

A Symmetric 4D Registration Algorithm for Respiratory Motion Modeling

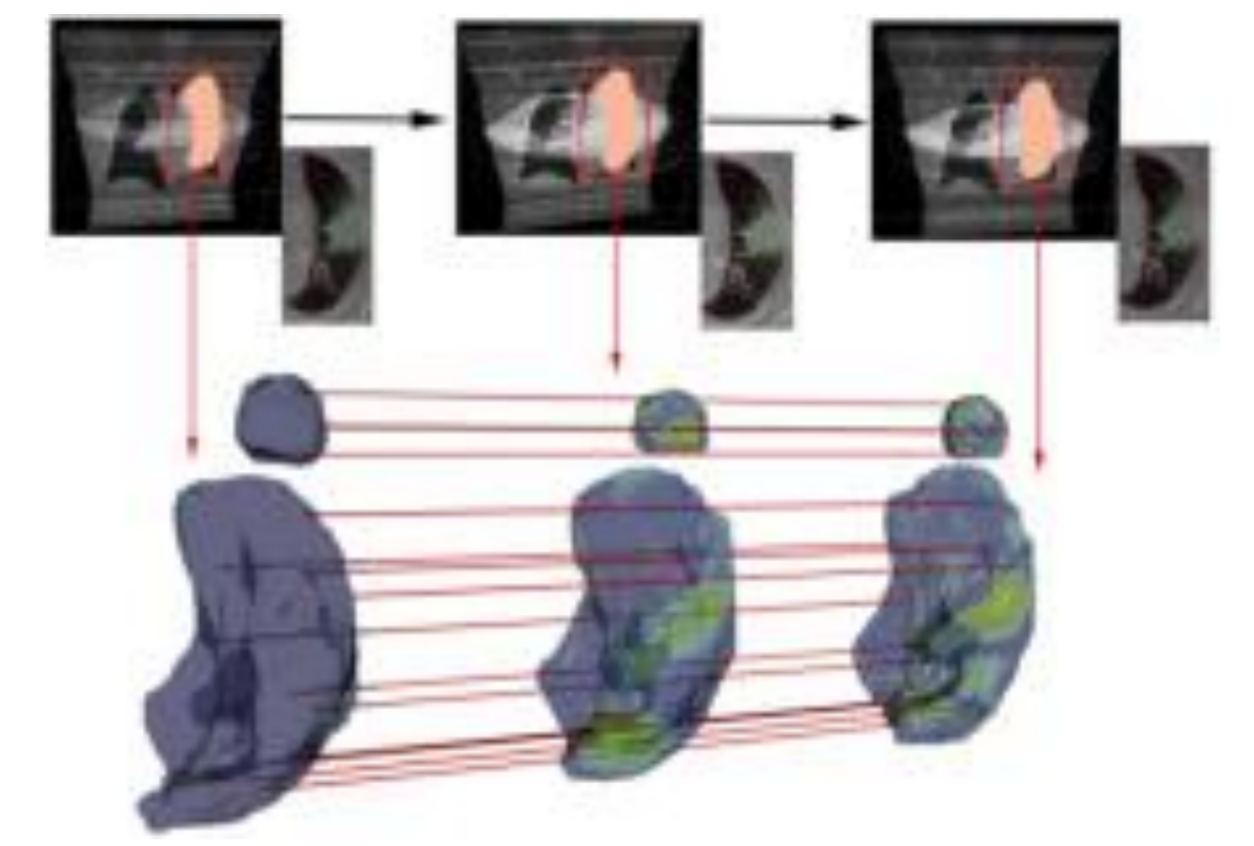
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Objective:

Given a sequence of 3D images describing a deforming volume, we want to establish spatial and temporal (4D) correspondence across these data and build a parametric motion model that mimics the deformation and trajectory of the organs. This framework can benefit image-guided radiotherapy planning and management.



Problem Formulation:

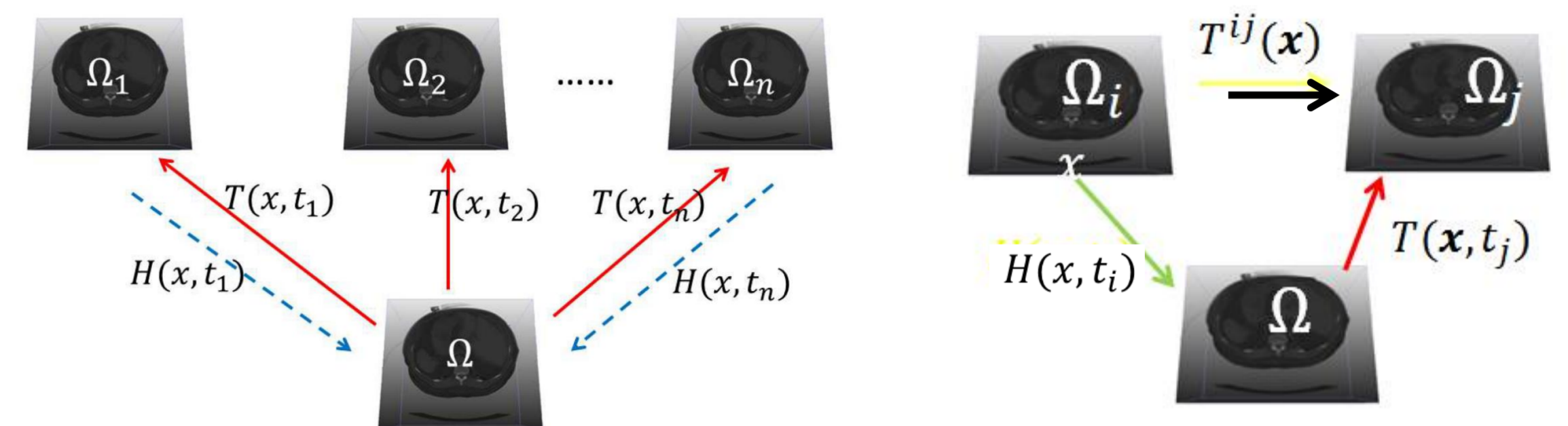
Given a time sequence of 3D images (I_1, I_2, \dots, I_T) , $I_i(x): \Omega_i \rightarrow \mathbb{R}^3$, to compute a 4D parametric representation $T(x, t): \Omega \times \mathbb{R} \rightarrow \mathbb{R}^3$, $T(x, t_i) = I_i$, with small spatial and temporal distortion on the deformation it indicates.

Background and Related Work on Sequential Image Registration:

- Conventional Pairwise 3D Registration + interpolation can match images well spatially, but cannot easily enforce the smoothness of the trajectory.
- 4D Registration [1,2]: directly incorporates constraints on temporal dimension to ensure natural deformation and motion.

Basic Idea:

- We use a 4D B-spline function to approximate the parameterization $T(x, t_i)$. To get cross-image correspondence, we need to solve two functions:
 - 1) a forward parameterization $T(x, t): \Omega \times \mathbb{R} \rightarrow \mathbb{R}^3$, $T(x, t_i) = I_i$, and
 - 2) its inverse mapping $H: \mathbb{R}^3 \times \mathbb{R} \rightarrow \Omega$ which maps coordinate space of the deforming images Ω_i to the common domain Ω .
- Solving T and H together could result in more natural motion modeling, we propose a symmetric objective function incorporating both of functions and solve them simultaneously.



Algorithm:

- We minimize a symmetric objective function integrating both forward and inverse parameterizations, penalizing four energy terms defined on both directions: $\min E(\mu, \nu) = E_I + \alpha E_F + \lambda E_S + \rho E_C$ where E_I is Intensity matching error, E_F is Feature alignment error, E_S is spatial and temporal Smoothness, and E_C is the inverse Consistency, and α, λ, ρ are weighting factors.
- We develop an optimization algorithm that starts with an initial forward parameterization, and iteratively fix the forward and inverse 4D map by optimizing the objective energy with respect to the map on the other direction, until it converges. The optimization is solved using an adaptive stochastic scheme, which offers better efficiency and robustness against image noise.

Results:

□ Datasets:

1. POPI [Vandemeulebrouche et al. 2007]: (Dimension: $482 \times 360 \times 141$ pixels, $\times 10$ frames)
2. DIR-Lab [Castillo et al. 2009]: Data Case-1 to Case-5
3. Clinical lung/tumor data from UT Southwestern Medical Center ($512 \times 512 \times 152$ pixels $\times 8$ frames).

□ Results and Comparisons

- We evaluate the Landmark Matching error: $D_r = \frac{1}{|\Gamma|N} \sum_{t \in \Gamma} \sum_{q_{r,i} \in Q_r} \|T^{r,t}(q_{r,i}) - q_{t,i}\|$ and its deviations

Table 1. The landmark prediction error D_i and its standard deviation σ_i (in mm) of i^{th} time frame on the POPI-data. \bar{D} is the average MTRE.

	$D_1(\sigma_1)$	$D_2(\sigma_2)$	$D_3(\sigma_3)$	$D_4(\sigma_4)$	$D_5(\sigma_5)$	$D_6(\sigma_6)$	$D_7(\sigma_7)$	$D_8(\sigma_8)$	$D_9(\sigma_9)$	$D_{10}(\sigma_{10})$	\bar{D}
3D Reg. [1]	3.6(2.3)	2.3(1.8)	2.1(1.7)	2.2(2.0)	2.4(2.3)	2.9(2.4)	2.8(2.3)	2.1(1.7)	2.1(1.5)	2.7(2.1)	2.5
4D Reg. [1]	3.8(2.3)	2.6(2.0)	2.2(1.8)	2.2(2.0)	2.5(2.2)	2.9(2.3)	2.8(2.3)	2.2(1.8)	2.2(1.5)	2.8(2.2)	2.6
4D Reg. [2]	2.1(1.6)	1.8(1.5)	1.6(1.3)	1.6(1.2)	2.1(1.4)	2.4(1.7)	2.1(1.6)	1.7(1.0)	1.6(1.2)	1.9(1.6)	1.9
Ours	1.1(0.8)	1.2(0.9)	1.3(0.9)	1.2(0.8)	1.5(0.9)	1.5(1.0)	1.4(1.1)	1.1(0.6)	1.2(0.8)	1.2(0.8)	1.3

Compared with several other effective 3D/4D registration approaches, our new algorithm demonstrates significantly improved matching accuracy, as indicated by the prediction errors on the landmarks (from the ground truth available in these public datasets).

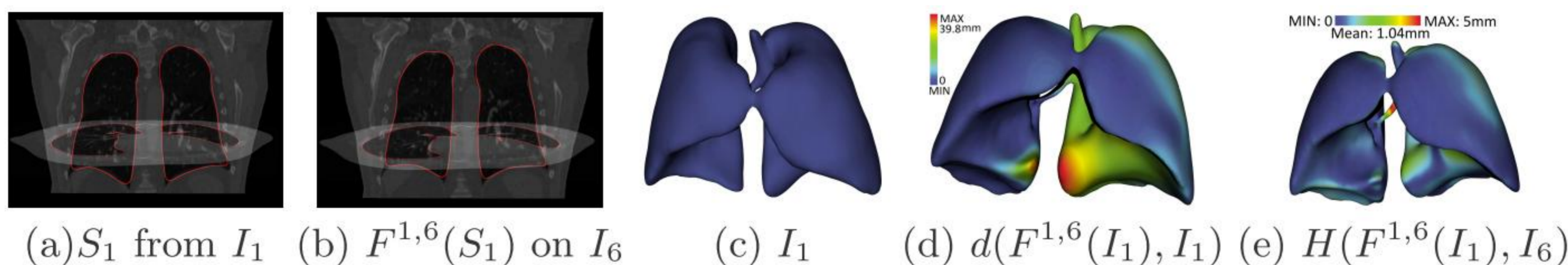
Table 2. The landmark prediction error and its standard deviation $\bar{D}_i(\sigma_i)$ (in mm) for the registration of DIR-LAB 4D dataset: $i = 1$ to 5 for Case-1 to Case-5.

Method/Results:	$\bar{D}_1(\sigma_1)$	$\bar{D}_2(\sigma_2)$	$\bar{D}_3(\sigma_3)$	$\bar{D}_4(\sigma_4)$	$\bar{D}_5(\sigma_5)$
3D Reg [1]	2.03(1.09)	0.72(0.44)	0.99(0.71)	1.14(0.81)	1.64(1.70)
4D Reg [1]	2.12(1.09)	0.92(0.61)	1.39(0.93)	1.44(0.96)	1.85(1.69)
4D Reg [2]	1.58(0.99)	0.70(0.57)	0.79(0.55)	0.91(0.75)	1.41(1.36)
Ours	1.28(0.76)	0.56(0.34)	0.59(0.43)	0.69(0.49)	1.10(0.94)

- From our clinical 4D CT scans, we construct the parametric deformation model to describe the motion/deformation of the lung.

We visualize the matching accuracy on each time frame t_i , by computing the intersection of the boundary surface from the parametric 3D deformation model and the CT image cross-section, this intersections are red contours, as shown in the following Fig. (a,b).

We also visualize the deformation by color-encode (1) the displacement field on each boundary surface (from the reference geometry to the one in a certain frame) (Fig.-(d)), and (2) the Hausdorff from this predicted geometry to the iso-surface directly extracted from the frame (Fig. e).



- Visit our project website: <http://www.ece.lsu.edu/xinli/CBiomedicine/TumorTracking.html> for the paper, video, poster, and other details.

Conclusion:

We develop a 4D image registration algorithm that simultaneously optimizing two coupled B-spline functions. The registration demonstrates better matching accuracy and trajectory smoothness in the induced deformation. This computational model can benefit the lung motion modeling from sequential volumetric images, and have promising applications in lung tumor radiotherapy treatment planning and management.

References:

- [1] C. Metz, S. Klein, M. Schaap, T. van Walsum, and W. Niessen, "Nonrigid registration of dynamic medical imaging data using nD+t B-splines and a groupwise optimization approach," Medical Image Analysis, 15(2):238-249, 2011.
- [2] H. Xu and X. Li, "Consistent feature-aligned 4D image registration for respiratory motion modeling," Proc. Int. Symp. on Biom. Imaging, 580-583, 2013.