Incremental Dimensionality Reduction for Respiratory Signal Extraction From X-Ray Sequences

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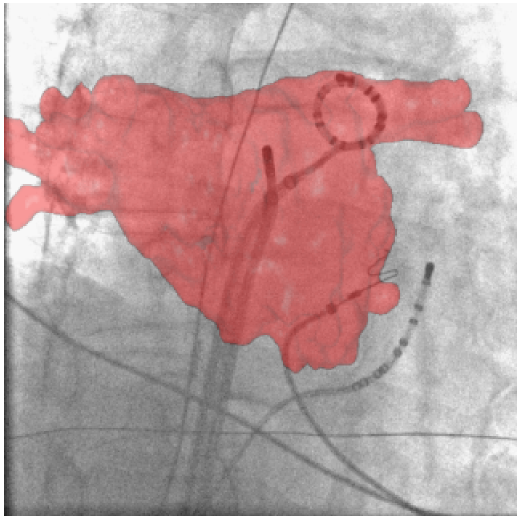
Introduction

Guidance for Fluoroscopy



- Guidance of minimally invasive interventions
- X-ray fluoroscopy visualizes high-density structures well
- Overlays to visualize low-density structures of interest
- Pre-procedural creation of overlays, e.g. segmentation from CT, MR, ...
- Clinical applications
  - Cardiology
  - Electrophysiology
  - Abdominal interventions

Guidance for Fluoroscopy

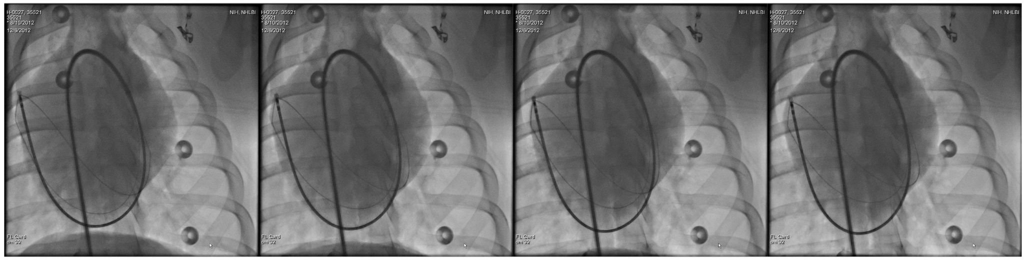
State of the art: static overlays

- Information about 3-D structure of soft tissue
- Navigation help for the physician
- Inconsistency between overlays and live images due to
  - patient motion
  - cardiac motion
  - **respiratory** motion

Motion compensation for overlays using motion models[1]

[1] Jamie R. McClelland et al. "Respiratory Motion Models: A Review." In: *Medical Image Analysis* 17.1 (2013), pp. 19–42.

Motion Compensation for Overlays



Motion Compensation for Overlays

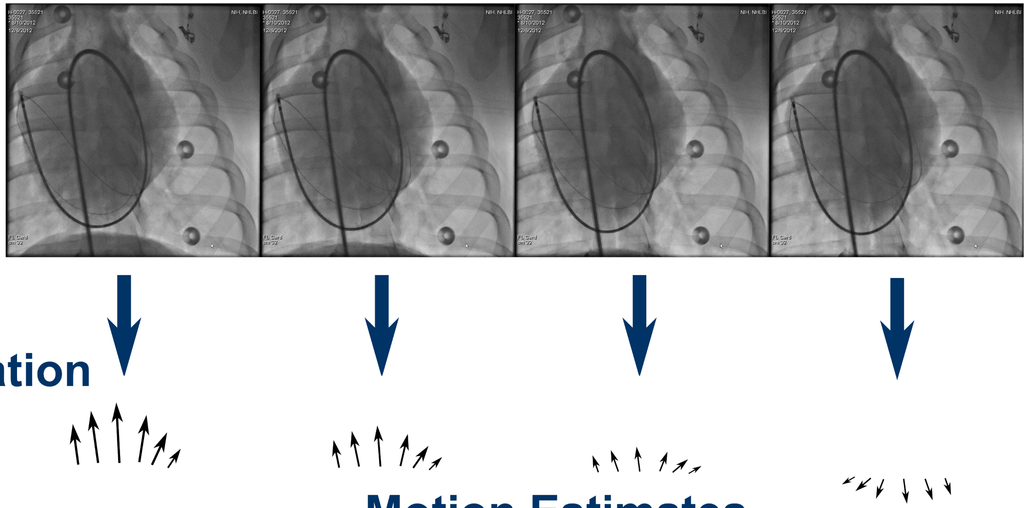
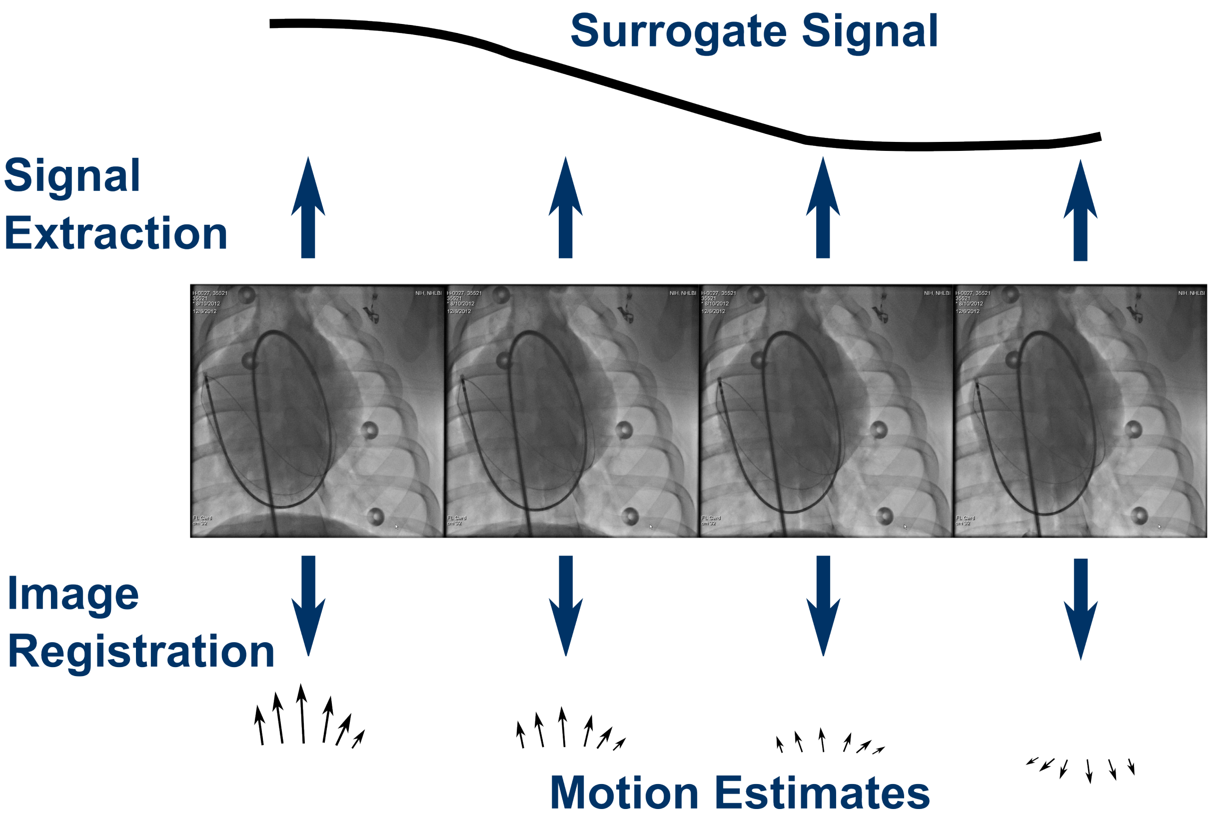


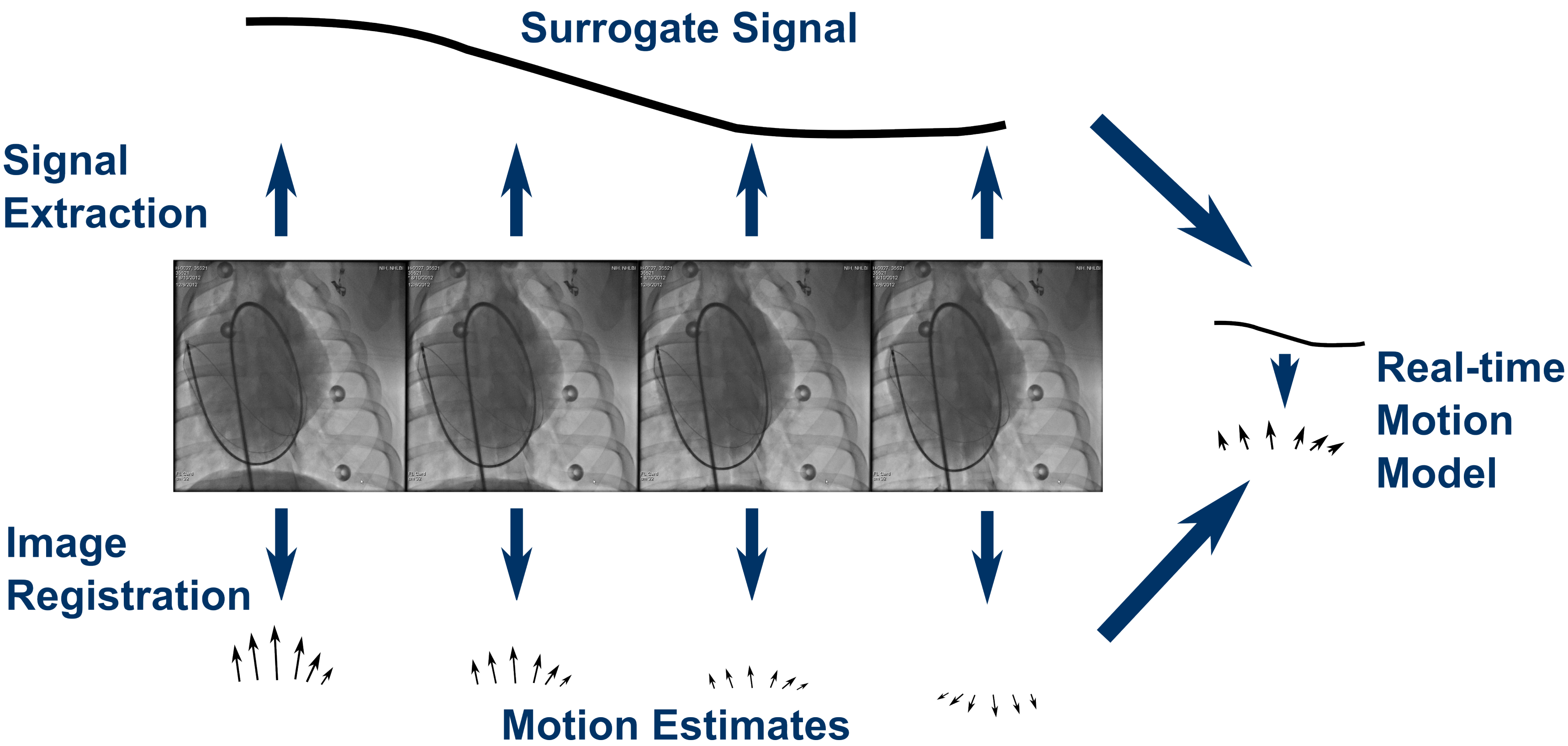
Image Registration

Motion Estimates

Motion Compensation for Overlays

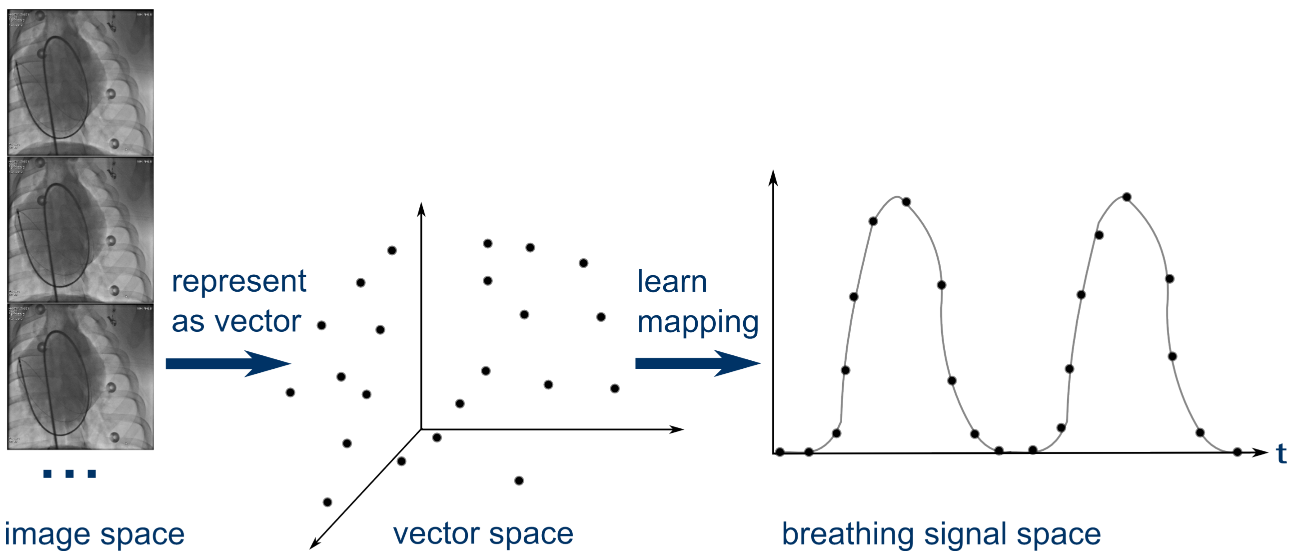


Motion Compensation for Overlays



Methods

Dimensionality Reduction for Respiratory Signal Extraction



Dimensionality Reduction

Recover underlying causes of image variation from the X-ray sequence by learning the relationship between images and causes

Dimensionality Reduction

- Dimensionality reduction: $\boldsymbol{X} \in \mathbb{R}^{N \times M} \rightarrow \boldsymbol{x} \in \mathbb{R}^{N \cdot M} \mapsto \boldsymbol{y} \in \mathbb{R}^1$
- Learn mapping from data in unsupervised manner
- Preserve geometric properties in the embedding
- Major distinction: **Linearity**
  - Linear approaches: Principal component analysis, multidimensional scaling
  - Nonlinear approaches: Manifold learning, clustering
- Respiratory signal extraction from X-ray feasible with manifold learning[2]

Are linear approaches sufficient?

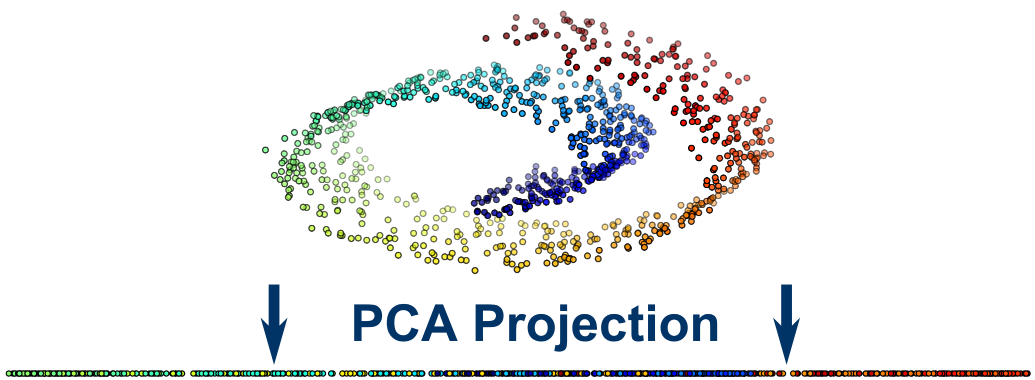
[2] Peter Fischer, Thomas Pohl, and Joachim Hornegger. "Real-Time Respiratory Signal Extraction from X-Ray Sequences using Incremental Manifold Learning". In: *Biomedical Imaging (ISBI), 2014 IEEE 11th International Symposium on*. IEEE. Beijing, China, 2014.

Incremental Principal Component Analysis

- Maximizes explained variance of projected components

$$\max \sum_i \operatorname{var}(y_i)$$

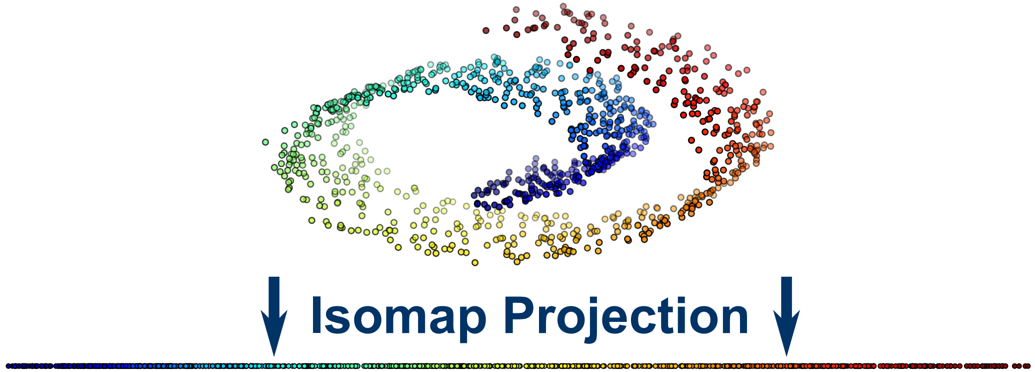
- Projection is restricted
  - Linear projection model $\boldsymbol{y} = \boldsymbol{W}\boldsymbol{x}$
  - Orthogonal dimensions $\boldsymbol{w}_0 \perp \boldsymbol{w}_1 \perp \ldots$
- Incremental version[3] approximates $\boldsymbol{W}$ iteratively for each new $\boldsymbol{x}$



[3] Juyang Weng, Yilu Zhang, and Wey-Shiuan Hwang. “Candid covariance-free incremental principal component analysis”. In: *Pattern Analysis and Machine Intelligence, IEEE Transactions on* 25.8 (2003), pp. 1034–1040.

Incremental Manifold Learning

- Preserve geodesic distance between images
- Geodesic distance approximated using neighborhood graph
- Incremental version saves unnecessary computations[4]



[4]Martin H. C. Law and Anil K. Jain. "Incremental Nonlinear Dimensionality Reduction by Manifold Learning." In: *IEEE Transactions on Pattern Analysis and Machine Intelligence* 28.3 (2006).

Evaluation

Evaluation Setup

Data

- 13 X-ray sequences of 76 to 465 images from animal studies
- Images of 1024×1024 pixels downsampled to 256×256 pixels
- Varying point of view and clinical devices
- Training phase of 40 images
- Number of neighbors in Isomap $k = 20$

[5] Juyang Weng, Yilu Zhang, and Wey-Shiuan Hwang. "Candid covariance-free incremental principal component analysis". In: *Pattern Analysis and Machine Intelligence, IEEE Transactions on* 25.8 (2003), pp. 1034–1040.

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Compared Algorithms

- IPCA: incremental PCA (linear)[5]
- INCISO: incremental manifold learning (nonlinear)[6]

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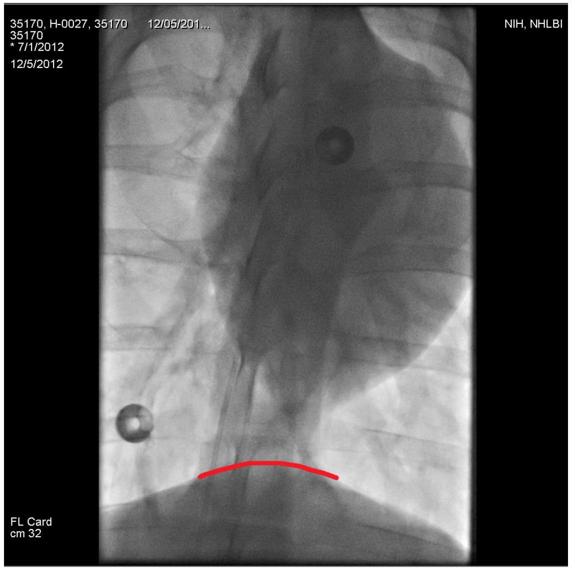
Correlation with Diaphragm Tracking

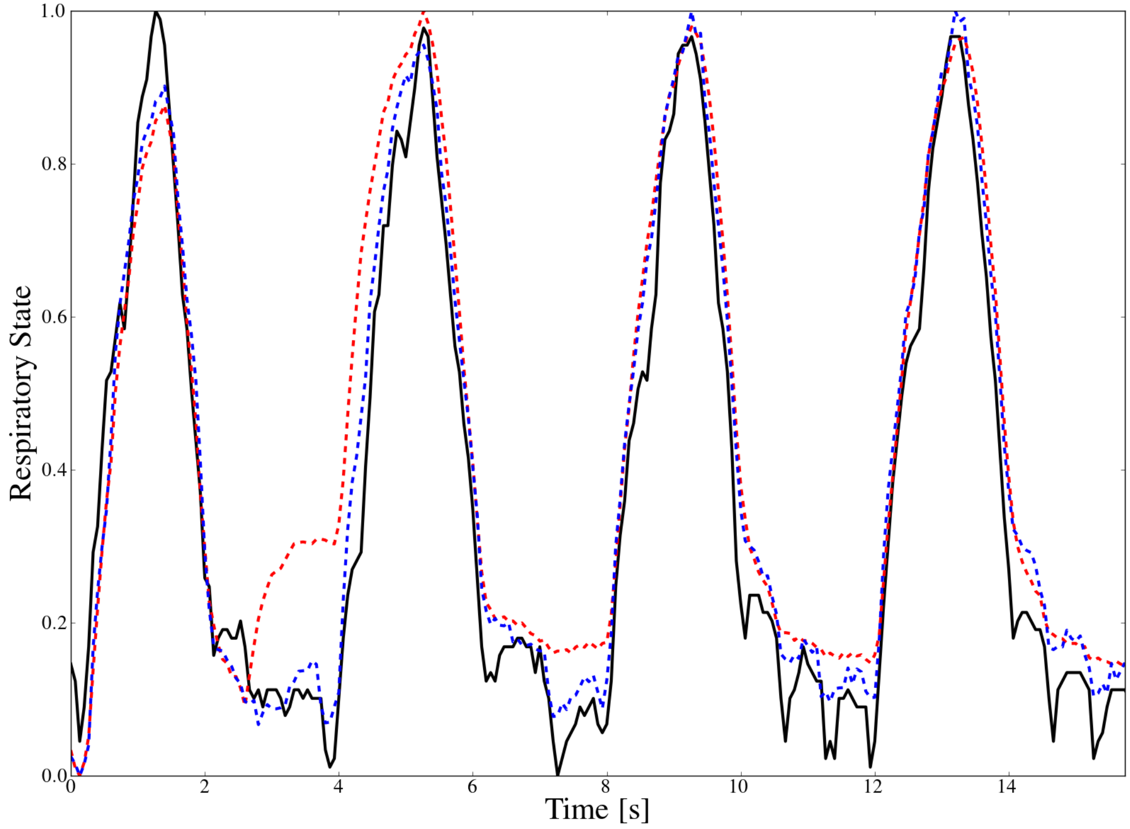


- Tracking of the diaphragm[7]
- Comparison with the y-coordinate of the diaphragm top
- Measure similarity using normalized cross-correlation $NCC_{\text{diaphragm}}$ (mean $\pm$ standard deviation)

Method	$NCC_{\text{diaphragm}}$	Runtime [ms]
IPCA	0.93 ± 0.05	4.6 ± 1.1
INCISO	0.97 ± 0.02	22.7 ± 12.0

[7] Marco Bögel et al. “Diaphragm Tracking in Cardiac C-Arm Projection Data”. In: *Bildverarbeitung für die Medizin*. 2012, pp. 33–38

Example Respiratory Signal from X-Ray Sequence



- Diaphragm tracking
- IPCA
- INCISO

Conclusion

Conclusion and Outlook

- Real-time respiratory signal extraction from X-ray sequences
- Linear and nonlinear dimensionality reduction to learn breathing manifold
    - In theory, nonlinear relationship between respiratory motion and image intensities
    - Tradeoff between accuracy and speed

$\Rightarrow$ Nonlinear dimensionality reduction is superior

Conclusion and Outlook

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- Future work
  combination with a motion model to enable motion compensation

Thank you for your attention!

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