A 3-D Non-Rigid Warping Method Based on Free Formed Deformation for Temporal Subtraction on Thoracic MDCT Images

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***Abstract*—Recently, the development of the Computer Aided Diagnoses (CAD) systems has been rapidly remarked. As one of the CAD systems, temporal subtraction technique can emphasize the temporal changes of interested regions by subtracting a previous image from a current image. However, subtraction artifacts are still remained due to mis-registration, which caused by the variation of pose and inhalation differences when a patient accepts CT inspection at different times. Therefore, high accurate registration technique between a previous image and a current image is necessary. The purpose of this paper is to propose a non-rigid warping algorithm in local image matching based on the feature-driven Free Formed Deformation (FFD). The proposal was performed on thoracic MDCT images and the satisfactory results were obtained.**

***Index Terms*—temporal subtraction technique, computer aided diagnosis, non-rigid image registration, free formed deformation**

I. Introduction

In medical fields, computer aided diagnosis (CAD) system to improve accuracy in visual screening has recently received broad attention. In general, the CAD system from medical images provides automatic analysis and quantification as a powerful tool to radiologists. It can be expected that CAD is useful as a “second opinion” to assist the diagnosis of various diseases [1]. As one of the CAD systems, temporal subtraction technique [2]-[6] can enhance the lesion parts by comparing a patient’s medical images inspected temporally. This technique improves diagnostic accuracy and reduces burdens to physicians. Some of the CAD systems using temporal subtraction technique on thoracic X-ray images based on 2-D analyzing have showed effects on detection [7]. Developments of the CAD using temporal subtraction technique on Computed Tomography (CT) images have attracted attention as well.

However, the temporal subtraction technique has a problem that artifacts are appeared on a subtraction image due to changes of a patient’s position or organic shapes between the previous image and the current one as shown in Fig. 1. We have already proposed a voxel-based non-rigid image registration algorithms for temporal subtraction image, which is obtained by subtraction of a previous image from a current one on Multiple Detector Computed Tomography (MDCT) of the same object [8]-[11]. Using our algorithms, the temporal changes of the lung region can be emphasized. But some subtraction artifacts still remained until now. Although the artifacts on subtraction images are eliminated properly by this method, it does not satisfy the clinical requirement yet. Therefore, further improvement for the performance is needed.

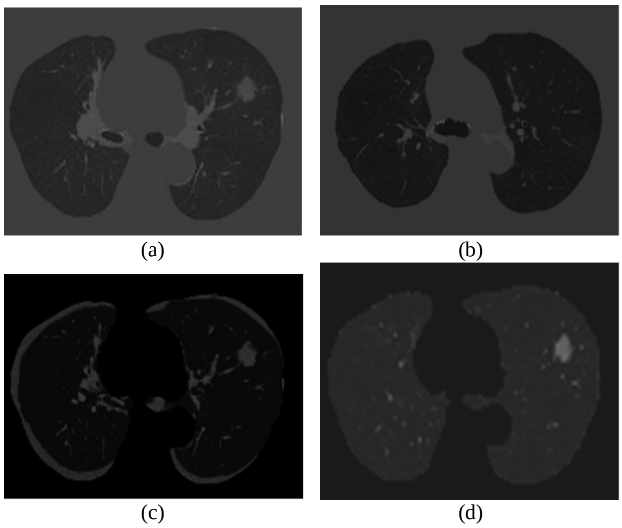

Figure 1. An example of temporal subtraction. (a) shows one slice of previous image, as well (b) is its corresponding current image at the same positon. (c) and (d) illustrate the subtracted images without/with warping implement respectively. Distinctly, normal structures such as vessels, airway regions are eliminated in (d). However, subtraction artifacts are still remained on the subtraction image.

In this paper, we propose an algorithm for registration using a non-rigid image warping technique in local matching based on the feature-driven FFD. Specifically, we use an optimization problem to minimize the discrepancy between a warped previous image and a current image by setting optimal parameters in free formed deformation proposed by Rueckert *et al.* [12]. Here we propose to apply feature-driven FFD [13]

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instead of FFD and the Quasi-Newton method to accelerate running speed.

The rest of this paper is organized as follows. In Section II, we describe image processing technique for non-rigid image registration. The results of the involved methods as produced by the registration are presented in Section III. Finally, discussion and conclusion are described in Section IV and V, respectively.

II. METHODS

Main image processing is shown in Fig. 2. In general, all images have been rectified for scaling because CT image volumes have different scaling. The first step incudes making current and previous images isotropic, and segmentation of the lung regions in these images using intensity and morphological filtering [14]. Then the parameters of deformation in a previous image are sought to correspond between the warped previous image and the current image. The optimization method for the previous image warping is feature-driven FFD algorithm, which proposed by Brunet *et al.* [13]. And finally the subtraction image is produced by subtracting the current image from the warped previous image.

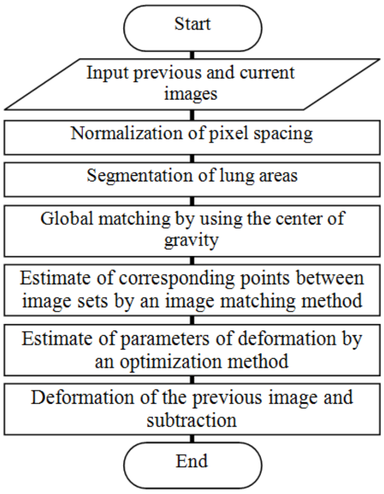


Figure 2. The overall algorithm of the proposed non-rigid registration.

A. Global Matching Using Center of Gravity of ROI

The lung area of a previous image is transformed as a rigid-object in order to match the position of the center of gravity of the lung area in the previous image with the position of the center of gravity of the lung area in the current image. The position of the center of gravity is defined as following (1) and (2).

$$(x_c, y_c, z_c) = \left(\frac{M(1,0,0)}{M(0,0,0)}, \frac{M(0,1,0)}{M(0,0,0)}, \frac{M(0,0,1)}{M(0,0,0)} \right) \quad (1)$$

$$M(p,q,r) = \sum_{i,j,k} i^p j^q k^r f_{i,j,k} \quad (2)$$

here (i, j, k) represents 3-dimentional coordinate in an image. $f_{i,j,k}$ represents the value of the pixel at coordinate (i, j, k) and is set 1 when the pixel is inside a lung area, elsewhere set 0.

B. Non-Rigid Warping Method

We applied feature-driven FFD as the non-rigid warping method, which is an improved FFD method proposed in the research of Rueckert *et al.* [12] whose parameters of deformation are corresponding points in a previous image before deformation and the previous image after deformation. The image after deformation can be estimated from parameters of deformation by this method, and similar performance of accuracy and shortening of processing time is expected compared with the conventional FFD. In this paper, the corresponding points selected by normalized cross-correlation are set as the initial points of deformation, which is described in *3)*. The final points of deformation are defined by the optimization method as described in *4)*.

1) Free formed deformation: The first step is to arrange control points $\mathbf{p}_{i,j,k}$ at fixed interval for each grid along *x*, *y*, *z* directions on an image which need to be deformed. The number of control points is represented as L×M×N. L, M, N control points are arranged respectively along *x*, *y*, *z* direction. Coordinate $\mathbf{q}'$ deformed from $\mathbf{q}$=(x,y,z) is defined as the following (3). The point set $\mathbf{p}_{i,j,k}$ is defined as the parameter of deformation.

$$\mathbf{q}' = \sum_{i=1}^{L} \sum_{j=1}^{M} \sum_{k=1}^{N} \mathbf{p}_{i,j,k} B_i(x) B_j(y) B_k(z) \quad (3)$$

where $B(x)$ is defined as a cubic curve function which is called basis function, and uniform cubic B-spline defined as (4) and (5) is applied in this paper.

$$B_i(x) = \begin{cases} b_1(x) = \frac{1}{6}\hat{x}^3 & x \in [k_i, k_{i+1}] \\ b_2(x) = \frac{1}{6}(-3\hat{x}^3 + 3\hat{x}^2 + 3\hat{x} + 1) & x \in [k_{i+1}, k_{i+2}] \\ b_3(x) = \frac{1}{6}(3\hat{x}^3 - 6\hat{x}^2 + 4) & x \in [k_{i+2}, k_{i+3}] \\ b_4(x) = \frac{1}{6}(-\hat{x}^3 + 3\hat{x}^2 - 3\hat{x} + 1) & x \in [k_{i+3}, k_{i+4}] \\ 0 & \textit{otherwise} \end{cases} \quad (4)$$

$$\hat{x} = \frac{x - k_I}{\delta} \qquad x \in [k_I, k_{I+1}] \quad (5)$$

where k_i represents a node of the basis function and is arranged at fixed interval δ in a range which satisfies the condition of Schoenberg-Whitney.

Additionally, (3) is also represented as the following (6) by using matrix $\mathbf{P}^{\mathrm{T}}=(\mathbf{p}_{1,1,1}, \cdots, \mathbf{p}_{L,M,N})$.

$$\mathbf{q}' = \mathbf{l}_{\mathbf{q}}^{\mathrm{T}} \mathbf{P} \quad (6)$$

$$\mathbf{l}_{\mathbf{q}}^{\mathrm{T}} = (B_1(x)B_1(y)B_1(z), \ldots, B_L(x)B_M(y)B_N(z)) \quad (7)$$

2) Feature-Driven free formed deformation: It is difficult to deform an image from control points accurately because deformation is constrained by the basis function in FFD. Thereby where to arrange control points should be selected by experiments. Whereas this matter is solved by setting corresponding points before deformation and after deformation as the parameters of deformation as $c_k \Leftrightarrow a_k$. c_k represents a coordinate before deformation, and a_k represents a coordinate after deformation, i.e. we arrange the number of corresponding points $c_k \Leftrightarrow a_k$, $k \in \{1, 2, ..., L \times M \times N\}$ as same as the number of control points. And then we solve the following simultaneous equations to a control point **P** in order to set these corresponding points as the parameters of deformation.

$$\mathbf{MP} = \mathbf{A} \tag{8}$$

$$\mathbf{M}^{\mathrm{T}} = (\mathbf{l}_{\mathbf{c}_1}, ..., \mathbf{l}_{\mathbf{c}_{L\times M\times N}}) \tag{9}$$

$$\mathbf{A}^{\mathrm{T}} = (\mathbf{a}_1, ...\mathbf{a}_{L\times M\times N}) \tag{10}$$

here matrix **M** needs to be a positive definite in order to get solution (8), which is guaranteed when corresponding point before deformation $\mathbf{c}_k$ satisfies the condition of Schoenberg-Whitney. Thus we arrange $\mathbf{c}_k$, which is a coordinate before deformation, as a basic point and set $\mathbf{a}_k$, which is a coordinate after deformation, corresponding with *eac*h basic point. The amount of deformation in **q** is obtained uniquely by setting parameter **P** in (6) and (8).

3) Estimation of corresponding points: Corresponding points between the previous image and the current image are used to calcurate the parameters of deformation in non-rigid warping method. The final parameters of deformation are estimated by optimization processing as described in *4)*. It is important that initial points for parameters of deformation should approach to the solutions in optimization processing. This step is to get the initial points by image matching method. Thus we attempted to improve accuracy of registration by applying this method. We arranged feature points at fixed interval inside each lung area both in previous and current images as shown in Fig. 3, and get correspondences between these images by using 3-dimentional template matching algorithm. Especifically, Volume of Interest (VOI), whose center is each feature point, are arranged inside lung area and the template matching is performed to each VOI. the overall template matching is shown in Fig. 4. Template VOI shows a VOI of current images, search VOI shows a VOI of previous images as shown in Fig. 4. Normalized cross-correlation, which is defined as (11), is applied to evaluate template matching results.

$$H(\mathbf{q}') = \frac{\sum_{q\in R}\left((f_t(\mathbf{q}) - \bar{f}_t)(f_s(\mathbf{q}+\mathbf{q}') - \bar{f}_s)\right)}{\sqrt{\sum_{q\in R}(f_t(\mathbf{q}) - \bar{f}_t)^2 \sum_{q\in R}(f_s(\mathbf{q}+\mathbf{q}') - \bar{f}_s)^2}} \tag{11}$$

where **q**' is coordinate in a search VOI. $f_t(\mathbf{q})$ is intensity of coordinate $\mathbf{q}=(x,y,z)$ in a template VOI. $f_s(\mathbf{q})$ is intensity of coordinate $\mathbf{q}=(x,y,z)$ in a search VOI. $\overline{f_t}$, $\overline{f_s}$ are average of intensities in a template VOI and a search VOI respectively. R is the set of all the voxel in a template VOI.

4) Deformation optimization method: A feature point in a current image, which is corresponding to a feature point in a previous image, is obtained by processing in 3). However, other points of registration except feature points are not yet considered. Therefore we apply an optimization algorithm to drive the parameters of deformation by minimizing the discrepancy between the previous image and the current image. We use Quasi-Newton kernel in this optimization processing. The function for evaluation of discrepancy between images is defined as (12).

$$C(\mathbf{u}) = \frac{\sum_{\mathbf{q}\in R}(f_{cur}(\mathbf{q}) - \bar{f}_{cur})(f_{pre}(W(\mathbf{q},\mathbf{u})) - \bar{f}_{pre})}{\sqrt{\sum_{\mathbf{q}\in R}(f_{cur}(\mathbf{q}) - \bar{f}_{cur})^2 \sum_{\mathbf{q}\in R}(f_{pre}(W(\mathbf{q},\mathbf{u})) - \bar{f}_{pre})^2}} \tag{12}$$

where $f_{cur}(\mathbf{q})$ represents intensity of coordinate **q** in a current image, $W(\mathbf{q},\mathbf{u})$ represents coordinate mapped from **q** by using parameter **u** in (3). $f_{pre}(W(\mathbf{q},\mathbf{u}))$ represents intensity of coordinate $W(\mathbf{q}, \mathbf{u})$.

5) Deformation and subtraction of image: Finally, the previous image is warped by feature-driven FFD using the parameters of deformation as described in *4)*, and the subtraction image is producing by subtracting the current image from the warped previous image.

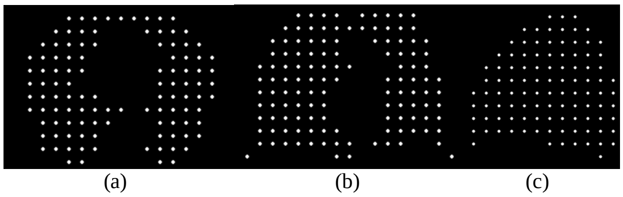


Figure 3. (a) Feature points arranged in axial plane. (b) Feature points arranged in sagittal plane. (c) Feature points arranged in coronal plane.

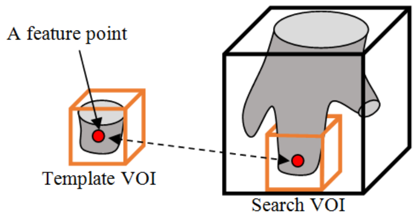


Figure 4. The concept of template matching method.

III. EXPERIMENT

A. *Experiments Method*

We have carried out experiments on 4 cases of CT images which are a previous image and a current image. We compared results of the following 4 method: 1) without registration; 2) registration with only global matching using the center of gravity; 3) registration by linear interpolation method; 4) registration by our proposed algorithm. In the method 3), a previous image is deformed by linear interpolation based on corresponding points instead of the proposed non-rigid warping deformation using the optimization processing.

We evaluated accuracy of each registration by normalized cross-correlation (NCC) and root mean square (RMS) shown in (13) and (14), respectively.

$$NCC = \frac{\sum_{\mathbf{q}\in R}(f_{cur}(\mathbf{q}) - \bar{f}_{cur})(f_{pre}(\mathbf{q}) - \bar{f}_{pre})}{\sqrt{\sum_{\mathbf{q}\in R}(f_{cur}(\mathbf{q}) - \bar{f}_{cur})^2 \sum_{\mathbf{q}\in R}(f_{pre}(\mathbf{q}) - \bar{f}_{pre})^2}} \tag{13}$$

$$RMS = \sqrt{\frac{1}{N}\sum_{\mathbf{q}\in R}(f_{cur}(\mathbf{q}) - f_{pre}(\mathbf{q}))^2} \qquad (14)$$

The NCC indicates 1 as max value if a previous image and a current image are corresponded. The RMS indicates 0 as min value if the previous image and the current image are corresponded. Image information is shown in Table I.

B. Results

Table II and Table III shows evaluation values from the methods 1) to 4) above mentioned. Table II shows evaluation values by NCC, Table III shows the evaluation values by RMS in each case. Additionally, the bottom row of each table shows average of evaluation values of all cases. Our proposed method achieved best performance compare with previous methods [8], as shown in Fig. 5. In all the temporal subtraction images, subtraction artifacts are reduced.

TABLE I. IMAGE INFORMATION

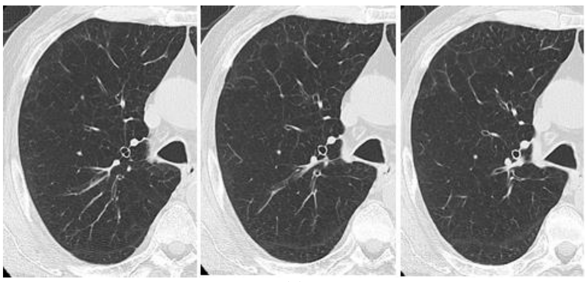
CT Scanner	TOSHIBA Aquilion
Image Size[pixel]	512×512
Pixel Size[mm]	0.625~0.702
Slice Thickness[mm]	2.0

TABLE II. EVALUATION VALUE (NCC)

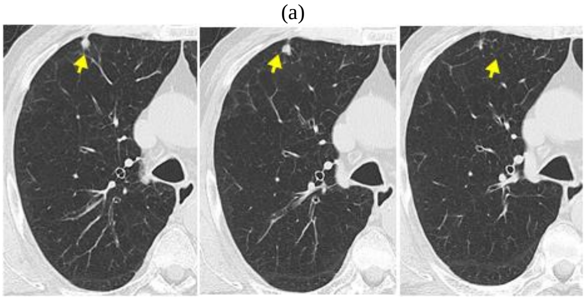
NCC	1)	2)	3)	4)
case 1	0.451	0.557	0.716	0.814
case 2	0.418	0.521	0.651	0.781
case 3	0.385	0.588	0.751	0.856
case 4	0.671	0.687	0.777	0.859
Average	0.481	0.588	0.724	0.828

TABLE III. EVALUATION VALUE (RMS)

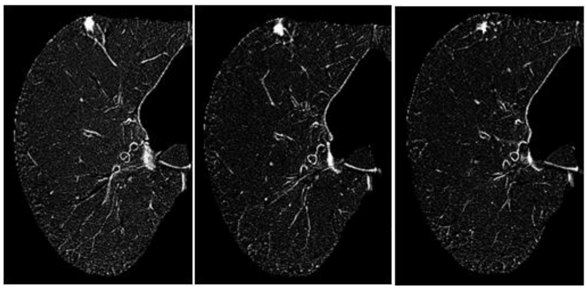
RMS	1)	2)	3)	4)
case 1	125.9	113.6	90.7	73.4
case 2	161.5	146.5	126.4	99.9
case 3	152.2	124.5	97.0	73.9
case 4	103.3	100.6	85.3	67.9
Average	135.7	121.2	99.9	78.8



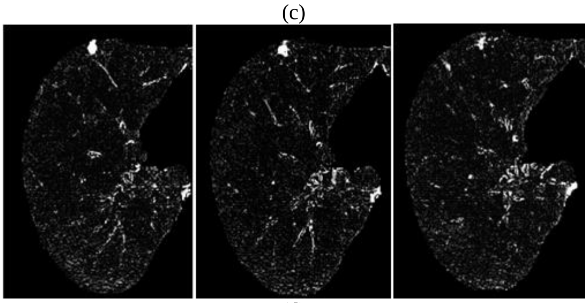
(a)



(b)



(c)



(d)

Figure 5. Experimental results. (a) shows sequential previous images. (b) shows sequential current images. (c) and (d) show sequential subtraction images by our previous [8] and proposed method, respectively.

IV. DISCUSSION

We have presented a registration method in the temporal subtraction using non-rigid image warping technique in order to correspond between the lung position and shape of a current image and the lung position and the shape of a previous image. Higher performance of registration by the proposed method have been proven in all cases processed by the methods 2) to 4) , of which output of NCC is higher compared with the method 1). Improvement of performance was observed in the methods 4) compared with other methods. Additionally, the tendency of evaluation in RMS has been proven to be similar with the tendency of evaluation in NCC. Furthermore, performance in the method 4) was higher compared with the method 2) in all cases. As a result, it has been proven that image matching methods lead to improvement of accuracy for registration.

Higher performance is shown in all cases processed by the method 4) compared with the method 3). The reason is that in the method 3) deformations between a current image and a previous image was led by linear interpolation based on corresponding points, hence the registration results were not sufficient in non-rigid shift.

Otherwise in method 4) deformation of corresponding points was effected by the proposed method using non-rigid warping technique, and the registration results were sufficient. Thereby the results show that the proposed method improves the accuracy of registration.

In our proposed method, parameters of deformation in feature-driven FFD are led from feature points arranged in images. Hence, arrangement of feature points affects performance of registration in the proposed method greatly. In this study, we arranged feature points at fixed interval in 3-dimentiolnal spacing, which was led by experiments. However, arrangement at fixed interval of feature points cannot always provide high performance of registration.

V. Conclusion

In this paper, we proposed an algorithm using non-rigid warping technique based on the feature-driven free formed deformation for temporal subtraction technique on thoracic MDCT Images. We evaluated accuracy of registration by the proposed method. The results of registration using the proposed method performed higher compared with the linear interpolation method. In the future, we will propose optimal arrangement of parameters of deformation and compare evaluation of subtraction images produced by proposed method with evaluation of that by conventional methods.

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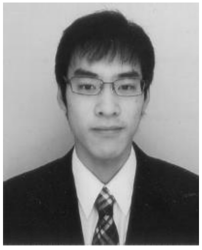

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