Decoupling Respiratory and Angular Variation in Rotational X-ray Scans Using a Prior Bilinear Model

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Introduction

In rotational X-ray scans angular effects overlap with respiration-induced changes. Conventional respiratory signal extraction
- only provides 1D signals used for binning [1]
- multiple features restricted to static angle acquisition [2]

Aim:
- obtain volumetric information within 2D projection images
- bilinear decoupling of features related to
  a) **rotation** and
  b) **respiration**

➢ drive a respiratory motion model [3] with the respiratory features

Material and Methods

X-ray projection $p_{i,j} \in \mathbb{R}^{N^2}$ at acquisition angle $\phi_i \in [0; 2\pi)$ and respiratory phase $t_j \in [0; 1)$:

$$\boldsymbol{p}_{i,j} = \boldsymbol{R}_i\, \boldsymbol{v}_j \qquad \boldsymbol{v}_j = \boldsymbol{M}\, \boldsymbol{a}_j + \overline{\boldsymbol{v}}$$

X-ray transform $\mathbb{R}^{N^2 \times N^3}$ *volume* $\mathbb{R}^{N^3}$ *PCA motion representation*

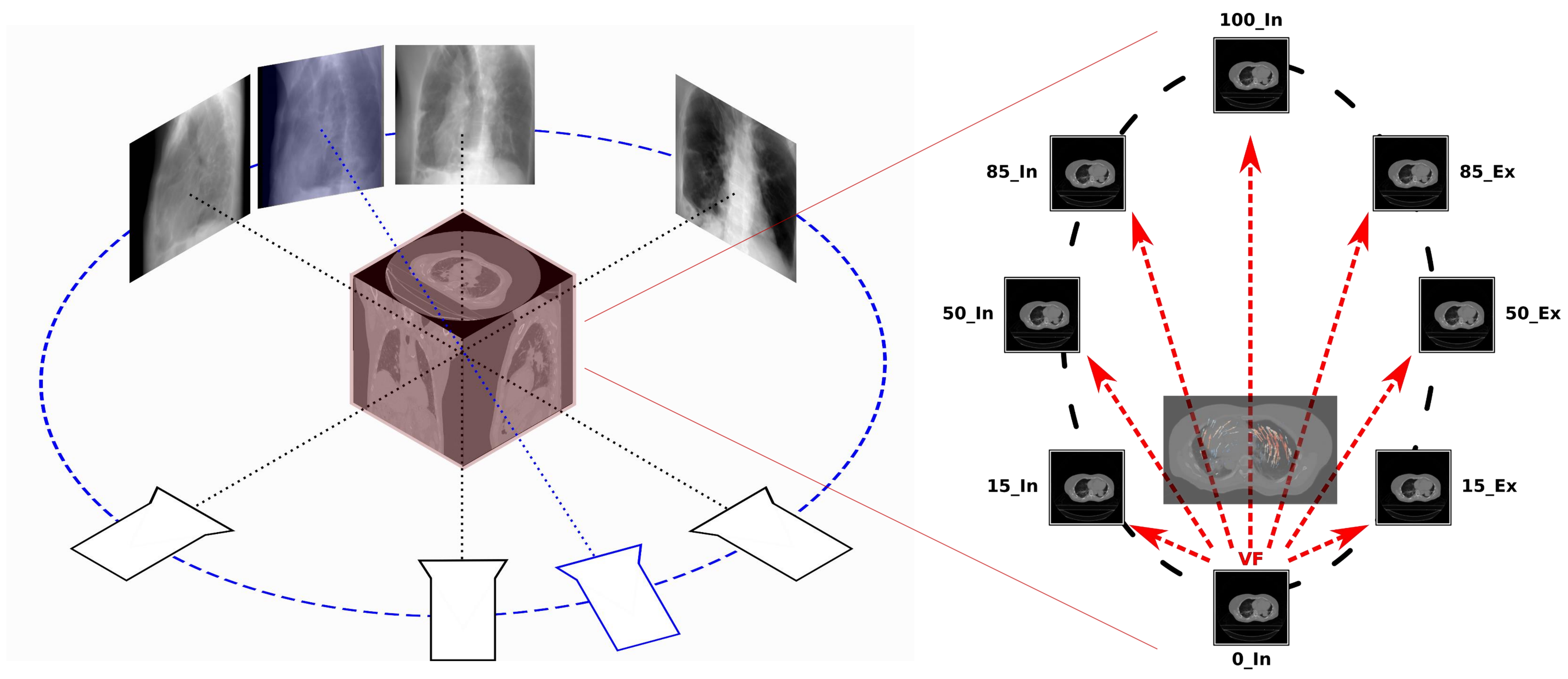

Fig. 1: Variation in projections caused by **respiration** in 3D and/or by changes in the **viewing angle** (left). Volumetric respiratory changes can be modeled using PCA on the displacement fields of a prior 4D CT (right).

$$\boldsymbol{p}_{i,j} = \mathfrak{M} \times_1 \boldsymbol{a}_j \times_2 \boldsymbol{b}_i$$

model tensor $\mathbb{R}^{N^2 \times f \times g}$ respiratory weight $\mathbb{R}^{f}$ *rotational weight* $\mathbb{R}^{g}$

Model Training
- based on forward projected prior 4D CT
- projection data tensor $\mathcal{D} \in \mathbb{R}^{N^2 \times F \times G}$
- Higher-order Singular Value Decomposition (HOSVD) [4,5]

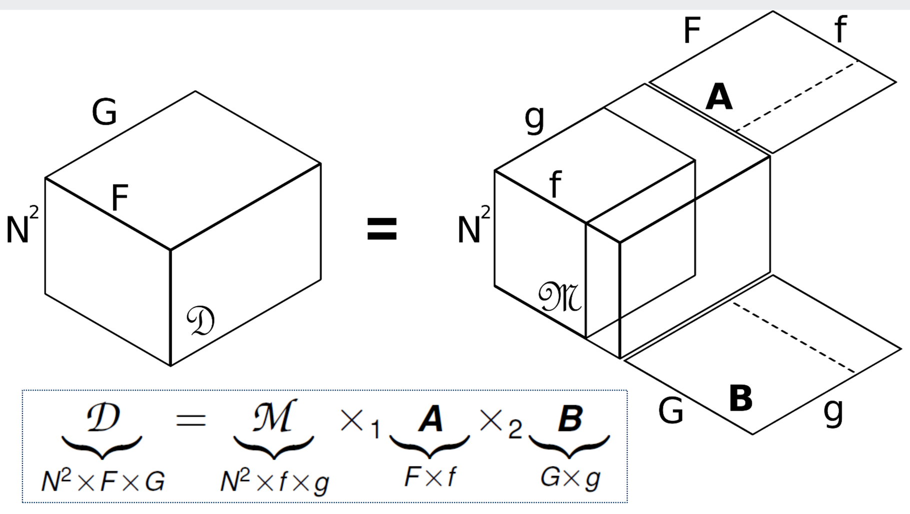

Fig. 2: HOSVD [5] reduces the G projections angles and F respiratory phases to rotational and respiratory feature space of lower dimensionality g and f.

Feature Estimation (from previously unseen projection image $p_{\phi,t}$)
- prior knowledge: B-spline interpolation of rotation weights from viewing angle ϕ

$$\boldsymbol{b}(u) = \sum_{i=1}^{G} \boldsymbol{b}_i \boldsymbol{N}_i(u) \qquad ; \qquad u(\phi) = \frac{\phi - \phi_{\min}}{\phi_{max} - \phi_{min}}$$

- respiratory weight estimation reduces to a **linear problem**

$$\boldsymbol{M}_\phi^R = \mathfrak{M} \times_2 \boldsymbol{b}\big(u(\phi)\big) \in \mathbb{R}^{N^2 \times f \times 1}$$

Results and Discussion

Exp. 1: Feature Comparison
- bilinear respiratory weights match the linear PC scores of the 4D CT (Fig. 3) except for dimension offset (due to missing mean subtraction)

Exp. 2: Decompose Projections
- remove angle and phase from data tensor (leave-one-out)
- corresponding X-ray image is decomposed by the model and subsequently rebuilt (Fig. 4).

➢ mean gray-value error: 3.01%

Exp. 3: Drive 4D Motion Model
- regression of leave-one-out estimated features to PC scores of 4D CT (see **QR**)

➢ mean error of 25 to 100 HU (depending on patient)

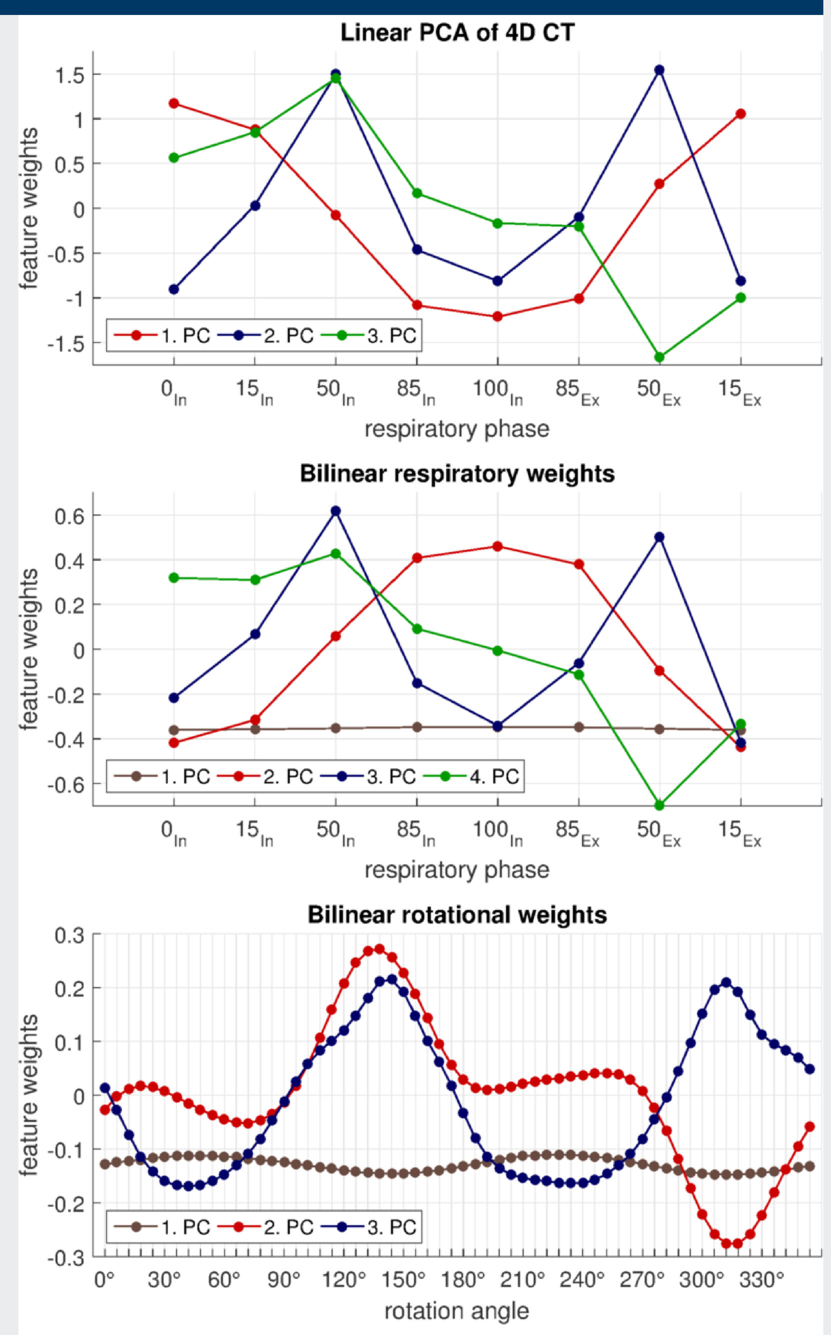

Fig. 3: Scores of the first few principal components for linear PCA on the 4D CT (top), bilinear respiratory (middle) and rotational weights (bottom).

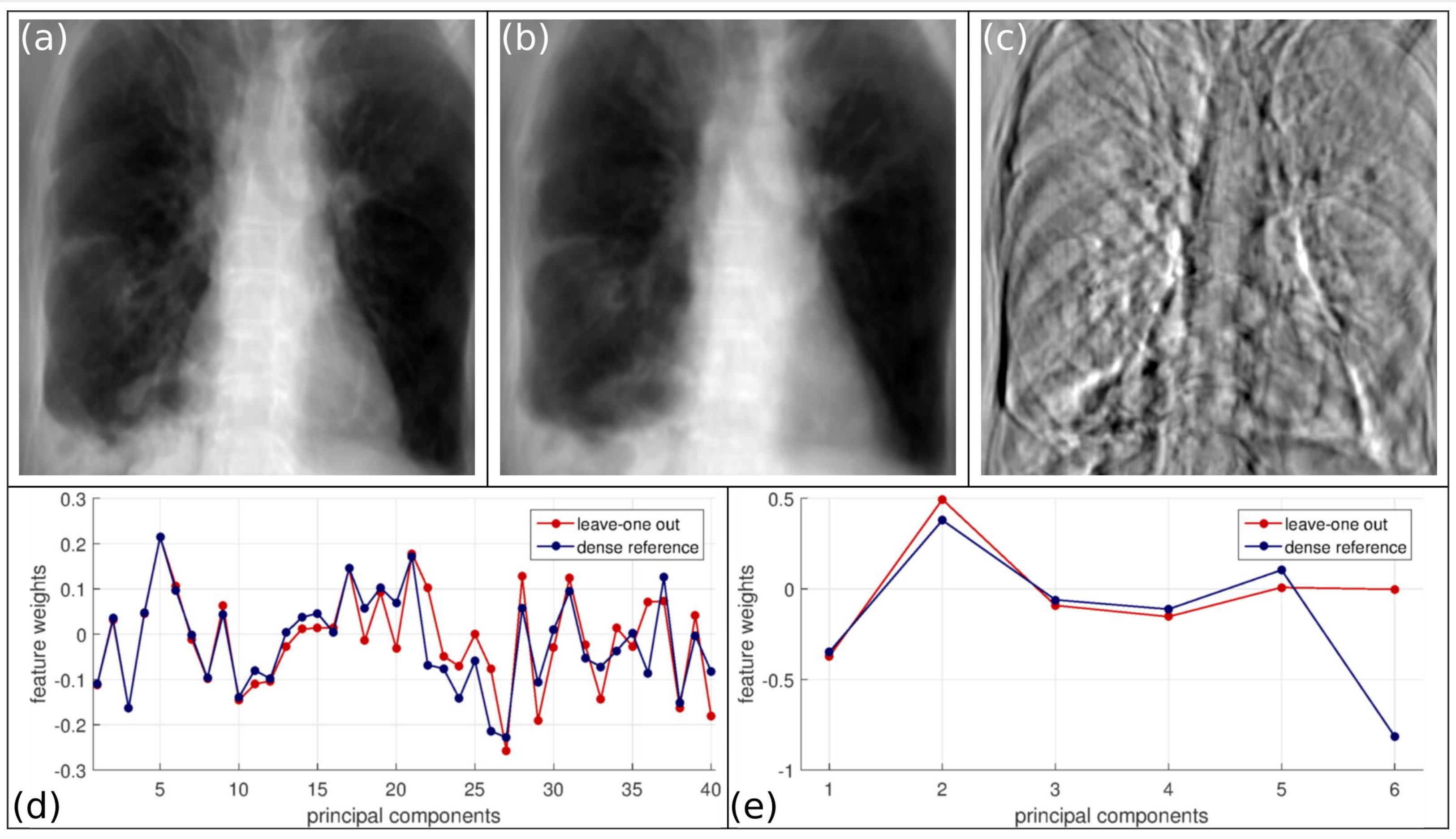

Fig. 4: Example reconstruction for 85% exhale phase at 234 angle. (a) Original DRR sample. (b) Leave-one-out bilinear reconstruction. (c) Dierence image with level/window 0.15/3.75. (d) Rotational weights from dense bilinear model and interpolated weights for the loo estimation. (e) Respiratory weight estimate.

Conclusion

Extracted bilinear features are suitable to drive a respiratory motion model independent of the X-ray acquisition angle.

Challenges
- leave-one-out evaluation doesn't consider inter-fractional change
- patient-specificity requires prior 4D CT

Outlook: Towards respiration-aware X-ray guided interventions
- population-based anatomical model & 4D atlas of motion patterns
- landmark-based fitting

References

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Video

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