes due to air trapping. However, their methods could be applied to data sets, which had small volumetric differences.

In this paper, we propose an automated non-rigid registration method for regional air trapping visualization in full inspiration and expiration chest CT scans. To cope with intensity differences between two scans, we segment the lung vessel and parenchyma in each scan. We match them without referring any intensity information. We globally align two lung surfaces by affine transformation. Then, locally deformable model is used for the subsequent non-rigid registration. Our registration method is implemented in multi-resolution scale using a Gaussian pyramid. Our method can model the global and local deformation between full inspiration and expiration chest CT scans.

2 Methods

2.1 The Generation of a Binary Image

We segment lung parenchyma and vessel as follows. For the preprocessing, we remove the background area by applying 2D seeded region growing [7] on every slice with outermost seed points of each slice in the threshold range of -1024HU(Hounsfield Unit) to -200HU. The airway is extracted by applying 3D seeded region growing with the automatically detected seed point, which is the center of the uppermost airway in the threshold range of -1024HU to -950HU. Lung parenchyma is extracted by applying 3D seeded region growing [7] with the same seed point and subtracting the airway. The threshold range for the full inspiration CT is from -1024HU to -400HU. And the threshold range for the full expiration CT is from -1024HU to -200HU. From the hole filled lung parenchyma, we can extract lung vessel in the threshold range of -400HU and 3095HU. Then, the intensity of lung parenchyma is replaced as 0. And the intensity of lung vessel and other areas is replaced as 1. Subsequent registration procedure is performed on this binary image.

2.2 Initial Lung Surface Registration

In a surface registration algorithm, the calculation of the distance from a surface boundary to a certain point can be rapidly calculated using a preprocessed distance map [8]. To generate a 3D distance map, we approximate the global distance computation with chamfer distance transform [9], which is repeated propagation of local distances. Chamfer distance transform can be computed by performing a series of local operations while scanning image twice. We explain chamfer distance transform in 2D coordinate for an illustration. In forward scan, we compute $f_1(p)$ for all $p \in$ image in a single standard scan of image. For each p, f_1 has already been computed for all of the *q*s in B(p). If p has coordinates (x, y), B(p) contains (x, y+1), (x-1, y), (x-1,y+1) and (x+1, y+1).

$$f_1(p) = \begin{cases} 0 & \text{if } p \in \text{boundary} \\ \min\{f_1(q)+1 : q \in B(p)\} & \text{if } p \notin \text{boundary} \end{cases}. \quad \textbf{(1)}$$

In backward scan, we compute $f_2(p)$ for all $p \in$ image in a single reverse standard (right-to-left, bottom-to-top) scan of image. A(p) contains the remaining neighbors of p, which are not contained in B(p).

$$f_2(p) = \min\{f_1(p), f_2(q)+1 : q \in A(p)\}. \quad \textbf{(2)}$$

After the generation of chamfer distance map, the average distance between two surfaces can be calculated as follows.

$$\textbf{average distance} = \frac{1}{N}\sum_{x \in \mathrm{Image}_1} \mathrm{DistanceMap}_{\mathrm{Image}_2}(\mathit{Transform}(x)), \quad \textbf{(3)}$$

where the point in image 1 is transformed into the point, $\mathit{Transform}(x)$ in image 2. $\mathrm{DistanceMap}_{\mathrm{Image}_2}(x)$ is the distance value at the position, x of chamfer distance map. N is the number of points in the overlapped area between image 1 and 2.
Transformation model is composed of translation, rotation, and scaling. The transformation is calculated as follows using three translation, rotation, and scaling parameters: T_x, T_y, T_z, R_x, R_y, R_z, S_x, S_y, S_z [10].

$$\begin{gathered} P_{\mathrm{Image}_1} - C_{\mathrm{Image}_1} = \\ R_x(\theta_x)\cdot R_y(\theta_y)\cdot R_z(\theta_z)\cdot S_x\cdot S_y\cdot S_z\cdot(P_{\mathrm{Image}_2} - C_{\mathrm{Image}_2}) \\ + T(T_x, T_y, T_z), \end{gathered} \quad \textbf{(4)}$$

where P_{Image_1} and C_{Image_1} are the position of voxel and center in image 1. P_{Image_2} and C_{Image_2} are the position of voxel and center in image 2. To search for transformation parameters, Powell's directional method [11] is applied as the optimization technique.

2.3 Non-rigid Registration based on Locally Deformable Model

Due to local deformation of lung, a point inside lung moves locally during the respiratory motion. Therefore, we can model the local movement of a point inside lung as the summation of linear transformation and translation. We calculate parameters of linear and translational transformation at each point, p around their neighborhood, Ω to minimize the following error functions.

$$\mathrm{E} = \sum_{\Omega \in P} [\mathrm{Image}_1(P) - \mathrm{Image}_2(L_p P + T_p)]^2 , \quad \textbf{(5)}$$

where L_p is 3×3 matrix including 9 linear transformation parameters at a point, p . And T_p is 3×1 matrix including 3 translational transformation parameters at a point, p . Ω can be approximated as 5×5×5 regular hexahedron. If we find the optimal transformation parameters according to Eq. (5), holes can occur when deformation parameters spatially change a lot. Therefore, we add the smoothness term [12] into locally deformable model to smooth the spatial change of deformation parameters. Eq. (5) with the smoothness term is optimized by Newton-Raphson iterative technique.

The range of Ω with respect to a point is limited in the neighborhood regular hexahedron centering the point. The degree of modeled deformation is limited by the size of a regular hexahedron. Therefore, multi-resolution approach is applied in this paper. Gaussian pyramid [13] for each image is generated. In Gaussian pyramid, the average intensity of 2×2×2 voxels in the current level is assigned as the intensity of one voxel in the next level. In this paper, five levels of hierarchical Gaussian pyramid are generated.

3 Results

Our method was performed on Intel Core2 Quad 2.4 GHz PC. Our method has been applied to ten pairs of clinical data sets, which were full inspiration and expiration chest CT images. Each image had a matrix size of 512 x 512 pixels with 0.75 mm slice thickness and spacing. For each scan, a stack of 450-550 contiguous slices were acquired.

The performance of our method was evaluated from the aspects of visual inspection, accuracy, and color mapping of subtraction images. First, 3D volume rendering images of each lung surface before and after the registration are shown in Fig. 1. Fig. 1(a), and (c) show a large amount of initial misalignments. This initial misalignment is completely corrected by proposed method. The lung boundaries of the full inspiration and expiration CT scans are aligned exactly, as in Fig. 1(b), (d).

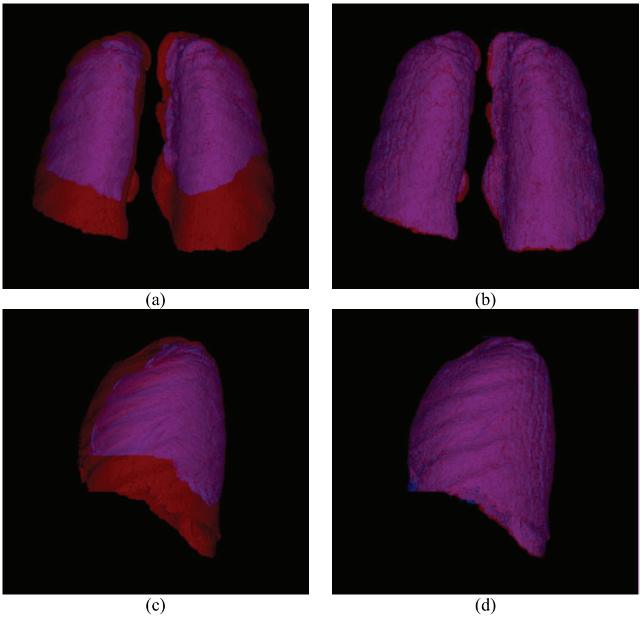


Fig. 1. 3D volume rendering images after the registration of full inspiration(red) and expiration(blue) CT images (a) before the registration(the front view) (b) after the registration(the front view) (c) before the registration(the side view) (d) after the registration(the side view)

We evaluate the registration accuracy of proposed method by measuring normalized mutual information(NMI) before and after the registration. Average NMI value measured inside the lung for ten patients was 1.00310 (before registration), 1.00394 (after initial registration), and 1.01246 (after non-rigid registration) as shown in Fig. 2. Average NMI value was the maximum after non-rigid registration.

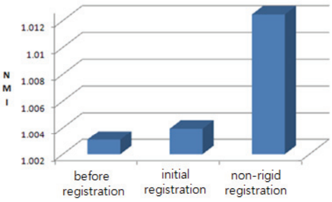
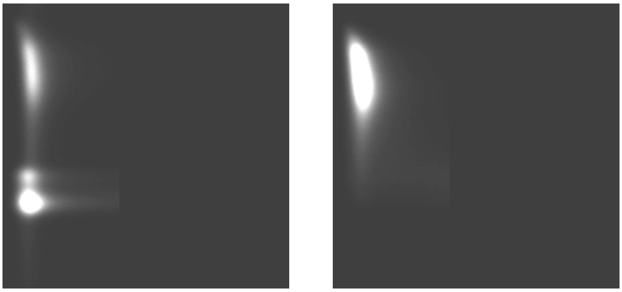


Fig. 2. Average NMI value

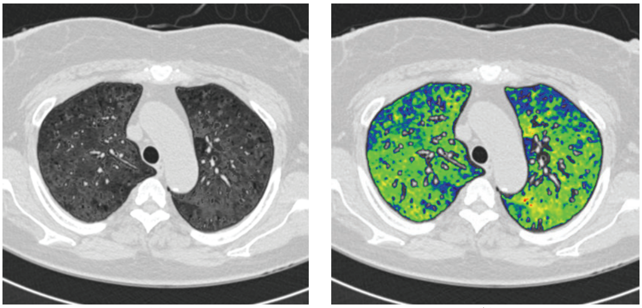
The joint histogram to measure NMI was shown in Fig. 3. The intensity value of CT images, which is in the range of -1024HU and 3095HU, was scaled in the range of 0 and 255. The joint histogram before the registration was dispersed as shown in Fig. 3(a). The joint histogram after the registration was congested as shown in Fig. 3(b), which meant the alignment of full inspiration and expiration CT images.



(a) (b)

Fig. 3. Joint histogram (a) before the registration (b) after the registration

Finally, we evaluated the clinical efficiency of proposed method by color mapping of the subtraction image of lung parenchyma after the registration. Fig. 4(a) showed the subtraction image between the full inspiration and expiration CT images after the registration. Fig. 4(b) showed the color mapped subtraction image using a rainbow color table. Blue colored regions represented that the intensity difference between the full expiration and inspiration CT images was small. These regions meant air trapping regions. The average processing time per each patient was about fifty minutes on Intel PC with Core2 Quad 2.4 GHz CPU and 2GB RAM.



(a) (b)

Fig. 4. Subtraction image after the registration (a) subtraction image (b) color mapped subtraction image

4 Conclusion

We have proposed an automatic non-rigid lung registration method for the visualization of regional air trapping in full inspiration and expiration chest CT scans. To cope with intensity differences between CT scans, we segmented the lung vessel and parenchyma in each scan. Then, we matched them without referring any intensity information. We globally aligned two lung surfaces by affine transformation. Then, locally deformable transformation model was developed for the subsequent non-rigid registration. Subtracted quantification results were visualized by pre-defined color map. Experimental results showed that proposed registration method was able to correctly align the full inspiration and expiration CT images in 10 patients.

References

1. Betke, M., Hong, H., Thomas, D., Ko, J.P., Landmark detection in the chest and registration of lung surfaces with an application to nodule registration, Medical Image Analysis, Vol. 7, No. 3 (2003) 265-281
2. Fan, L., Chen, C.W., 3D warping and registration from lung images, Proceedings of SPIE Medical Imaging 3660 (1999) 459 - 470
3. Fan, L., Chen, C.W., Reinhardt, J.M., Hoffman, E.A., Evaluation and application of 3D lung warping and registration model using HRCT images, Proceedings of SPIE Medical Imaging 4321 (2001) 234 - 243
4. Dougherty, L., Asmuth, J.C., Gefter, W.B., Alignment of CT lung volumes with an optical flow method, Academic Radiology, Vol. 10 (2003) 249-54
5. Dougherty, L., Torigian, D.A., Affusso, J.D., Asmuth, J.C., Gefter, W.B., Use of an optical flow method for the analysis of serial CT lung images, Academic Radiology, Vol 13, No. 1 (2006) 14-23
6. Torigian, D.A., Gefter, W.B., Affuso, J.D., Emami, K., Dougherty, L., Application of an optical flow method to inspiratory and expiratory lung MDCT to assess regional air trapping: a feasibility study, American Journal of Roentgenology, Vol. 188 (2007) 276-280
7. Gonzalez, R.C., Woods, R.E., Digital image processing, Prentice Hall, (2008).
8. Lee, J.J., Kim, N.K., Lee, H., Kang, S.H., Park, J.W., Chang, Y.I., Automatic skull segmentation and registration for tissue change measurement after mandibular setback surgery, Lecture Notes in Computer Science, Vol. 4319 (2006) 322-331.
9. Borgefors, G., Distance transformations in arbitrary dimensions, Computer Vision, Graphics, and Image Processing, Vol. 27 (1984) 321-345
10. Maes, F., Collignon, A., Vandermeulen, D., Marchal, G., Suetens, P., Multimodality image registration by maximization of mutual information, IEEE Transactions on Medical Imaging, Vol. 16, No. 2 (1997) 187-198
11. Maes, F., Vandermeulen, D., Suetens, P., Comparative evaluation of multiresolution optimization strategies for multimodality image registration by maximization of mutual information, Medical Image Analysis, Vol. 3, No. 4 (1999) 373-386
12. Horn, B.K.P., Robot vision, MIT Press, (1986).
13. Adelson, E.H., Anderson, C.H., Bergen, J.R., Burt, P.J., Ogden, J.M., Pyramid method in image processing, RCA Engineer, Vol. 29, No. 6 (1984) 33-41