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

A Comparison of Principal Component Analysis and Manifold Learning

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Introduction: X-ray fluoroscopy is used for guidance of many minimally-invasive interventions. The contrast of high-density structures like bones and interventional devices is good, whereas low-density structures like the heart are difficult to discern. Overlays obtained from other modalities like MR can be used to visualize this soft-tissue. A respiratory motion model can be employed to move the overlay according to the breathing motion of the patient [1]. The motion model requires a real-time surrogate signal. Extraction of the respiratory signal directly from the X-ray images requires no additional hardware and synchronization. In this work, we compare linear and nonlinear dimensionality reduction techniques to assess whether linear methods are sufficient for this purpose.

Materials and Methods: The input data to the dimensionality reduction is a sequence of T X-ray images $\boldsymbol{X}_t \in \mathbb{R}^{N \times M}$. Each image is vectorized to $\boldsymbol{x}_t \in \mathbb{R}^{NM}$. The output is a low-dimensional respiratory surrogate signal $\boldsymbol{y_t} \in \mathbb{R}^{d}$. Principal component analysis (PCA) is a well-established linear dimensionality reduction technique. Incremental versions (IPCA) exist [2]. In theory, the relationship between non-rigid 3-D respiratory motion and image intensity is nonlinear. This cannot be modeled by linear methods like PCA, but by nonlinear manifold learning. We investigate the use of incremental Isomap (INCISO) for respiratory signal extraction from X-ray sequences [3,4].

Results: For evaluation, 13 X-ray sequences are used. The images are downsampled to $M = N = 256$ pixels. The training phase for both methods is 40 images, in order to comprise at least one breathing cycle. The neighborhood parameter of INCISO is empirically set to $k = 20$. We compare the $d = 1$-dimensional surrogate signal with diaphragm tracking using the correlation coefficient [5], see Figure 1.

The correlation coefficient of IPCA with diaphragm tracking is 0.93 ± 0.05 (mean $\pm$ standard deviation) and of INCISO 0.97 ± 0.02. For none of the cases, the correlation coefficient of IPCA is higher than that of INCISO. The mean runtime of IPCA is 4.2 ms per image while that of INCISO is 22.7 ms. Both comply with the real-time constraint.

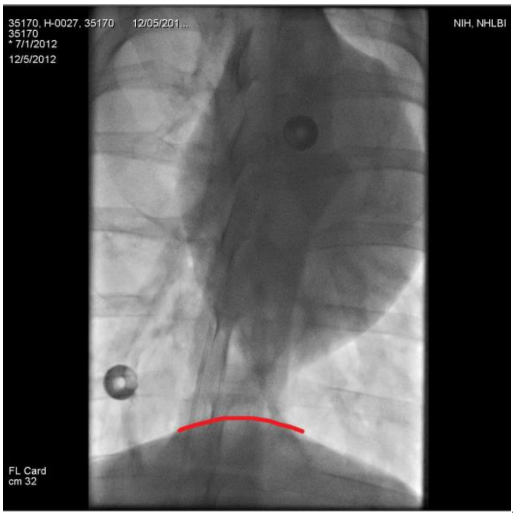

Figure 1: X-ray image with overlaid diaphragm tracking result (red).

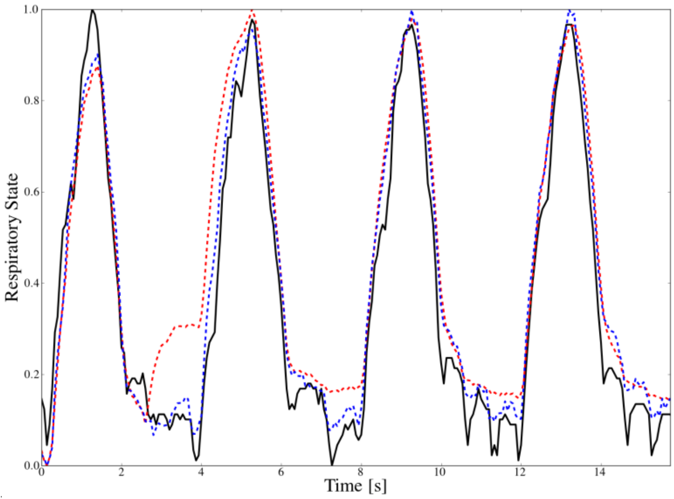

Figure 2: Diaphragm tracking (black), IPCA (red), and INCISO (blue) signals for an exemplary sequence.

Discussion: The higher correlation coefficient of INCISO shows that the relationship between image intensity and respiratory state can be modeled better by nonlinear methods. However, the runtime of IPCA is faster, leading to a tradeoff between accuracy and computational speed. As both are sufficiently fast for real-time applications and accuracy dominates runtime, INCISO is better suited for the task.

Summary: Respiratory motion models for soft-tissue overlays in X-ray fluoroscopy require a respiratory signal, which can be extracted directly from the X-ray images using incremental dimensionality reduction. We assess linear IPCA and nonlinear INCISO by correlating the results with diaphragm tracking. The correlation coefficient of INCISO is on average 0.97 and consistently higher than that of IPCA. In conclusion, incremental manifold learning is an accurate and fast tool to extract respiratory signals from X-ray sequences.

Disclaimer: The concepts and information presented in this paper are based on research and are not commercially available.

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