A New Registration Algorithm for Motion−Compensated Computed Tomography for Image−Guided Radiation Therapy

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Purpose:

An additional kV imaging system next to the linear particle accelerator provides information in image−guided radiation therapy (IGRT) for an accurate patient positioning. However, due to the limited gantry rotation speed during treatment the typical acquisition time is much longer than the patient's breathing cycle resulting in low image quality. In particular, respiratory motion causes severe artifacts such as blurring and streaks in tomographic images.

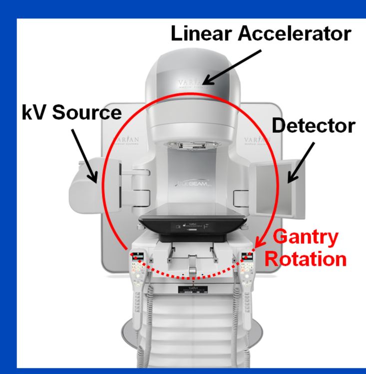
Our purpose is to estimate the motion and compensate for it to provide high quality respiratory−correlated 4D volumes. Moreover, it is necessary that the algorithm is capable to handle standard cone−beam CT (CBCT) scans and in particular standard on−board CBCT scans for image−guided radiation therapy without any particular slow, multiple or adaptive gantry rotation technique[1] and without knowledge from another acquisition like a planning CT[2].

Materials and Methods:

Standard CBCT reconstruction approaches, e.g. using Feldkamp algorithm[3], apply all projection data without considering patient motion properly and thereby suffer from motion artifacts. Retrospective phase gating sorts all data into different sets according to the respiratory motion phase. Performing a separate reconstruction of each phase reduces motion artifacts, but the sparsification results in an increased angular spacing. Thus, few−view artifacts and a high noise level deteriorate the image quality. Nevertheless, these phase−correlated images are used as intermediate images for motion estimation with the new registration algorithm.

For motion estimation a strategy is developed to deal with image artifacts. Motion vector fields (MVF) containing just small motion are estimated first, i.e. the MVFs for adjacent phases. These form a cycle which allows to add temporal constraints like the cyclic breathing motion patterns. The MVFs of non−adjacent phase bins are obtained by concatenation and can be refined by a re−registration using again the cycles on higher levels.

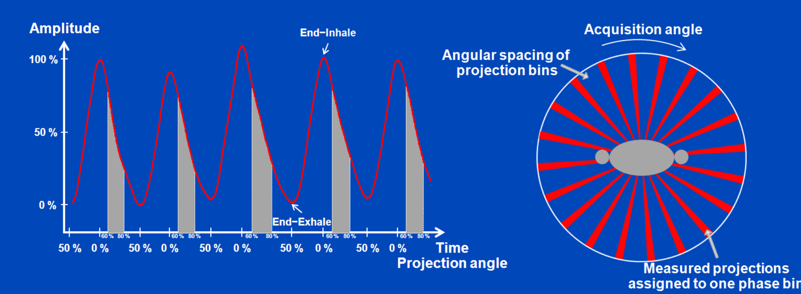
Slowly Rotating CBCT Devices



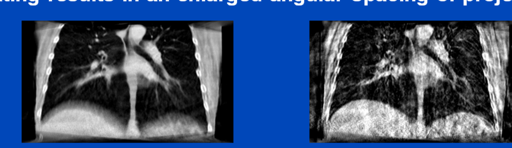
- CBCT imaging unit (kV source and flat panel detector) mounted on the gantry of a linear particle accelerator (LINAC) treatment system
- Comes with a maximum gantry rotation speed of 6° per second
- Much slower than clinical CT devices (about 300 ms per rotation)
- Cycle of respiratory motion usually in the magnitude of 2 – 5 seconds, i.e. 12 – 30 respirations per minute (rpm)

Aim is to provide high quality respiratory−correlated 4D volumes from on−board CBCT scans without any particular slow, multiple or adaptive gantry rotation technique and without knowledge from prior scans like planning CTs.

Phase Gating – Angular Spacing

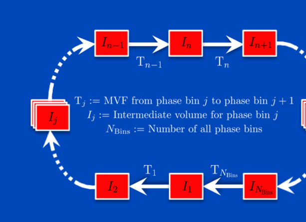


Retrospective phase gating reduces motion artifacts.
BUT: Gating results in an enlarged angular spacing of projection bins.



Without gating ⇒ Motion artifacts   With gating ⇒ Few−view artifacts

Motion Estimation

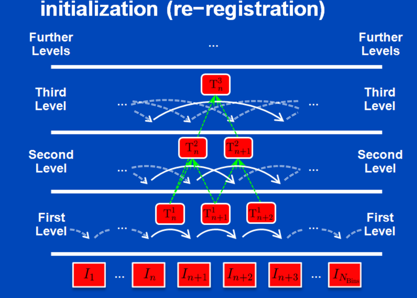


Adjacent phases first:

- Motion vector fields (MVFs) for adjacent phases are estimated first (first level)
- MVFs form a cycle
- Allows for incorporating temporal restrictions in registration process
  - Cyclic breathing motion patterns

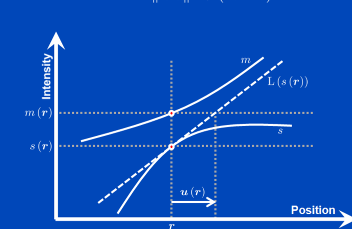
Re−registration:

- MVFs for each phase pair required
- Given by concatenation of MVFs from adjacent phases
  $$\mathrm{T}_n^k \leftarrow \mathrm{T}_n^1 \circ \mathrm{T}_{n+1}^{k-1}$$
- Repeated registration on further levels with the concatenation as initialization (re−registration)



Registration Algorithm – Spatial Part

- Static scene s (Target)
- Moving model m (Source)
- Find transformation vector field T, i.e. $s = m \circ \mathrm{T}$
- Demons algorithm[a]
  - Displacement update u by intensity matching on linear approximation
  $$u = \frac{m - s}{\|\nabla s\|^2 + (m-s)^2} \nabla s$$



- Iterative scheme
  - Maximum step width[b] α
  - Two Gaussian convolution kernels[b] $G_{\mathrm{fluid}}, G_{\mathrm{diffusion}}$
  - Displacement update by symmetric forces[c]
  $$\boldsymbol{u} = \frac{\frac{1}{2}(m \circ \mathrm{T} - s)(\nabla s + \nabla(m \circ \mathrm{T}))}{\left\|\frac{1}{2}(\nabla s + \nabla(m \circ \mathrm{T}))\right\|^2 + \alpha^2 (m \circ \mathrm{T} - s)^2},$$
  - Transformation vector field given by vector field exponentials[d]
  $$\mathrm{T} \leftarrow G_{\mathrm{diffusion}} * (\mathrm{T} \circ \exp(G_{\mathrm{fluid}} * \boldsymbol{u}))$$

[a] Thirion, "Image matching as a diffusion process: An analogy with Maxwell's demons," Medical Image Analysis, vol. 2, no. 3, pp. 243–260, Sep. 1998.
[b] Cachier et al., "Fast non rigid matching by gradient descent: Study and improvements of the "demons" algorithm," Institut national de recherche en informatique et en automatique, Tech. Rep. 3706, Jun 1999.
[c] Wang et al., "Validation of an accelerated 'demons' algorithm for deformable image registration in radiation therapy," Phys. Med. Biol., vol. 50, no. 12, pp. 2887–2905, Jun. 2005.
[d] Vercauteren et al., "Diffeomorphic demons: Efficient non−parametric image registration," NeuroImage, vol. 45, no. 1, pp. 61–72, Mar. 2009.

Registration Algorithm – Temporal Part

- Adjacent phases first
  - Intermediate phase images I_j
  - MVFs T_j with $I_{j+1} = I_j \circ \mathrm{T}_j$
- Temporal constraint
  - Cyclic form of breathing motion patterns
  - Minimization of cost function E
  $$E := \sum_{k=1}^{N_{\mathrm{Bins}}} \|\mathrm{E}_k\|^2 := \sum_{k=1}^{N_{\mathrm{Bins}}} \left\| \left(\prod_{j=k+1}^{N_{\mathrm{Bins}}+k} \mathrm{T}_j \right) - \mathrm{Id} \right\|^2$$
  - Concatenation error vector fields (CEVF) E_k
- Apply error information from CEVFs equally on MVFs to minimize E
  - Constant gantry rotation speed
  - Almost regular breathing pattern
  - Almost constant angular spacing
- Incorporation of error information
  - CEVF by CEVF
  - With refinement after each CEVF

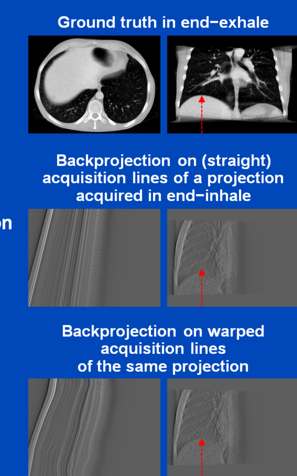
$$j = k: \quad \mathrm{T}_j \leftarrow \mathrm{T}_j - \frac{E_k}{N_{\mathrm{Bins}}}$$
$$j < k: \quad \mathrm{T}_j \leftarrow \mathrm{T}_j - \frac{E_k \circ \prod_{l=k+1}^{N_{\mathrm{Bins}}+j} \mathrm{T}_l}{N_{\mathrm{Bins}}}$$
$$j > k: \quad \mathrm{T}_j \leftarrow \mathrm{T}_j - \frac{E_k \circ \prod_{l=k+1}^{j} \mathrm{T}_l}{N_{\mathrm{Bins}}}$$

Nomenclature: $\prod_{l=1}^{j} \mathrm{T}_l := \mathrm{T}_1 \circ \mathrm{T}_2 \circ \ldots \circ \mathrm{T}_j \qquad \mathrm{T}_{N_{\mathrm{Bins}}+j} :\Leftrightarrow \mathrm{T}_j$

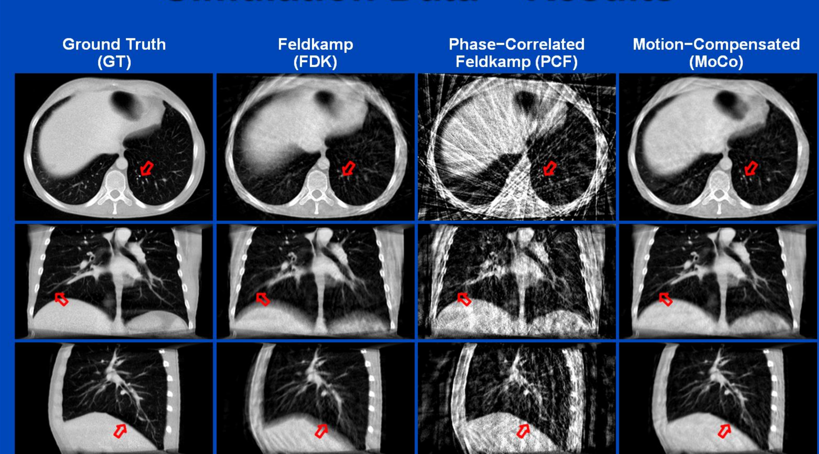
Motion Compensation (MoCo)

- Combine benefits
  - High temporal resolution of phase−correlated images
  - Low noise level from standard reconstructions
- Use of all projections
  - Even those of other phase bins
  - Compensate for motion using motion vector fields (MVF) determined via motion estimation
  - In our case motion estimation is performed on phase−correlated Feldkamp images
- Backprojection along curved lines corresponding to the acquisition lines warped with respect to the MVFs
  - Projection data p, phase-correlated reconstruction operator $\mathrm{X}_{\mathrm{PCF}}^{-1}$, MVF $\mathrm{T}_{i,j}$ from phase bin j to phase bin i

$$f_{\mathrm{MoCo}(i)} := \sum_j \left(\mathrm{X}_{\mathrm{PCF}(j)}^{-1}\, p \right) \circ \mathrm{T}_{i,j}$$



Simulation Data – Results



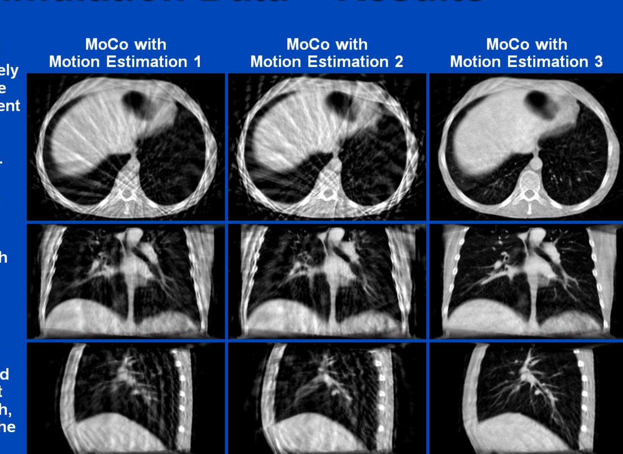
End–exhale phase bin shown at grayscale window of C = –200 HU / W = 1400 HU.

Simulation Data – Results

Motion Estimation 1: Each MVF is separately estimated without the approaches of adjacent phases first, re−registration and temporal constraints.

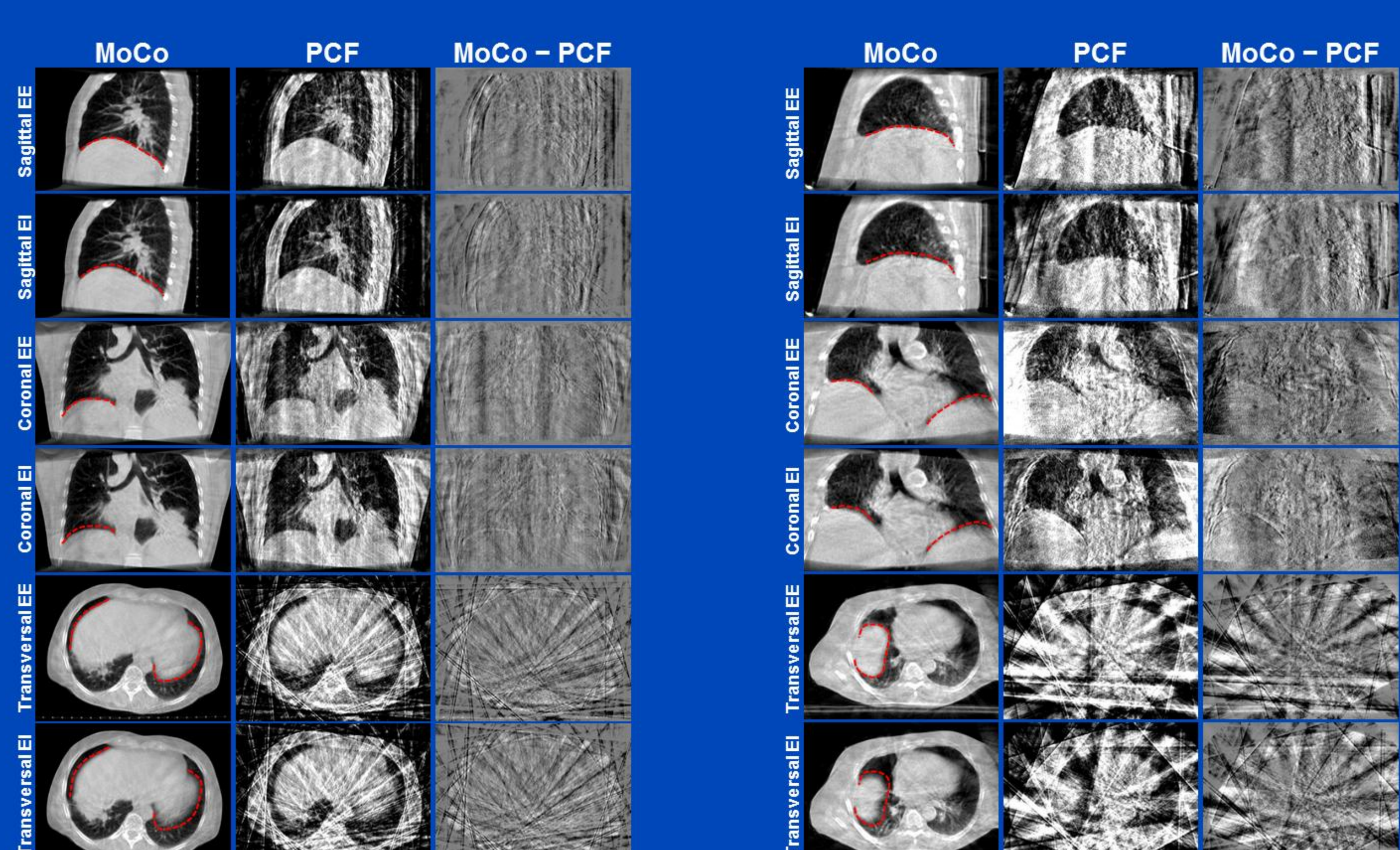
Motion Estimation 2: MVFs are estimated using the adjacent phases first approach and re−registration, but without any temporal constraint.

Motion Estimation 3: The proposed method is used with adjacent phases first approach, re−registration and the temporal constraint.



End–exhale phase bin shown at grayscale window of C = –200 HU / W = 1400 HU.

Patient Data – Results



For two different patients the end–exhale (EE) and end–inhale (EI) phase bin are shown at grayscale window of C = –200 HU / W = 1400 HU. Difference images are shown at C = 0 HU / W = 2000 HU and the red dotted lines mark edge positions in end–exhale.

The basis of our new registration algorithm is an enhanced version of the demons algorithms[4]. In addition, the temporal constraint is considered by minimizing the respective cost function.

We compensate for motion by backprojecting along curved lines that correspond to the acquisition lines warped with respect to the MVFs.

To evaluate the new registration algorithm we apply motion–compensated image reconstruction using the estimated MVFs. The test set consists of synthesized data, obtained by deforming a clinical patient dataset, and patient scans including RPM information acquired with the On–Board Imager's® and the TrueBeam's™ integrated kV imaging unit (Varian Medical Systems, Palo Alto, USA).

Results:

The registration algorithm shows low sensitivity on image artifacts and is able to recover respiratory motion. Finer details like pulmonary vessels hidden by motion or streak artifacts become visible in motion−compensated images.

Conclusion:

Motion–compensated image reconstruction without knowledge from prior scans or particular acquisition techniques becomes feasible in image–guided radiation therapy.

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[2] J. Lu, T. M. Guerrero, P. Munro, A. Jeung, P.-C. M. Chi, P. Balter, X. R. Zhu, R. Mohan, and T. Pan, "Four–dimensional cone beam CT with adaptive gantry rotation and adaptive data sampling," Med. Phys., vol. 34, no. 9, pp. 3520–3529, Sep. 2007.

[3] L. Feldkamp, L. Davis, and J. Kress, "Practical cone–beam algorithm," 1 Journal of the Optical Society of America, vol. 1, no. 6, pp. 612–619, Jun. 1984.

[4] J.-P. Thirion, "Image matching as a diffusion process: An analogy with Maxwell's demons," Medical Image Analysis, vol. 2, no. 3, pp. 243–260, Sep. 1998.