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In-room breathing motion estimation from limited projection views using a sliding deformation model

V Delmon[1], J Vandemeulebroucke[2,3], R Pinho[1], M Vila Oliva[1,4], D Sarrut[1] and S Rit [1]

[1] Université de Lyon, CREATIS ; CNRS UMR5220 ; Inserm U1044 ; INSA-Lyon ; Université Lyon 1 ; Léon Bérard Cancer Center ; F-69373 Lyon, France
[2] Vrije Universiteit Brussel (VUB), Dept. ETRO, Pleinlaan 2, B-1050 Brussels, Belgium
[3] iMinds, Dept. FMI, Gaston Crommenlaan 8 (box 102), B-9050 Ghent, Belgium
[4] iMagX project, ICTEAM Inst., Université catholique de Louvain, Louvain-la-Neuve, Belgium

E-mail: `vivien.delmon@creatis.insa-lyon.fr`

Abstract.
Purpose: To estimate in-room breathing motion from a limited number of 2D cone-beam (CB) projection images by registering them to a phase of the 4D planning CT.
Methods: Breathing motion was modelled using a piecewise continuous B-spline representation [1], allowing to preserve the sliding along the thoracic wall while limiting the degrees of freedom. The deformed target 3D image was subsequently used to generate Digitally Reconstructed Radiographs (DRR). The Normalized Correlation Coefficient (NCC) between the measured projection images and the DRR was computed in the 2D projection space. However, the partial derivatives of the NCC relative to the transform parameters were backprojected into the 3D space, avoiding the projection of the transform Jacobian matrix which is computationally intractable [2].
Results: The method was quantitatively evaluated on 16 lung cancer patients. 40 CB projection images were simulated using the end-exhale phase of the 4D planning CT and the geometric parameters of a clinical CB protocol. The end-inhale phase was deformed to match these simulated projections. The Target Registration Error (TRE) decreased from 8.8 mm to 2.0 mm while the TRE obtained from the 3D/3D registration of the reconstructed CBCT was significantly worse (2.6 mm), due to view aliasing artefacts. We also provide the motion compensated image reconstructed from a real CB acquisition showing the quality improvement brought by the in-room deformation model compared to the planning motion model.
Conclusions: We have developed a 2D/3D deformable registration algorithm that enables in-room breathing motion estimation from cone-beam projection images.

1. Introduction

In-room imaging systems are widely used in radiotherapy and provide a better knowledge of the patient motion during and between treatment fractions. Nowadays, the cone-beam (CB) system is mostly used to check the patient positioning before each fraction by reconstructing a 3D CBCT and registering it to the 3D planning CT. The set of projections contains information about the breathing motion and could be used to adapt the treatment. Breathing motion can be estimated from a respiratory correlated 4D CBCT [3], but 4D CBCT images are impacted by the reduced number of projections that lead to streak artefacts. Instead, we propose a method to estimate the breathing motion directly from the set of CB projections.

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2. Method

Problem description From the planning of the radiotherapy treatment, we dispose of a 4D CT image of the patient from which we retain the 3D image corresponding to the end-exhale $f(\boldsymbol{x})$. From the in-room CB system, we dispose of N 2D projections $g_{\boldsymbol{t}}(\boldsymbol{u})$ with $\boldsymbol{t} \in [0..N-1]$. The acquisition geometry is known, providing the CB projection operator

$$\mathcal{P}_{\boldsymbol{t}} f(\boldsymbol{u}) = \int f(\boldsymbol{s} + l \cdot \zeta(\boldsymbol{u}))dl \tag{1}$$

with ζ the direction of the line going from $\boldsymbol{s}$ the source to $\boldsymbol{u}$ a pixel of the detector.

The goal is to estimate the 4D non-rigid transformation $\boldsymbol{T} : \mathbb{R}^3 \times [0..N-1] \mapsto \mathbb{R}^3$ that best describes the motion of the patient during the CB acquisition. To simplify the problem, we assume a cyclic motion consisting of ten phases as the 4D CT. The projection subset corresponding to each phase $\boldsymbol{P_p} \subset [0..N-1]$ is obtained by extracting the breathing signal from the complete projection set [4] and selecting one projection for each phase in each breathing cycle. To obtain a 4D deformation field, each subset is registered to the end-exhale CT image.

Mapping function The motion between the reference phase of the planning CT and a subset of projections is represented by a multi B-spline transform modeling sliding [1] $\mathcal{B}_{\boldsymbol{p}} : \mathbb{R}^3 \mapsto \mathbb{R}^3$ and parameterized by $\delta_{\boldsymbol{p}}$. This mapping function is a linear combination of B-spline transforms allowing sliding to occur at the motion mask interface [5] while preserving a smooth deformation elsewhere. The motion mask encompasses organs with the largest displacements during breathing, comprising the lung, the mediastinum and the abdomen.

Similarity metric To measure the similarity between the deformed 3D CT image and the subset of projections corresponding to a single phase, we use the known projection geometry to generate a new subset of projections from the deformed 3D CT and compute the *NCC* with the CB projections.

$$\begin{aligned} \tilde{f}(\boldsymbol{x}) &= f\big(\mathcal{B}_{\boldsymbol{p}}(\boldsymbol{x})\big) \\ NCC_{\boldsymbol{p}} &= \frac{1}{|\boldsymbol{P_p}|} \sum_{\boldsymbol{t} \in \boldsymbol{P_p}} NCC\big(g_{\boldsymbol{t}}(\boldsymbol{u}), \mathcal{P}_{\boldsymbol{t}} \tilde{f}(\boldsymbol{u})\big) \end{aligned} \tag{2}$$

Optimization We used a gradient based approach to find the set of parameters $\delta^*_{\boldsymbol{p}}$ that minimizes the NCC. This approach requires the partial derivatives according to the parameters of the transformation $\frac{\partial NCC_{\boldsymbol{p}}}{\partial \delta_{\boldsymbol{p}}}$. By using the chain rule these partial derivatives are split into two terms,

$$\frac{\partial NCC_{\boldsymbol{p}}}{\partial \delta_{\boldsymbol{p}}} = \frac{1}{|\boldsymbol{P_p}|} \sum_{\boldsymbol{t} \in \boldsymbol{P_p}} \frac{\partial NCC(g_{\boldsymbol{t}}, \mathcal{P}_{\boldsymbol{t}} \tilde{f})}{\partial \mathcal{P}_{\boldsymbol{t}} \tilde{f}} \frac{\partial \mathcal{P}_{\boldsymbol{t}} \tilde{f}}{\partial \delta_{\boldsymbol{p}}}. \tag{3}$$

The first term is the partial derivative of the NCC in each pixel of the projection, while the second term is the projection of a vectorial image with a large number of components equal to $|\delta_{\boldsymbol{p}}|$

$$\frac{\partial \mathcal{P}_{\boldsymbol{t}} \tilde{f}(\boldsymbol{u})}{\partial \delta_{\boldsymbol{p}}} = \mathcal{P}_{\boldsymbol{t}} \frac{\partial \tilde{f}(\boldsymbol{x})}{\partial \boldsymbol{x}} \frac{\partial \mathcal{B}_{\boldsymbol{p}}(\boldsymbol{x})}{\partial \delta_{\boldsymbol{p}}}. \tag{4}$$

Depending on the smoothness of the sought deformation the number of parameters can vary from hundreds to thousands of parameters, which makes the projection of this vectorial image intractable. The solution proposed by Vandemeulebroucke and Zeng [2, 6] is to integrate over the 3D space instead the 2D space of each projection. By rearranging the sum they obtain

$$\frac{\partial NCC_{\boldsymbol{p}}}{\partial \delta_{\boldsymbol{p}}} = \frac{1}{|\boldsymbol{P_p}|} \sum_{\boldsymbol{t} \in \boldsymbol{P_p}} \mathcal{P}_{\boldsymbol{t}}^{*} \Big(\frac{\partial NCC}{\partial \mathcal{P}_{\boldsymbol{t}} \tilde{f}} \Big) \frac{\partial \tilde{f}}{\partial \boldsymbol{x}} \frac{\partial \mathcal{B}_{\boldsymbol{p}}}{\partial \delta_{\boldsymbol{p}}} \tag{5}$$

with $\mathcal{P}_{\boldsymbol{t}}^{*}$ the backprojection operator. The projection of the 3D vectorial image of $|\delta_{\boldsymbol{p}}|$ components is replaced by the backprojection of a 2D scalar image.

3. Experiment

In order to dispose of a ground truth, we evaluated the proposed method on 16 4D CT images of the thorax using the end-inhale phase to simulate a CB acquisition and registering the end-exhale phase to it. The evaluation was done using the TRE computed on manually defined anatomical landmarks.

Image data The first 6 4D CT image were acquired at our hospital. The resolution was approximately $1 \times 1 \times 2$ mm and $512 \times 512 \times 150$ voxels [7]. The next 10 patients were obtained from the DIR-labs (DL) database `www.dir-lab.com` [8, 9]. Their spatial resolution was between $0.97 \times 0.97 \times 2.5$ mm and $1.16 \times 1.16 \times 2.5$ mm.

To simulate each CB acquisition, we extracted the respiratory signal of a real acquisition made at our hospital, containing 632 projection images and 40 breathing cycles. We extracted the geometric parameters associated to the end-inhale projections. Then we generated each simulated CB acquisition by projecting the 3D CT phase corresponding to the end-inhale using the RTK projection tool [10] and the extracted geometric parameters.

Implementation The proposed method was implemented as a new component of elastix (`http://elastix.isi.uu.nl/`), which is a toolbox for intensity-based medical image registration [11]. This component also uses RTK [10] to handle projection, backprojection and CB geometry.

We compared the end-inhale to end-exhale registration using the proposed method (2D/3D) with one that first reconstructs the 3D image from the simulated CB projections (3D/3D FDK). To obtain a sufficiently smooth result, we used a multi resolution approach, reducing the B-spline control point spacing and image resolution in subsequent levels. For the finest resolution, the spacing of the B-spline control points was 32 mm in every direction, which is large enough to impose spatially smooth deformations without additional regularization.

Quantification To measure the quality of the registration, we used the TRE which is the mean Euclidean distance between corresponding landmarks defined in the reference image and in the target image. These landmarks correspond to recognizable structures like bronchial tree bifurcations, manually selected by experts, on both the reference and the target image. For the first 6 patients, 100 landmarks were obtained with a semiautomatic method [7]. For DL patients, 300 landmarks were also extracted with a semiautomatic method [8, 9].

4. Results

Target registration error Before the registration, the mean Target Registration Error (TRE) was 8.8 ± 5.1 mm. After the registration using 3 resolutions, the 3D/3D FDK obtains a mean TRE of 2.6 ± 2.3 mm and the 2D/3D a mean TRE of 1.8 ± 1.3 mm. The 3D/3D FDK registration is affected by the streak artefacts present in the reconstructed CB due to the limited number of projections. The TRE obtained with the proposed method is always better than the one obtained with the 3D/3D FDK method.

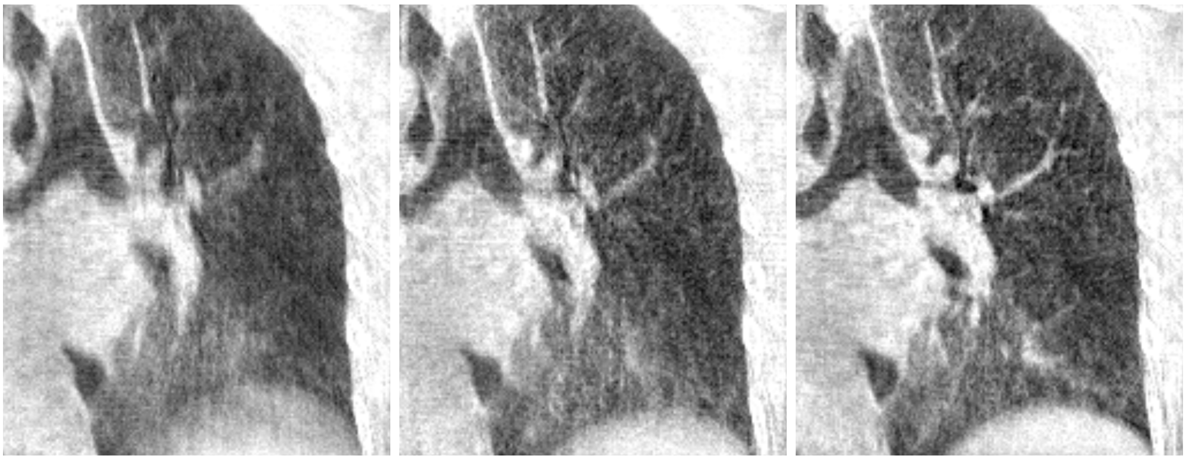

Figure 1. Cone-beam motion compensated reconstructions with the FDK algorithm, assuming no motion (left), with an *a priori* motion (middle) and with the in-room motion (right)

Motion compensated reconstruction To assess the quality of the deformation fields estimated with the proposed method on real data, we registered the end-exhale phase of a 4D planning CT with the 10 phases of a real CB acquisition. The average time per iteration of our unoptimized implementation was 35 min and we used 50 iterations per phase. The amplitude of the found breathing motion was 32 mm around the diaphragm. Figure 1 shows the motion compensated reconstructions of this CBCT without motion compensation, an *a priori* motion extracted from the 4D planning CT [12], and the motion of the day found with the proposed method. On this selected example, the reconstruction compensated with an *a priori* model is visually better than the reconstruction assuming no motion but we can still see blurred structures. The proposed method corrects most of these blurred structures and reveal some bronchi that where not distinguishable with the previous method.

5. Discussion

These results show the potential benefits of using the motion information contained in the CB acquisition. In this study, it was applied to motion compensated CB reconstruction, but it can also serve to adapt treatment, to derive population-based treatment margins, etc. By computing an independent deformation for each phase, the proposed method does not enforce the temporal smoothness on the sought deformation field. It would be interesting to evaluate the improvement that can be brought by a temporal regularization. The signal extraction is also a concern, the quality of the motion compensated reconstructions that have been made using the proposed method were highly correlated to the quality of this signal.

6. Conclusion

We have proposed a 2D/3D registration method that extracts motion information from limited projection views. The method was quantitatively evaluated on simulated data and qualitatively evaluated on real cone-beam acquisitions. Motion compensated reconstruction using the motion estimated from cone-beam projections showed an improved image quality over non-compensated reconstruction and motion compensated reconstruciton using an *a priori* motion model.

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