Deformable Lung CT Registration by Decomposing Large Deformation

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Abstract. Deformable lung CT registration plays an important role in image-guided navigation systems, especially in the situation with organ motion. Recent progress has been made in image registration by utilizing neural networks for end-to-end inference of a deformation field. However, there are still difficulties to learn the irregular and large deformation caused by organ motion. In this paper, we propose a patient-specific lung CT image registration method. We first decompose the large deformation between the source image and the target image into several continuous intermediate fields. Then we compose these fields to form a spatio-temporal motion field and refine it through an attention layer by aggregating information along motion trajectories. The proposed method can utilize the temporal information in a respiratory circle and can generate intermediate images which are helpful in image-guided systems for tumor tracking. Extensive experiments were performed on a public dataset, showing the validity of the proposed methods.

Keywords: Image registration · Lung CT · Organ movement · Deformation field decomposition · Attention layer.

1 Introduction

Image-guided navigation systems have greatly enhanced the therapeutic efficiency of complicated interventions [1]. However, in such systems, organ motions caused by respiration is a major challenge of accurate lesion targeting. In current practice, this challenge is often handled by asking the patients to hold their breath and scanning repeated CTs. This will either cause distress to patients or increase the radiation exposure. To the end, registration is a promising technique to correct the position offset of the targeting organ or tumor.

Recently, deep networks have been applied to address deformable registration problems and achieved remarkable success [3, 6, 9, 7, 8, 10]. However, it is still difficult to accurately estimate the large deformation due to respiration (tumors and sensitive structures in the thorax can move more than $20mm$ [12]). In this paper, we propose a lung CT registration method that utilizes temporal information during respiration. During training, the images at extreme phases , as well as the intermediate images, are employed as training data. Once the network is trained, it can infer a deformation field without the intermediate images.

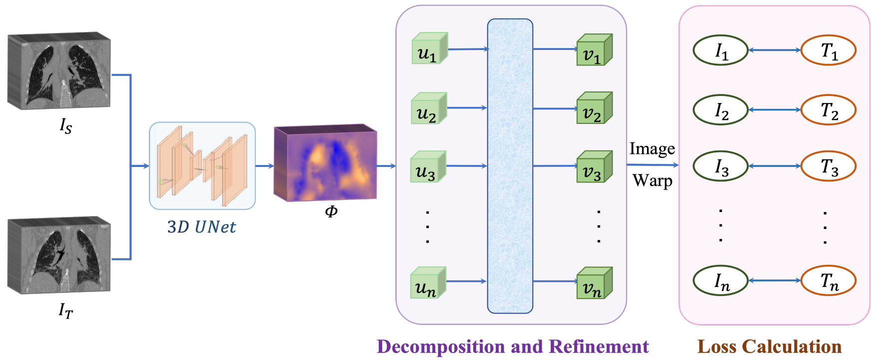

Fig. 1. The illustrative pipeline of our method.

2 Methodology

Let I_S and $I_T \in \mathbb{R}^{H\times W\times C}$ be the source and target lung CT images, respectively. Our aim is to figure out the deformation filed $\Phi \in \mathbb{R}^{H\times W\times C\times 3}$ that stores the coordinate offset between I_S and I_T. We employ a deep network f that takes I_S and I_T as the input to predict Φ by solving the below problem:

$$\underset{f\in\mathcal{F}}{\operatorname{argmin}}\, \ell(I_T, I_S \circ \Phi_f) + \lambda \mathcal{R}(\Phi_f), \tag{1}$$

where $\mathcal{F}$ denotes the function space of f and Φ_f stands for Φ with f given the input (I_S, I_T). $I_S \circ \Phi_f$ represents I_S warped by Φ_f, and ℓ is the loss function to measure the discrepancy between I_T and $I_S \circ \Phi_f$. $\mathcal{R}(\Phi_f)$ stands for the regularization term with the hyperparameter λ to balance its importance.

This training paradigm can work well when the deformation of lungs is small [4], but fail for a large and irregular deformation, in which pixels are dramatically deformed, diminishing the accuracy of the registration. Our method aims to solve this issue by decomposing the deformation field into several ones with small deformations and gradually refining them through an attention layer. An overview of the proposed method is shown in Fig. 1.

Decomposition. We first decompose the deformation field Φ. This field describes the directions and the distances for all voxels moving from I_S to I_T. Considering the progressive movement of the lung, the deformation field can be decomposed by incremental steps to obtain intermediate deformation fields u_i. We assume that each voxel deforms along a straight line [11]. Thus the decomposition can be achieved by linear interpolation: $u_i = \Phi/n$, where n denotes the phases in a respiratory circle.

Refinement. Above mentioned linear interpolation of the deformation field relies on the assumption that the displacement of each voxel is homogeneous. However, in practice, the deformation may be irregular. So we refine these small deformation fields by firstly concatenating them to form a spatio-temporal motion field U, which contains spatial and temporal information during respiration.

Then we input the motion field U to a self-attention layer, and output the refined field V. At last, V is decomposed again to obtain refined intermediate fields v_i, with which I_S are warped to generate intermediate images I_n that are used to calculate loss with ground truth intermediate images T_n. Finally, our decomposition method aims to train the deep network f for deformable registration by solving the following problem:

$$\underset{f \in \mathcal{F}}{\operatorname{argmin}} \sum_{t=1}^{n} \ell_t(T_t, I_S \circ (t\Phi_f/n)) + \lambda \mathcal{R}(\Phi_f). \tag{2}$$

3 Experiments

Experimental Setup: Our method was evaluated on a public dataset [5], which has ten thoracic 4D CTs obtained at ten different respiratory phases in a respiratory cycle. In each 4D CT, 300 anatomical landmarks were manually annotated at two extreme phases. We evaluate our method with target registration error (TRE), which is formulated as the average Euclidean distance between the fixed landmarks and the warped moving landmarks. We implemented our method with Pytorch on an NVIDIA RTX 3090 GPU.

Experimental Results: We compare our method with five competitive methods: BL [2] (CVPR 2018), IL [6] (MedIA 2019), VM [3] (TMI 2019), MAC [7] (MedIA 2021), and CM [8] (MedIA 2021), denoting the baseline and existing methods that use iterative learning strategy, lung masks as the supervision, landmarks as the supervision, and the cycle consistency, respectively. For a fair comparison, we employed the same backbone network (3D UNet) and the same learning setting.

The results via cross-validation are reported in Table 1. We can see that our method achieved the best performance of the average *TRE* (denoted as *Ave.* in the table). It improves the performance over the second-best method (VM) with 8.0%. This demonstrates the validity of our method. We also can see that our method works consistently well in the best and worst cases (denoted as *Best* and *Worst*). Moreover, the performance of our method is less diverse than others as we have the lowest *Std.* (1.06). These evidences suggest that our algorithm is more reliable and effective. We also checked the statistical significance of the performance improvement by paired t-test. We can see that, expect VM (whose p-value is 0.053), other p-values are less than 0.05, which implies that our method significantly improves the registration performance.

Table 1. The *TRE* (*mm*) results of our algorithm and compared methods.

	BL	IL	VM	MAC	CM	Ours
Ave.	3.53	3.85	3.38	3.53	3.56	**3.11**
Std.	1.38	1.25	1.17	1.25	1.56	**1.06**
Best	1.97	2.19	2.19	2.19	1.97	**1.75**
Worst	6.02	5.93	5.79	6.27	6.77	**4.8**
p-value	0.015	0.001	0.053	0.022	0.045	—

4 Conclusion

In this paper, we have investigated a simple and effective method to learn the large deformation field in lung CT image registration, which is helpful in image-guided navigation systems. This method decomposes the large deformation field into small fields, and then composes these small fields and refines them by attention layer. The experimental results show that our method works better than existing methods.

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