Construction of 4D-CT motion model using deformable registration: comparison of Eulerian and Lagrangian approaches

1 Introduction

A precise modeling of pulmonary volume requires a considerable internal detail which is now available mainly thanks to medical image modalities like four-dimensional computed tomography (4D-CT) and fast magnetic resonance imaging (MRI). These image modalities allow to observe the internal morphology over the free-breathing cycle. 4D-CT images are one of the solutions proposed in lung cancer radiotherapy treatment to deal with respiratory movement, but they must be associated to new medical imaging analysis tools. Accurate motion modeling within the lung is an important consideration in different clinical applications. In radiation therapy for example, for lung cancer patients treatment planning purposes, the motion is assessed for determination of planning margins as well as 4D optimization and new delivery adaptations. The goal of this study is to compute, analyze and compare two motion models constructed from 4D-CT using deformable registration. The first model is built using an Eulerian approach. It is based on small deformations computed between neighboring phases. The second model, based on large deformations computed between the end-of-exhale reference phase and all other phases, is built using an Lagrangian approach. We compared these methods for accuracy and consistency to conclude which one is more appropriate to use for generating a motion model.

2 Material and methods

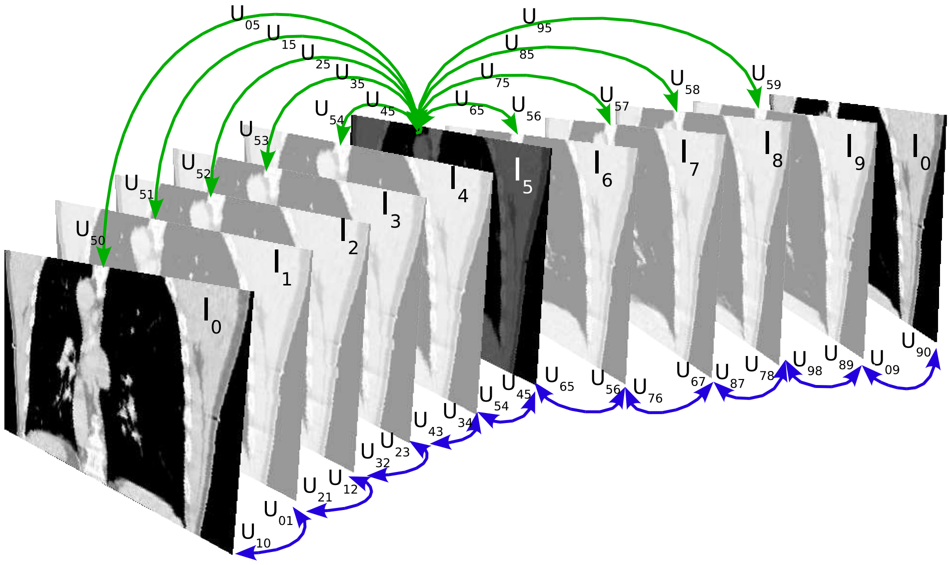
4D-CT acquisition 4D-CTs were acquired using a 4-slice fan-beam CT scanner (GE Lightspeed QX/i; GE Heathcare Technologies, Waukesha, WI), and a respiratory surrogate (Real-time Position Management; Varian Medical Systems, Palo Alto, CA). A complete description of the process is described in Rietzel et al. [1]. We consider 4D-CT scans for three patients treated in radiotherapy for lung cancer. 3D-CT images of the 4D-CT have an in-plane spatial resolution of 512 × 512, between 88 and 120 slices, and a voxel size of $0.977 \times 0.977 \times 2.5\ \mathrm{mm}^3$.

Deformable registration Deformable image registration is an important topic in medical imaging, with direct application to radiotherapy to: estimate of organ motion, follow-up treatment delivery, assess lesion evolution over time, and for automated organ and tumor contouring [2]. In this work the motion models were constructed from vector fields computed using the "demons" algorithm with Gaussian regularization. We used also a pre-treatment method of images [3], called a priori lung density modification (APLDM) to handle this limitation of the demons based algorithm : due to air variation in lung during free-breathing, lung intensities change from one image to another and so, a physical point has no more the same intensity in each 3D-CT image of the 4D-CT.

Motion model construction Movement and deformation through time of a body can be described with two different approaches : Eulerian and Lagrangian. In the Eulerian approach, each body state is expressed locally, at each instant. In the Lagrangian description of movement, each body state through time is expressed from a reference state. We used these two different approaches for constructing the motion models: the Eulerian approach denoted by M_1 and the Lagrangian approach denoted by M_2. The first motion model is built using the Eulerian approach. Deformable registration is performed in both directions between each neighboring pair of images. For example starting from I_5, we compute U_{56}, U_{65}, U_{67}, U_{76},$\cdots$, U_{45}. With M_1 we estimated twenty deformation fields to generate the model. From the model, a deformation field between arbitrary states can be generated by vector field composition ($\circ$). For example, the deformation field U_{52} is calculated as $U_{52} = U_{54} \circ U_{43} \circ U_{32}$. The deformation could also be generated as $U_{52} = U_{56} \circ \cdots \circ U_{12}$, but in this method we will prefer to use the shorter path. The second motion model, built with the Lagrangian approach, is computed by applying deformable registration between the reference image and all the other phases of the 4D-CT. For example, considering I_5 as reference, we compute U_{50}, U_{51}, $\cdots$, U_{59}, and then we compute U_{05}, U_{15}, $\cdots$, U_{95}. Thus, a model generated by M_2 is comprised of eighteen deformable fields. Given these eighteen fields, a deformation field between arbitrary states can be generated by composition. For example, the deformation field U_{13} is calculated as $U_{13} = U_{15} \circ U_{53}$. The figure illustrates the computation of deformable registration in both-directions between end-exhale I_5 image and intermediate 3D-CT images of exhalation, of inhalation and the end-inhale image I_0 with methods M_1 and M_2. The method M_1 has the advantage of estimating only small deformations between each pair of images, which can be more accurately computed than large deformations. However, vector field compositions may induce accumulated errors. The advantage of method M_2 is that any deformation field can be formed from the composition of only two vector fields.

Landmark-based validation For each patient, about 60 landmark points were manually identified by an expert within the lung of the end-inhale image of the 4D-CT. Then, two additional expert observers identified corresponding landmark points on all other 4D-CT phases. For each landmark and for each phase, a composite reference location was obtained by calculating the mean value of the observer positions. These reference locations are used for validation. The mean distance between observers was 1.9 mm, and the standard deviation was 2.0 mm. The model accuracy is estimated by computing the distances (the mean and standard deviation) between the reference landmark locations and the estimated locations generated using the deformation fields.

Consistency The consistency of a deformation field U_{XY} is evaluated by computing the mean and standard deviation of the displacement vector norms of the composite deformation field $U_{XY} \circ U_{YX}$. It is usually computed from four vector fields: $U_{X5} \circ U_{5Y} \circ U_{Y5} \circ U_{5X}$. Only two vector fields are required when $Y = X \pm 1$. If the model was consistent, the composed vector field would be zero everywhere.



3 Results and discussion

Even though M_1 requires computation of twenty deformation fields, while M_2 requires only eighteen, computation times were similar. Convergence is reached faster with method M_1 because the deformations are smaller between successive phases. Approximatively 20-50 iterations of deformable registration were needed for one vector field estimation with method M_1, while for M_2, the end-inhale to end-exhale vector field needed about 250 iterations. For 1 million voxels, the computation time is about 1.5 seconds on a PC Pentium 4 (3.2 GHz, 2 GB Ram). We evaluated the accuracy and the consistency of the vector fields computed with both methods in order to conclude on the superiority of one model over the other. The table summarizes the mean (μ) and standard deviation (σ) values for accuracy and consistency and the significance of the difference between the two models for the three patients. The last two columns of the table depict Student t-tests results of comparison between the two estimating deformation field methods (M_1 and M_2) for accuracy and consistency. "=" denotes that the two methods were not significantly different. "+" denotes the two methods are significantly different. The p-values are also given. For each patient, about 60 points were used for accuracy estimation. Differences between M_1 and M_2 were not significant, and the values of the mean and standard deviation were similar. For consistency, this may be due to the fact that we proceeded to a global evaluation. Maybe for particular regions significant differences would be noticed. Accuracy results of the two models were not significantly different except for patient 1. Mean values of accuracy were on the order of the image resolution and comparable to inter-observer variability (1.9 mm), with slightly better results for M_2: 2.3 mm vs. 2.6 mm.

	Accuracy(mm)		**Consistency**(mm)		**Difference** $\mathbf{M_1}$-$\mathbf{M_2}$(p value)	
	M_1-$\mu(\sigma)$	M_2-$\mu(\sigma)$	M_1-$\mu(\sigma)$	M_2-$\mu(\sigma)$	Accuracy	Consistency
Patient 1	2.3(1.3)	2.1(1.3)	0.8(1.1)	0.8(1.1)	+(0.07)	=(0.97)
Patient 2	3.2(2.2)	2.9(2.2)	1.1(1.3)	1.2(1.5)	=(0.41)	=(0.47)
Patient 3	2.2(1.2)	1.9(1.2)	0.7(0.9)	0.8(1.0)	=(0.95)	=(0.68)

4 Conclusion

In this work we studied two motion models constructed from 4D-CT using deformable registration, generated with two different approaches: Eulerian and Lagrangian. The first one, the Eulerian approach, uses small deformation estimations between successive phases of the 4D-CT. The second motion model, constructed with a Lagrangian approach, was generated by estimation of larger deformations between the end-exhale phase and all other states. The models were validated and compared using consistency and accuracy metrics. The Lagrangian approach gave slightly better results for accuracy. The differences were not statistically significant for consistency. Works are ongoing to evaluate the two motion models for more patient data. We also plan to use lung and GTV contours in order to conclude on the superiority of one motion model over the other for an automatic contour propagation tool, and for lung physiological information computation and analysis.

References

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