

Medical Applications for Manifold Learning:

- I) Multi-Modal Registration
- II) Breathing Gating

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Presented by Loren Schwarz

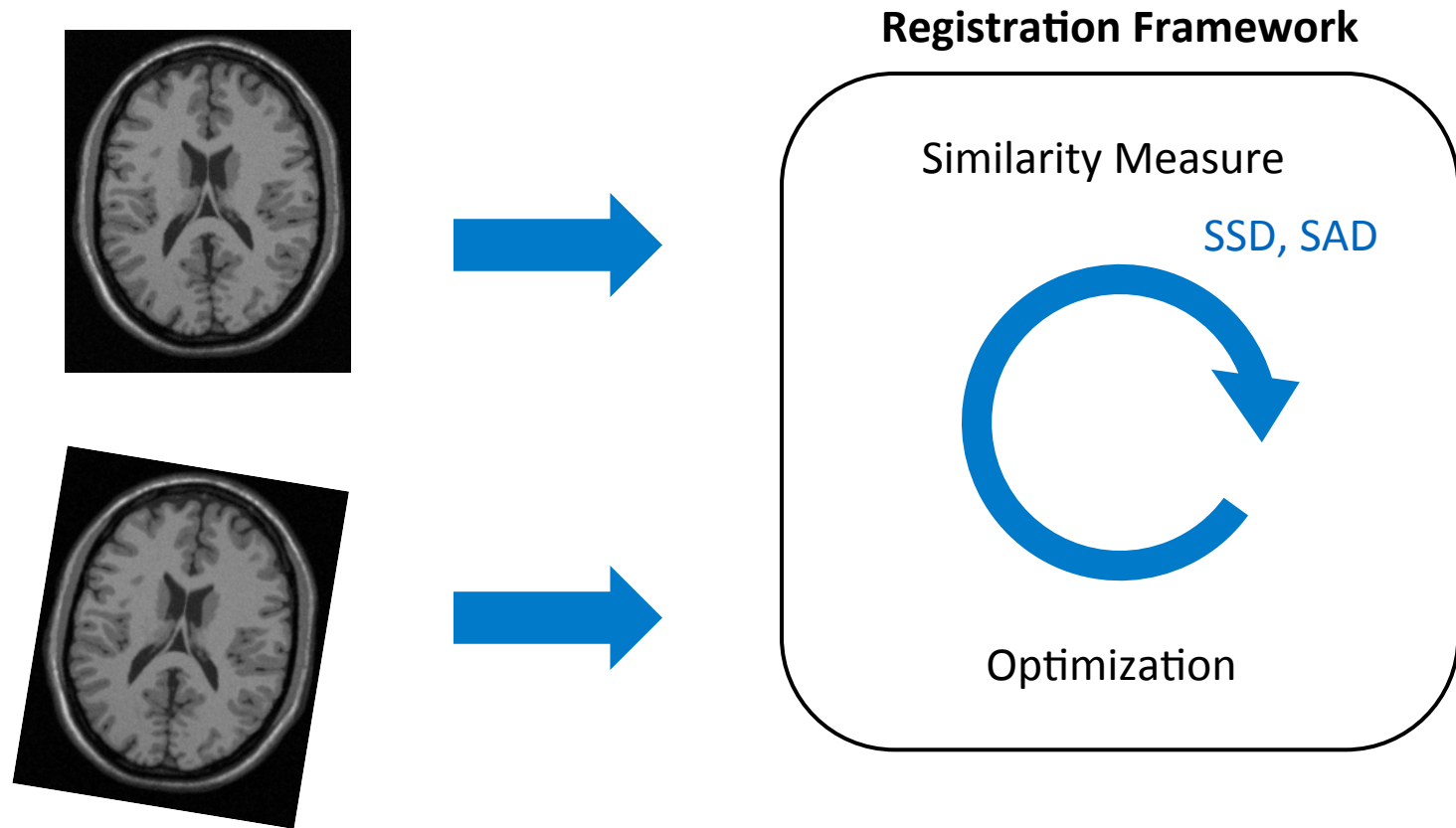
Multi-Modal Registration with Manifold Learning

C. Wachinger, N. Navab, *Entropy and Laplacian Images: Structural Representations for Multi-Modal Registration*, Medical Image Analysis, accepted for publication.

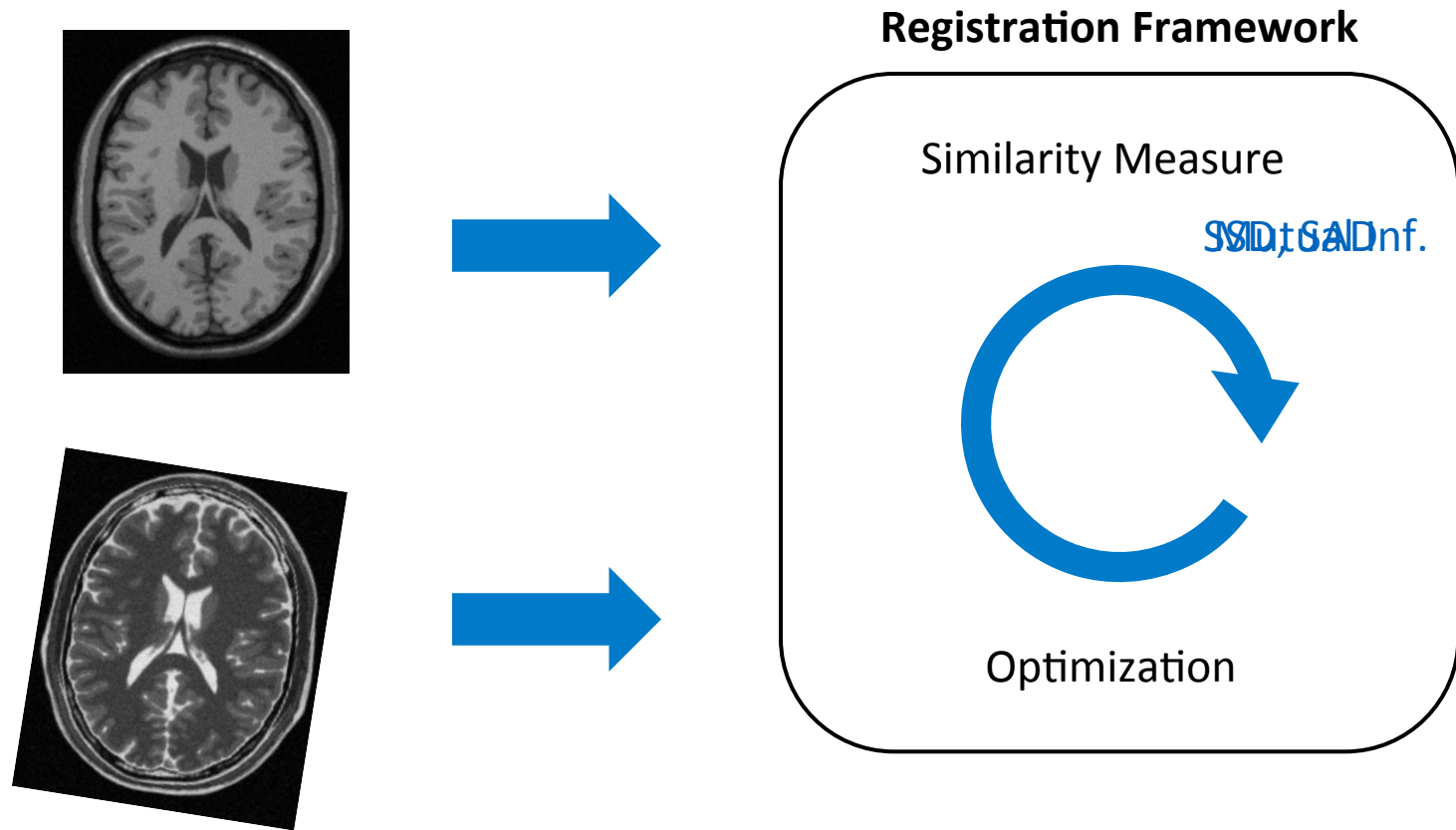
C. Wachinger, N. Navab, *Manifold Learning for Multi-Modal Image Registration*, British Machine Vision Conference (BMVC), 2010.

C. Wachinger, N. Navab, *Structural Image Representation for Image Registration*, MMBIA, 2010.

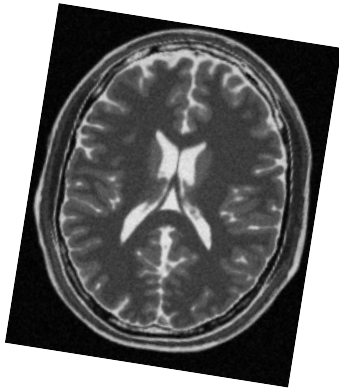
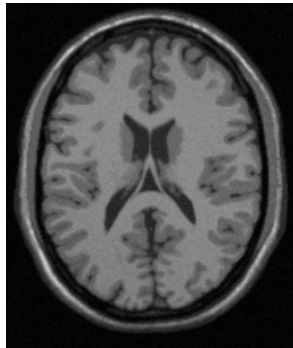
Mono-modal, Intensity-based Registration



Multi-modal, Intensity-based Registration



Registration with Structural Representation



Registration Framework

Advantages:

- Faster similarity evaluation
 - Interactive registration
 - Amortization of pre-processing time
 - Groupwise registration
- Easier assessment of performance
- Seamless integration
- Efficient optimization with ESM

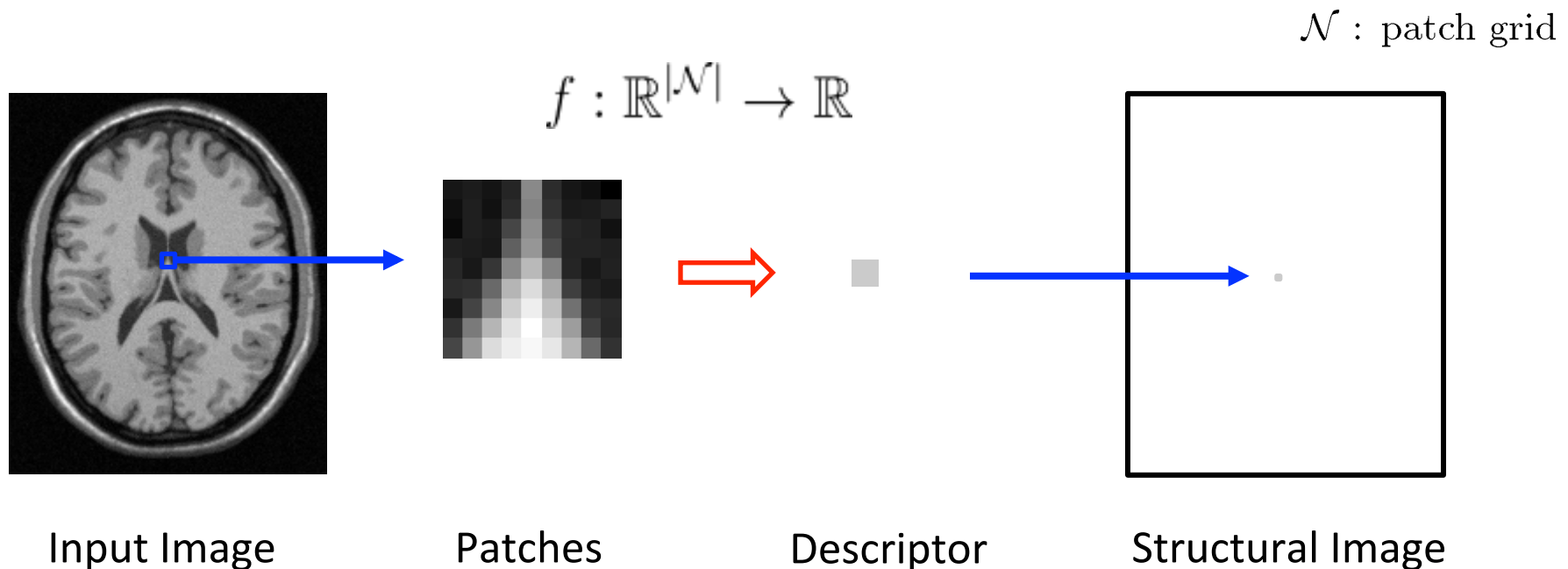
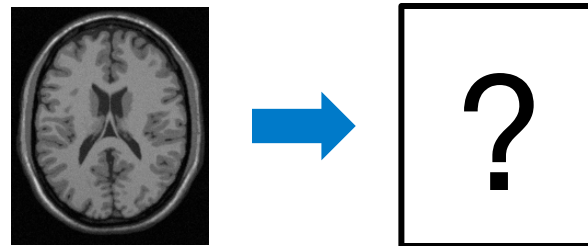
ure

SD, SA, Dnf.



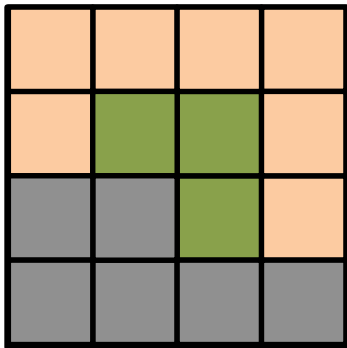
n

How to calculate structural representations?

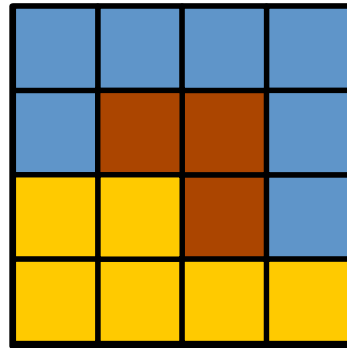


Which patches are structurally equivalent?

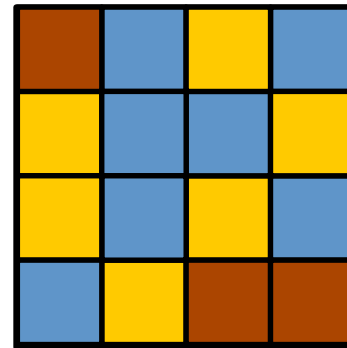
Patch 1



Patch 2



Patch 3



$$P_1 \sim P_2$$

$$P_1 \not\sim P_3$$

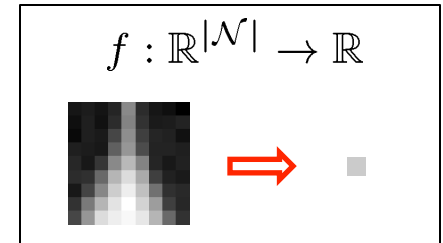
$$P_2 \not\sim P_3$$

Patches P_i and P_j are structurally equivalent $P_i \sim P_j$ if

$$\exists g : \mathcal{I} = \{0, \dots, 255\} \rightarrow \mathcal{I}, \text{ bijective}$$

$$\forall y \in \mathcal{N} : P_i(y) = g(P_j(y))$$

Model for structural representation

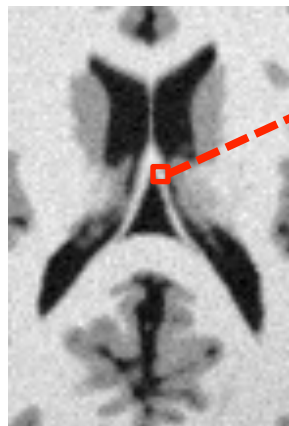


(P1) Locality preservation:

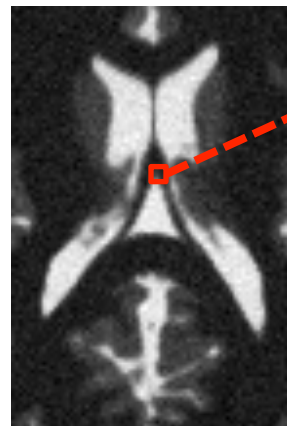
$$\|P_x - P_y\| < \varepsilon \implies \|f(P_x) - f(P_y)\| < \varepsilon'$$

(P2) Structural equivalence:

$$P_x \sim Q_x \iff f(P_x) = f(Q_x)$$



P_x



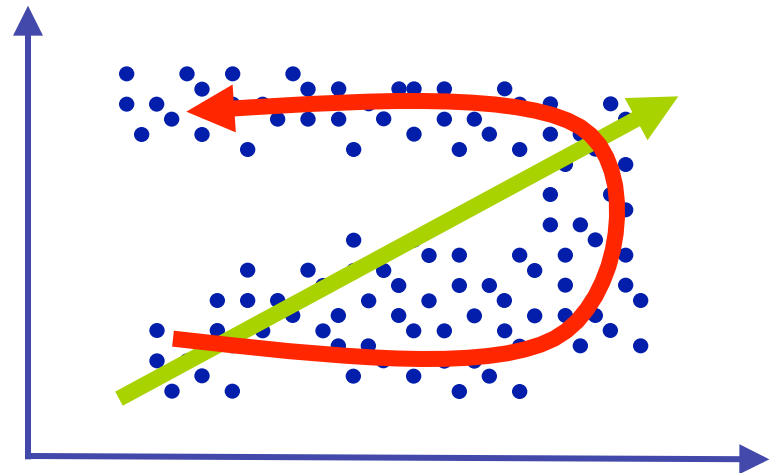
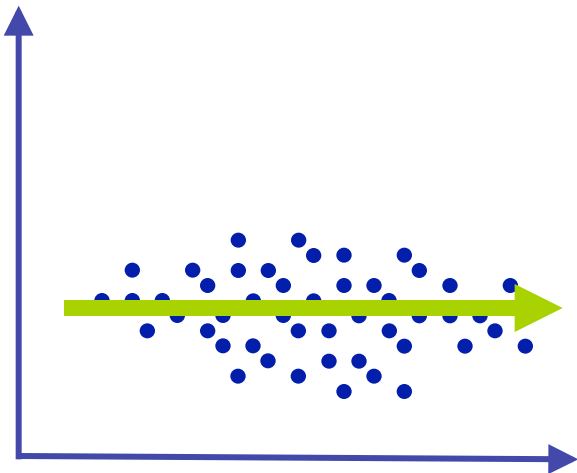
Q_x

Manifold Learning

- Dimensionality reduction, Visualization
- Techniques
 - Isomap : Tenenbaum et al., Science, 2000
 - Locally-Linear Embedding : Roweis, Saul, Science, 2000
 - Laplacian Eigenmaps : Belkin, Niyogi, Neural Comp, 2004

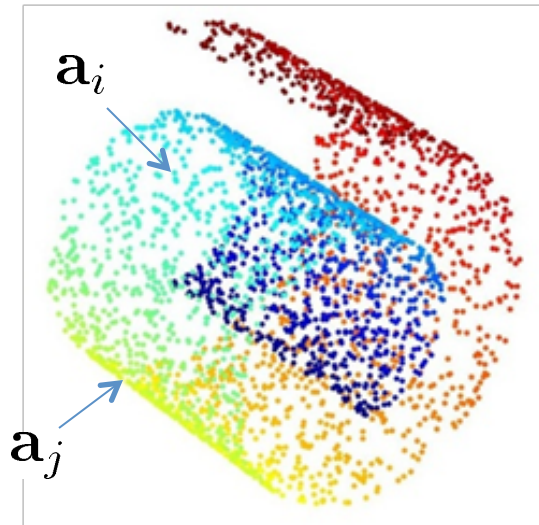
Dimensionality Reduction

Can't we use PCA?

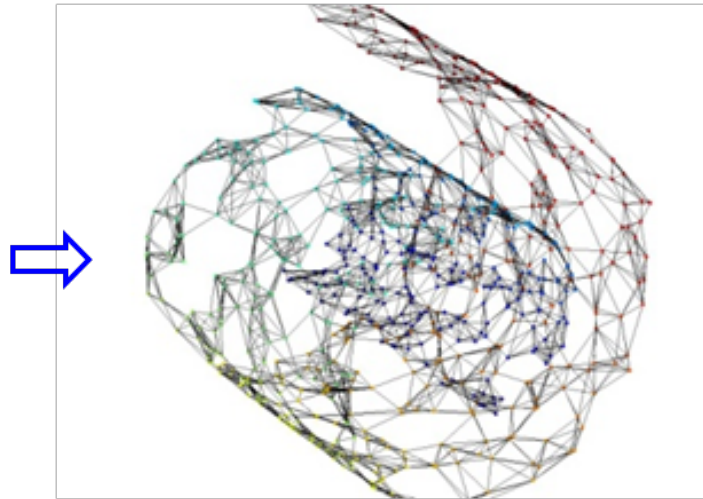


Manifold Learning

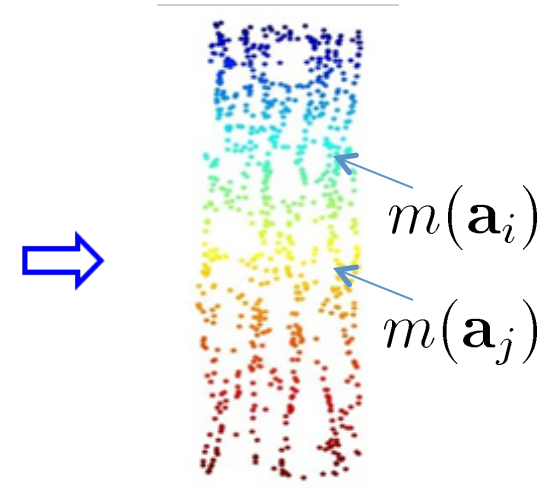
Swiss roll



Manifold



Neighborhood graph

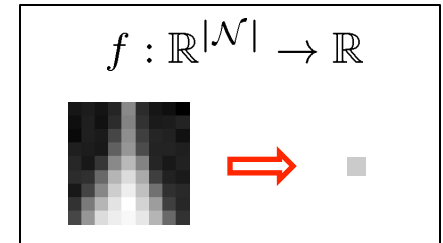


Projection

Locality Preservation:

Laplacian Eigenmaps ensures that points that are close in the high-dimensional space are mapped to close-by points in the low-dimensional projection.

Model for structural representation

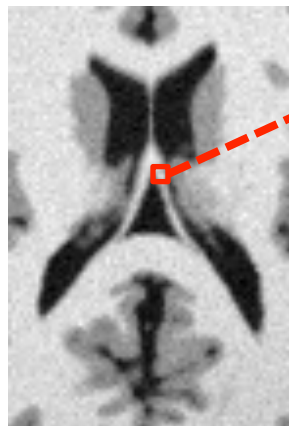


(P1) Locality preservation:

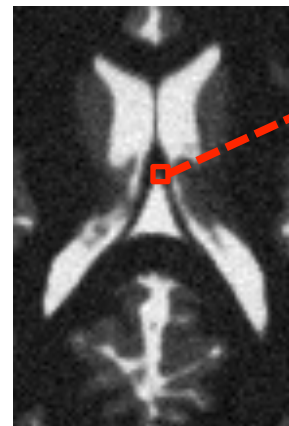
$$\|P_x - P_y\| < \varepsilon \implies \|f(P_x) - f(P_y)\| < \varepsilon'$$

(P2) Structural equivalence:

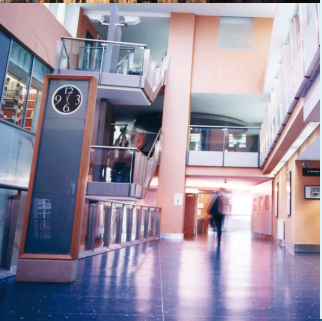
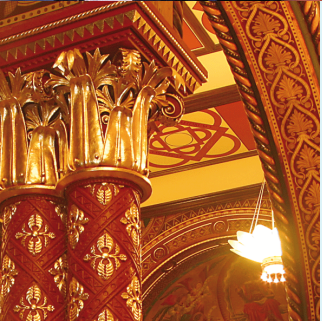
$$P_x \sim Q_x \iff f(P_x) = f(Q_x)$$



P_x



Q_x



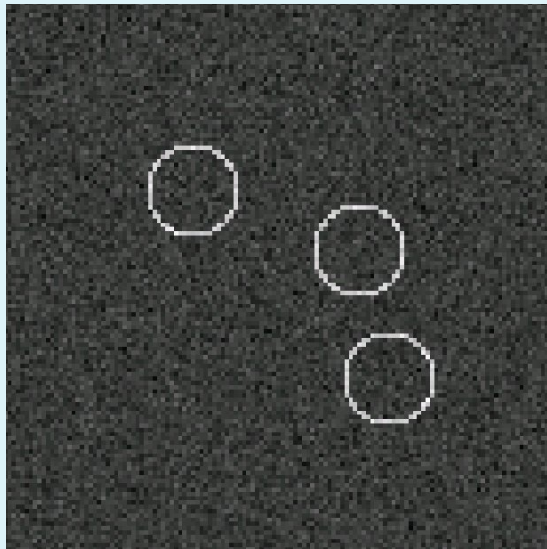
A novel framework for multi-modal intensity-based similarity measures based on **internal similarity**

G.P.Penney^a, L.D.Griffin^b, A.P.King^a and D.J.Hawkes^b

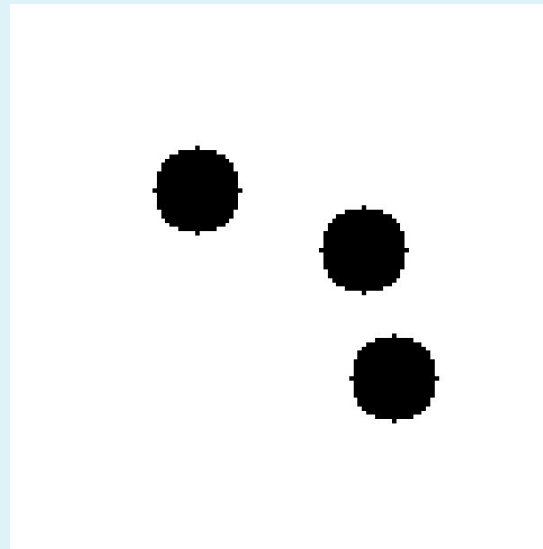
^a Interdisciplinary Medical Imaging Group, Kings College London UK;
^b Centre of Medical Image Computing, University College London, UK.

Worked Example

Example synthetic images:



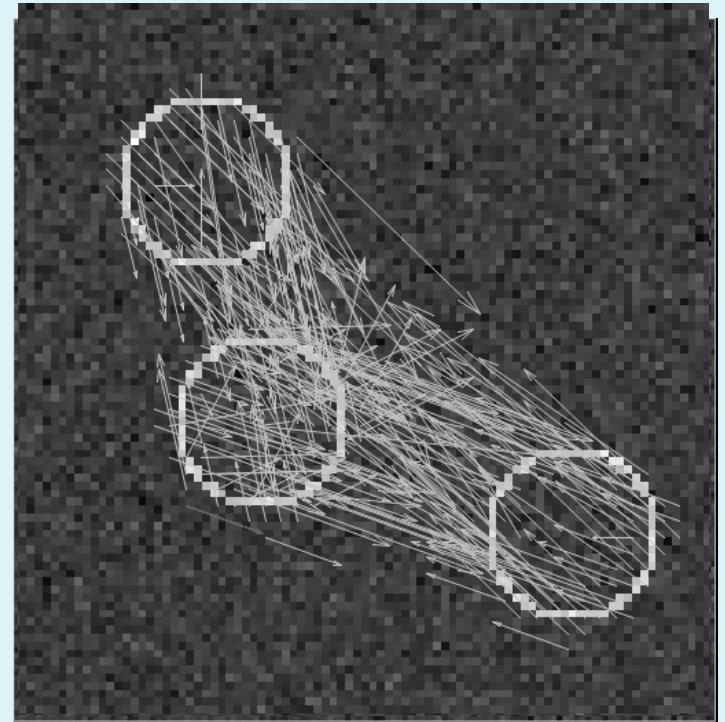
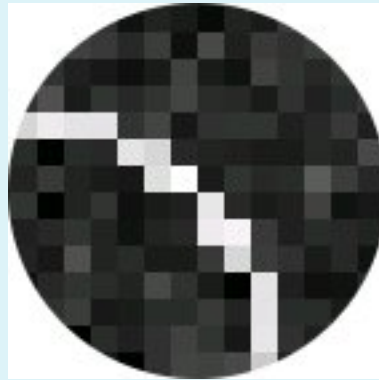
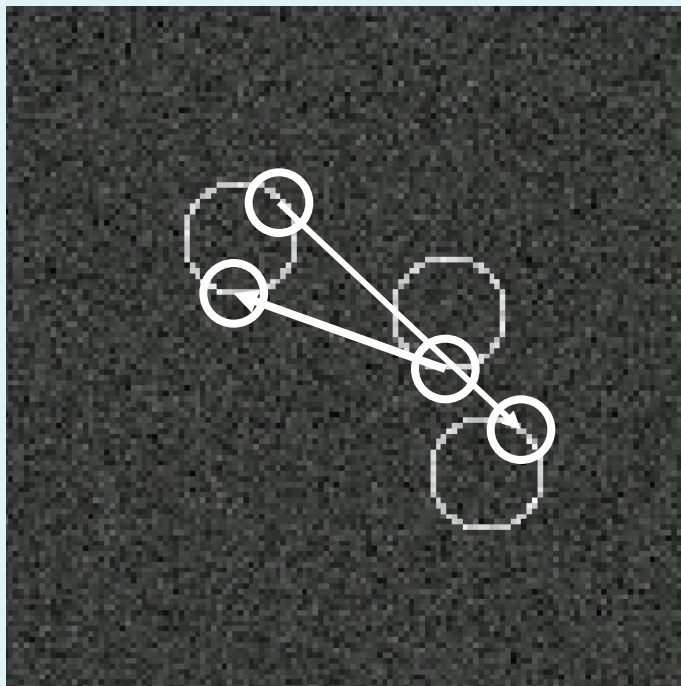
Fixed Image $F(\mathbf{x})$



Moving Image $M(\mathbf{x})$

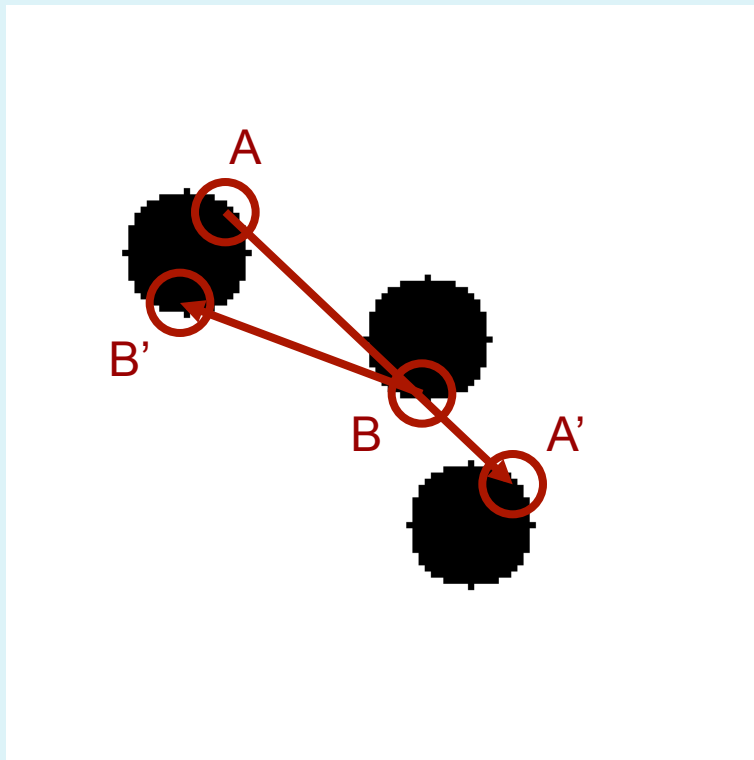
First Stage: Fixed Image

Aim is to find internally similar regions



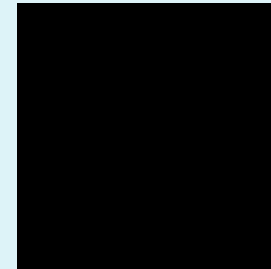
Second Stage: Moving Image

- Involves
1. Moving Image $M(\mathbf{x})$
 2. Patch positions and rotations (\mathbf{T}_{pi} , \mathbf{x}_i)
 3. Registration transformation \mathbf{T}

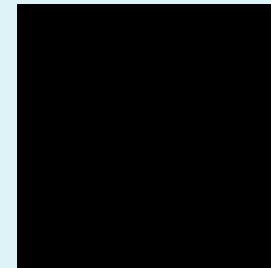


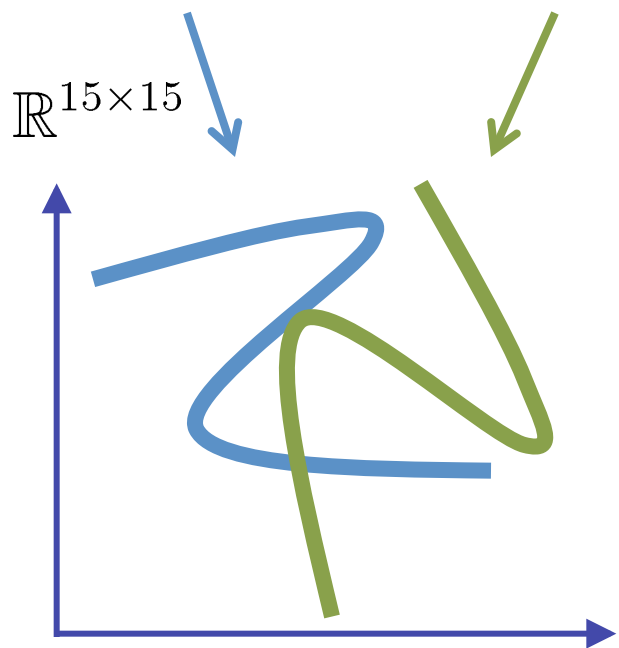
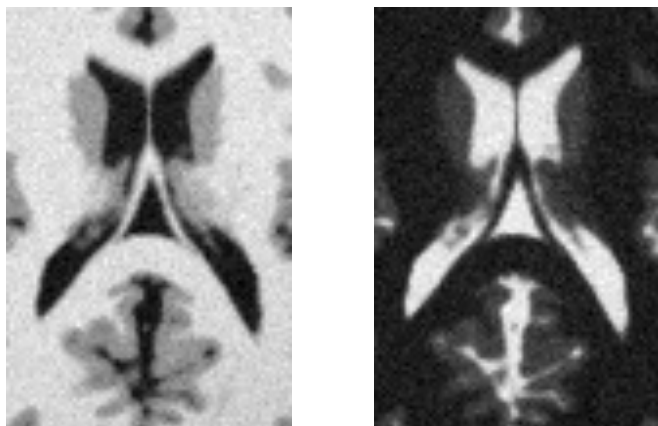
Difference Images

Patches
A and A'



Patches
B and B'





Two times manifold learning

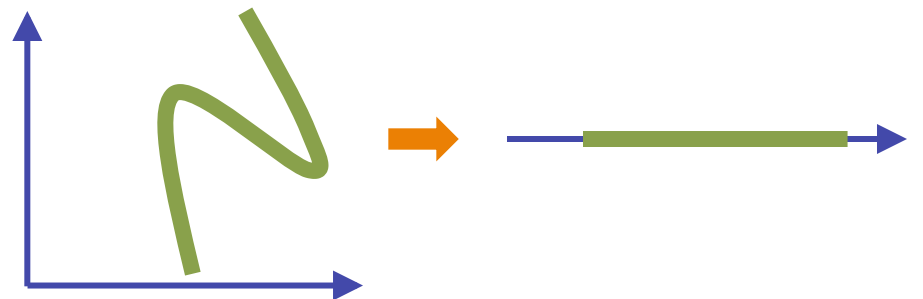
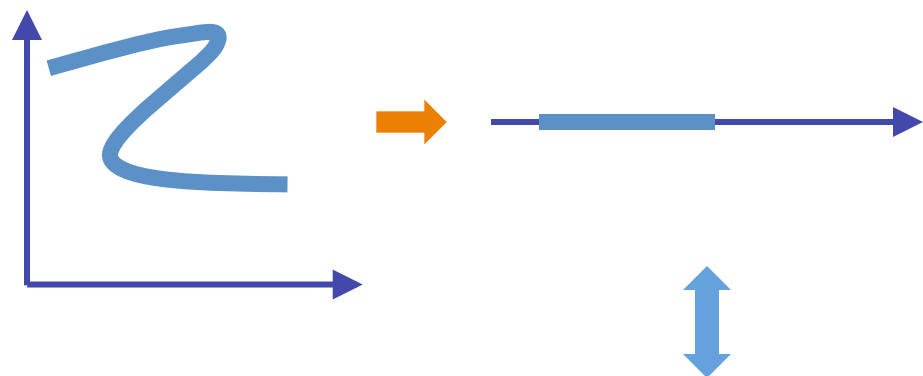
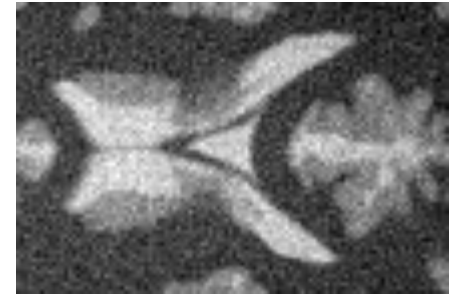
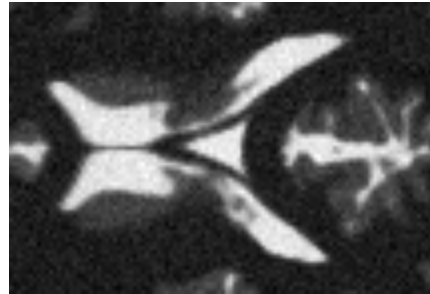
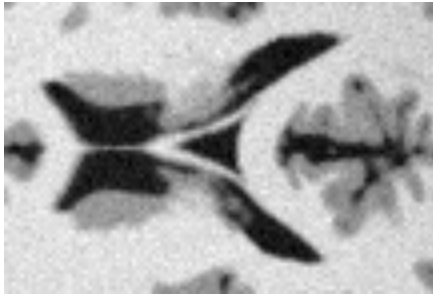
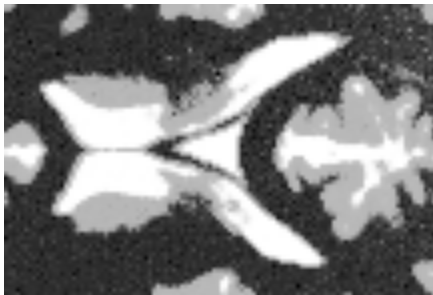


Image Results T1, T2, PD

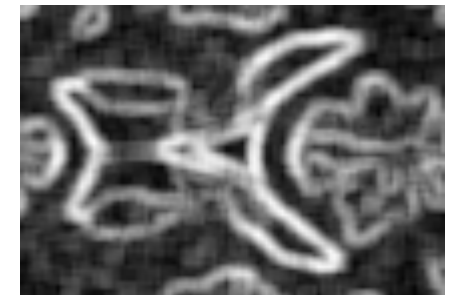
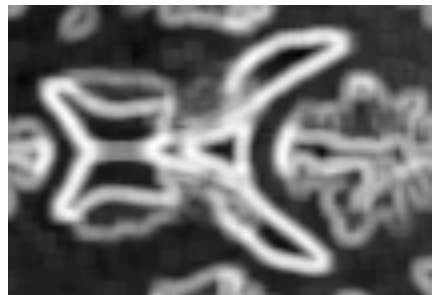
Images



Laplacian
(this work)

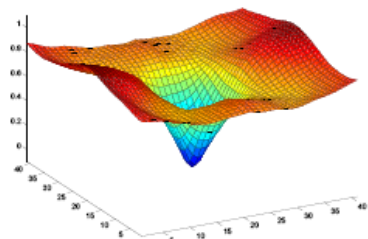


Entropy
(previous approach)

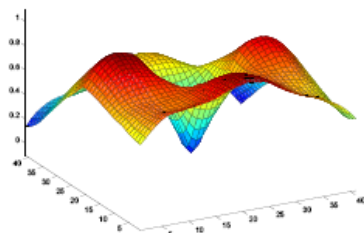


Errors from registration study

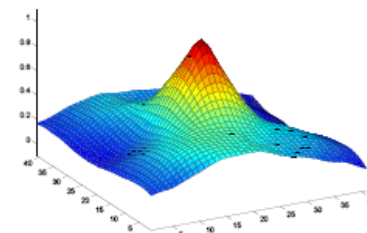
Datasets	Similarity	Rotation	Trans X	Trans Y	RMS
T1-T2	L2	4.879	9.019	6.471	7.000
	MI	2.325	3.768	5.226	3.954
	Entropy	2.084	4.539	5.231	4.180
	Laplacian	2.584	2.061	2.1680	2.271
T1-PD	L2	2.760	6.422	5.755	5.227
	MI	2.304	4.138	4.907	3.937
	Entropy	2.283	4.782	4.750	4.108
	Laplacian	1.750	3.007	1.929	2.297
T2-PD	L2	1.784	2.947	2.916	3.942
	MI	2.161	4.628	3.812	3.680
	Entropy	1.723	4.296	3.780	3.450
	Laplacian	1.171	2.350	1.984	1.900



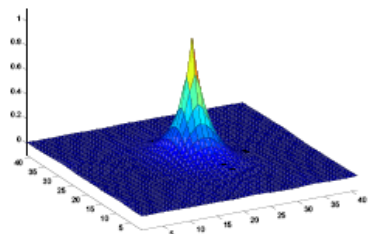
(a) L2 Original, T1-T2



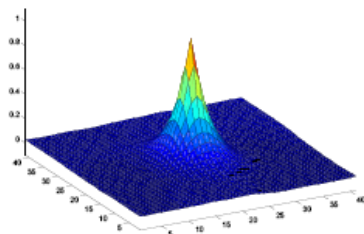
(b) L2 Original, T1-PD



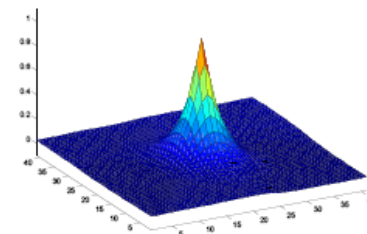
(c) L2 Original, T2-PD



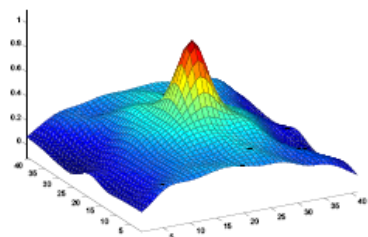
(d) MI Original, T1-T2



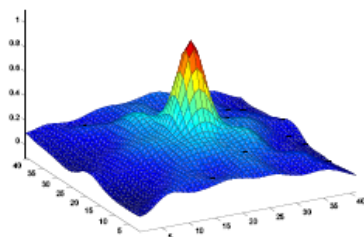
(e) MI Original, T1-PD



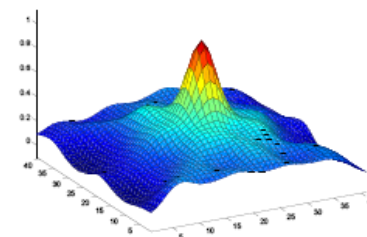
(f) MI Original, T2-PD



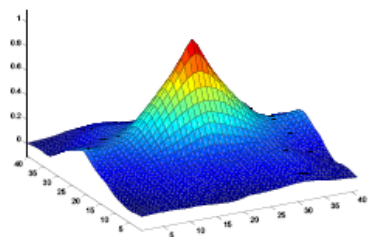
(g) L2 Entropy, T1-T2



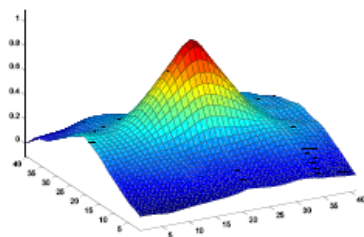
(h) L2 Entropy, T1-PD



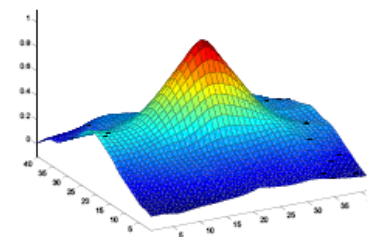
(i) L2 Entropy, T2-PD



(j) L2 Laplacian, T1-T2



(k) L2 Laplacian, T1-PD

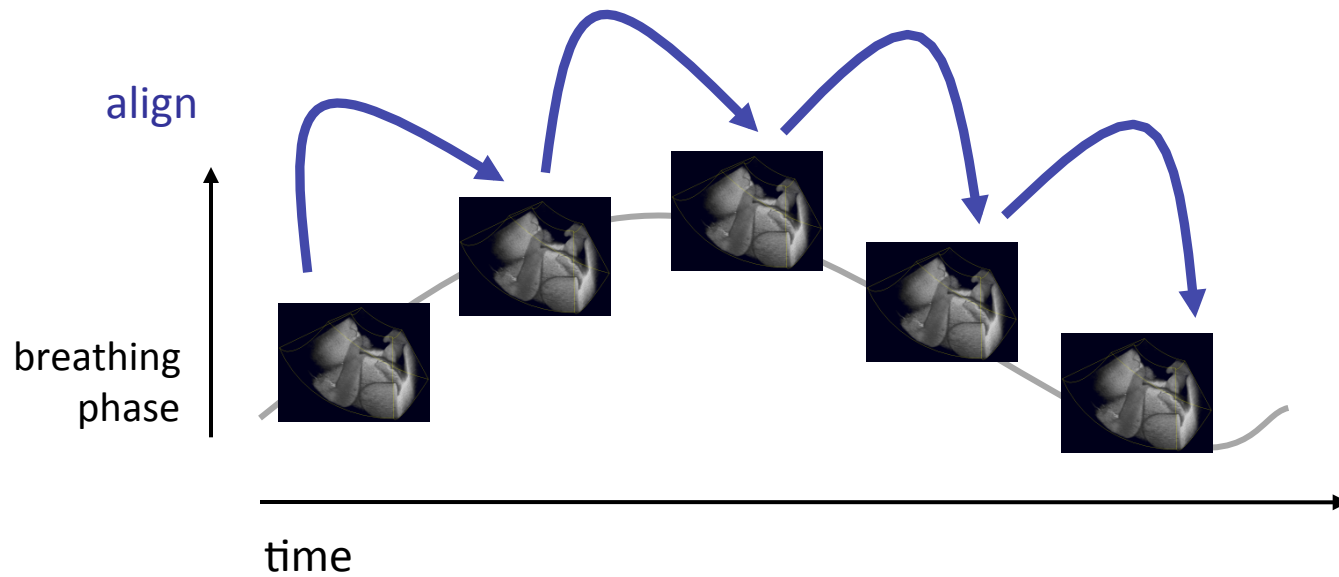


(l) L2 Laplacian, T2-PD

Ultrasound Breathing-Gating with Manifold Learning

C. Wachinger, M. Yigitsoy, N. Navab, *Manifold Learning for Image-Based Breathing Gating with Application to 4D Ultrasound*, MICCAI 2010

Breathing Modeling from Ultrasound

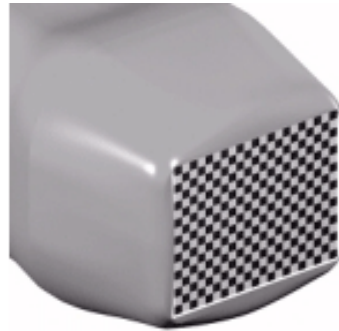


Volumetric Ultrasound

Freehand



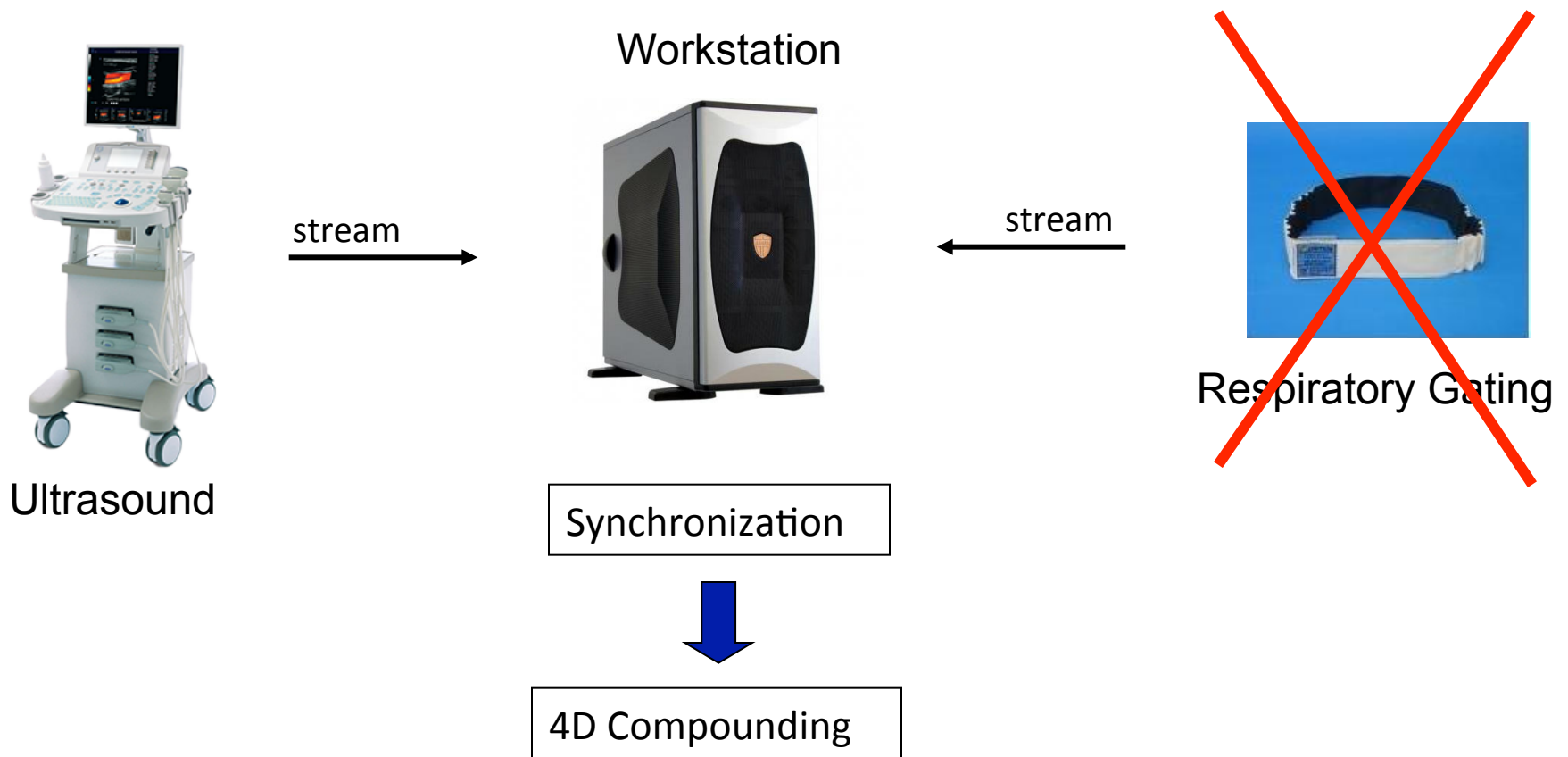
2D Array



Wobbler



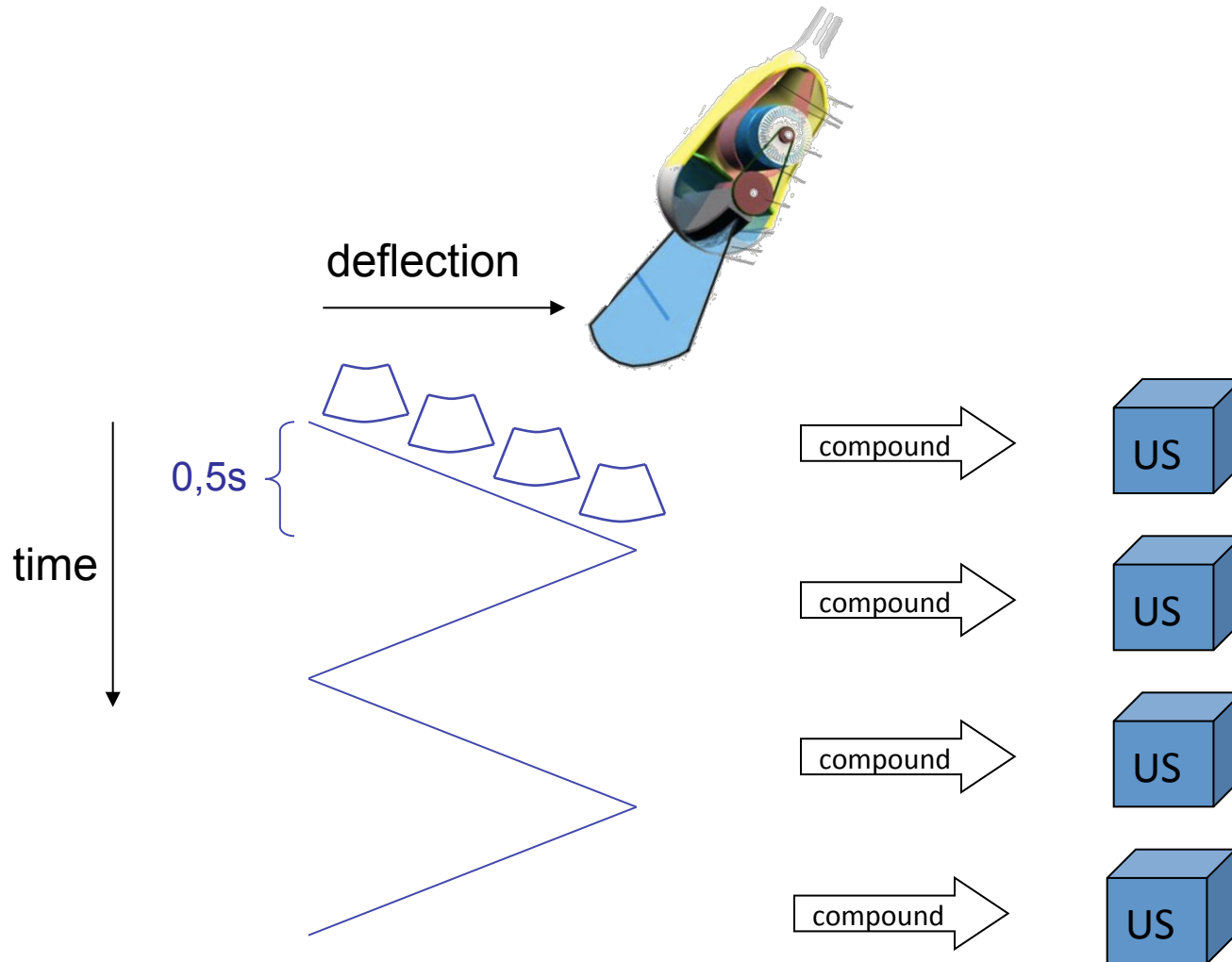
4D Breathing Ultrasound with Wobbler



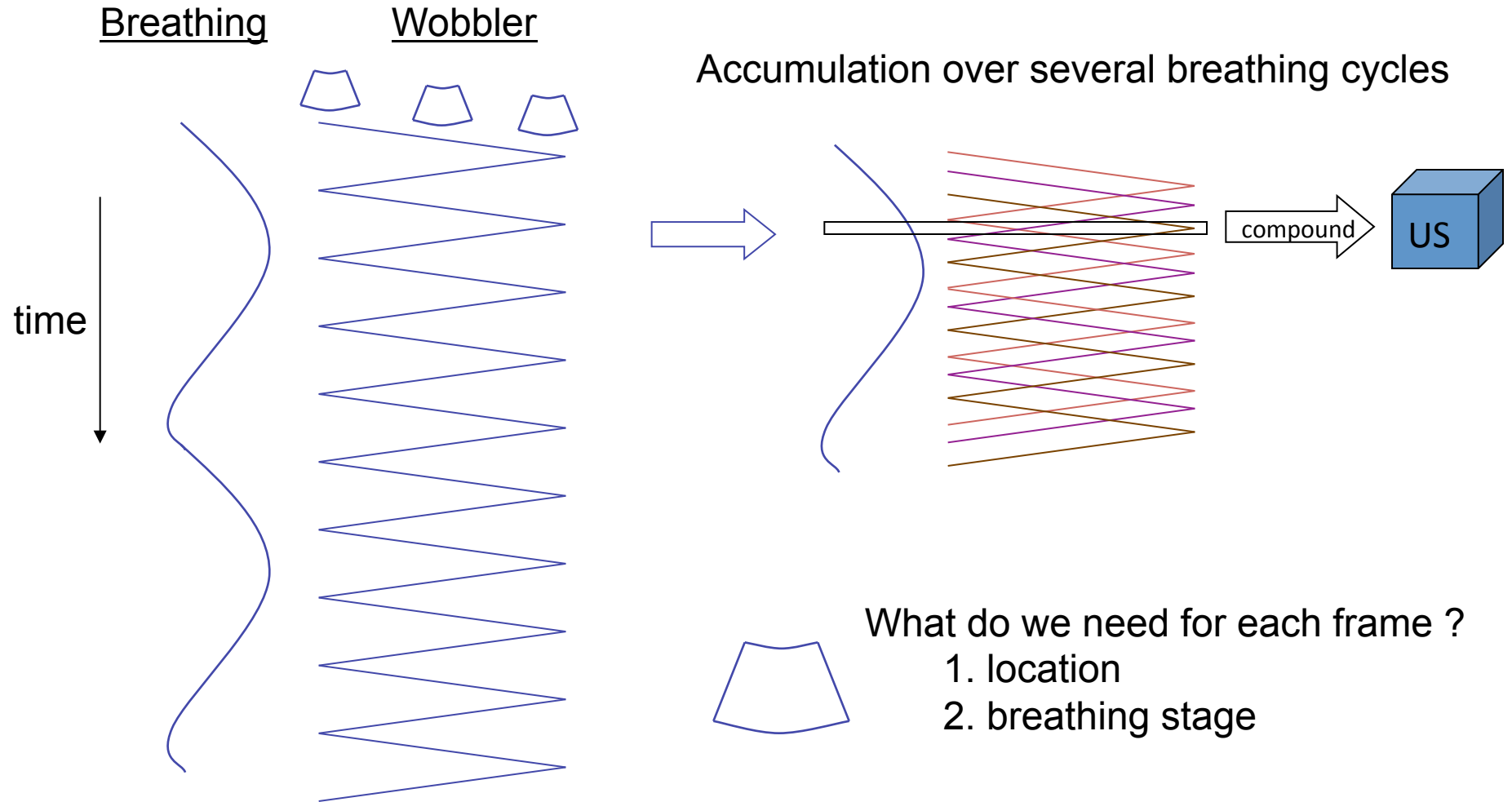
Manifold Learning for Image-Based Breathing



4D Breathing Ultrasound with Wobbler



4D Breathing Ultrasound with Wobbler



Manifold Learning for Image-Based Breathing Gating



- No need for gating system
- No synchronization

Application of Manifold Learning

- Each image is a point in high dimensional space

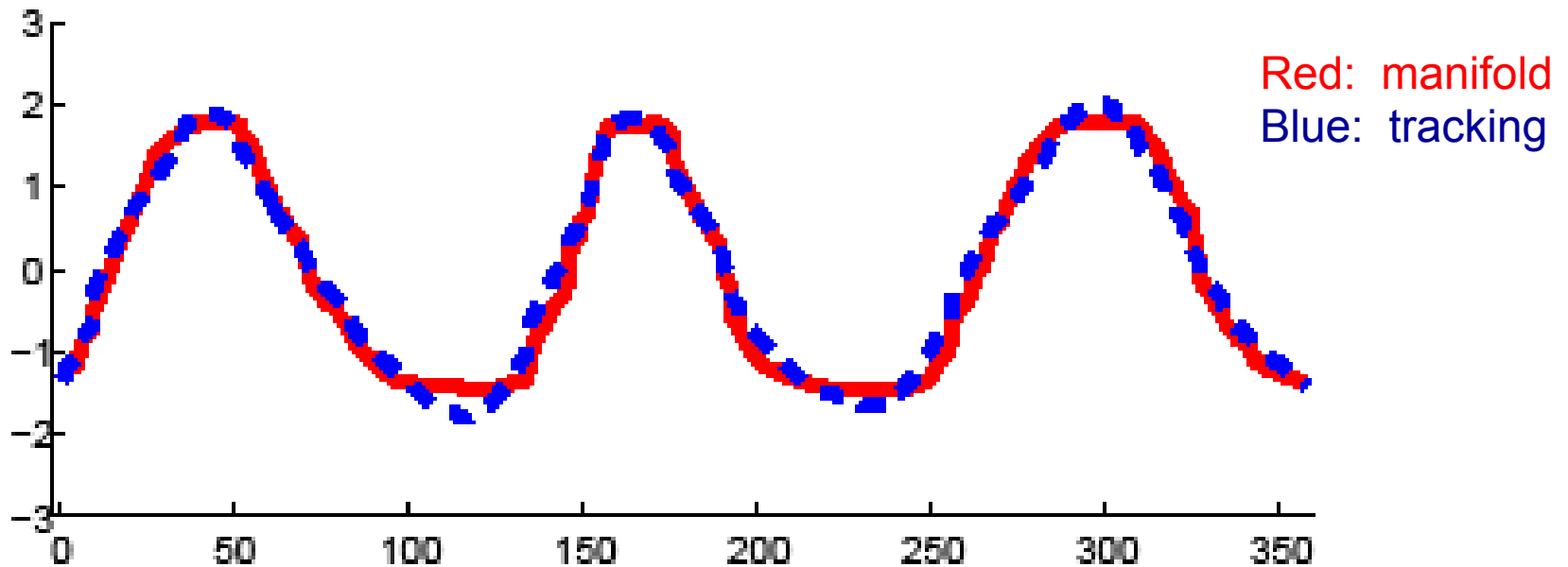
$$\left(\text{Image} \right) \in \mathbb{R}^{640 \times 480}$$

- Changes between images are smooth
- Images at different times but same breathing stage are similar
- Learn manifold that image points are lying on
- Project to 1-dimensional subspace

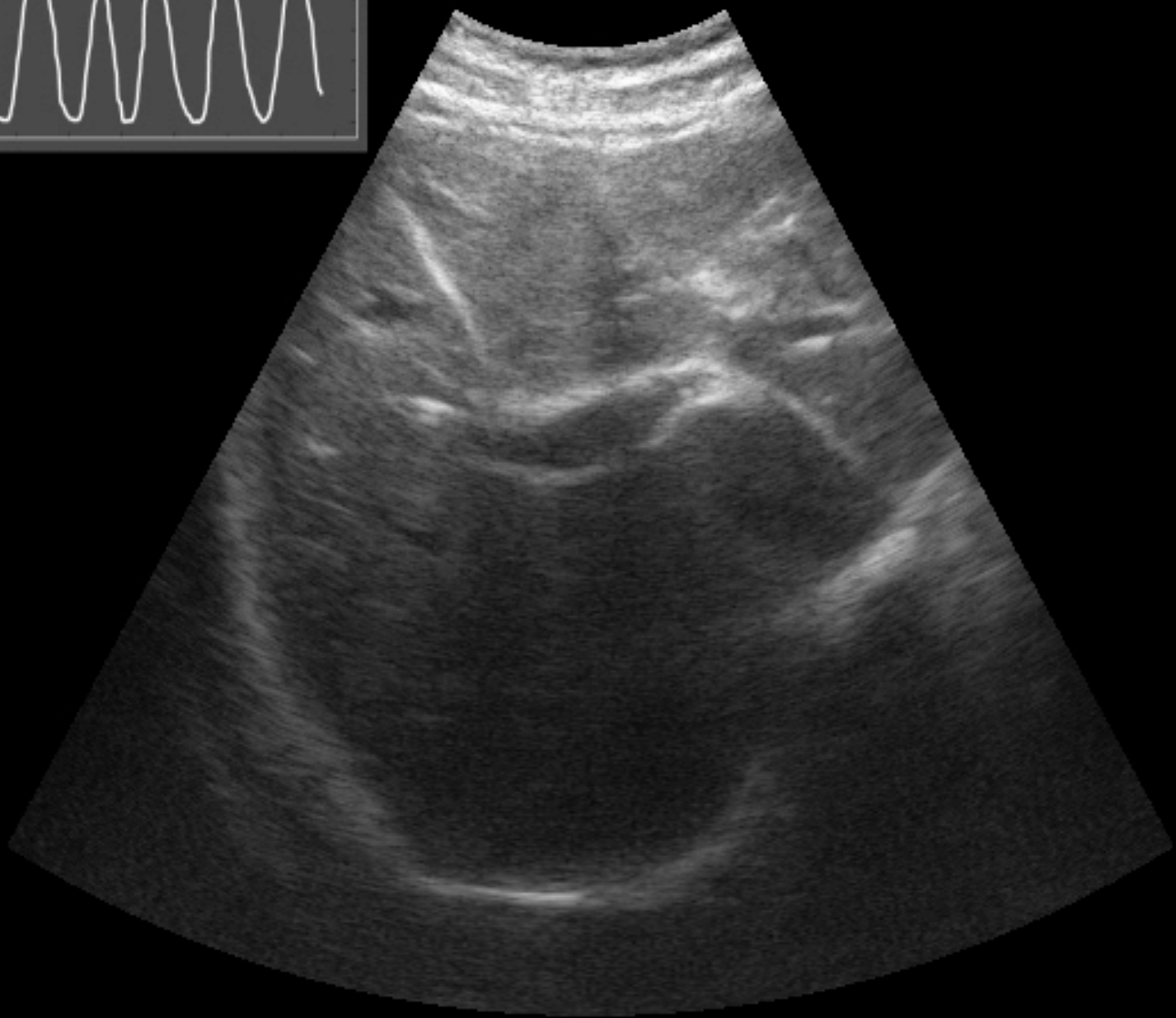
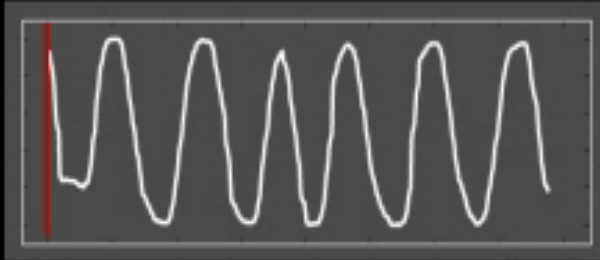
Laplacian Eigenmaps Facts

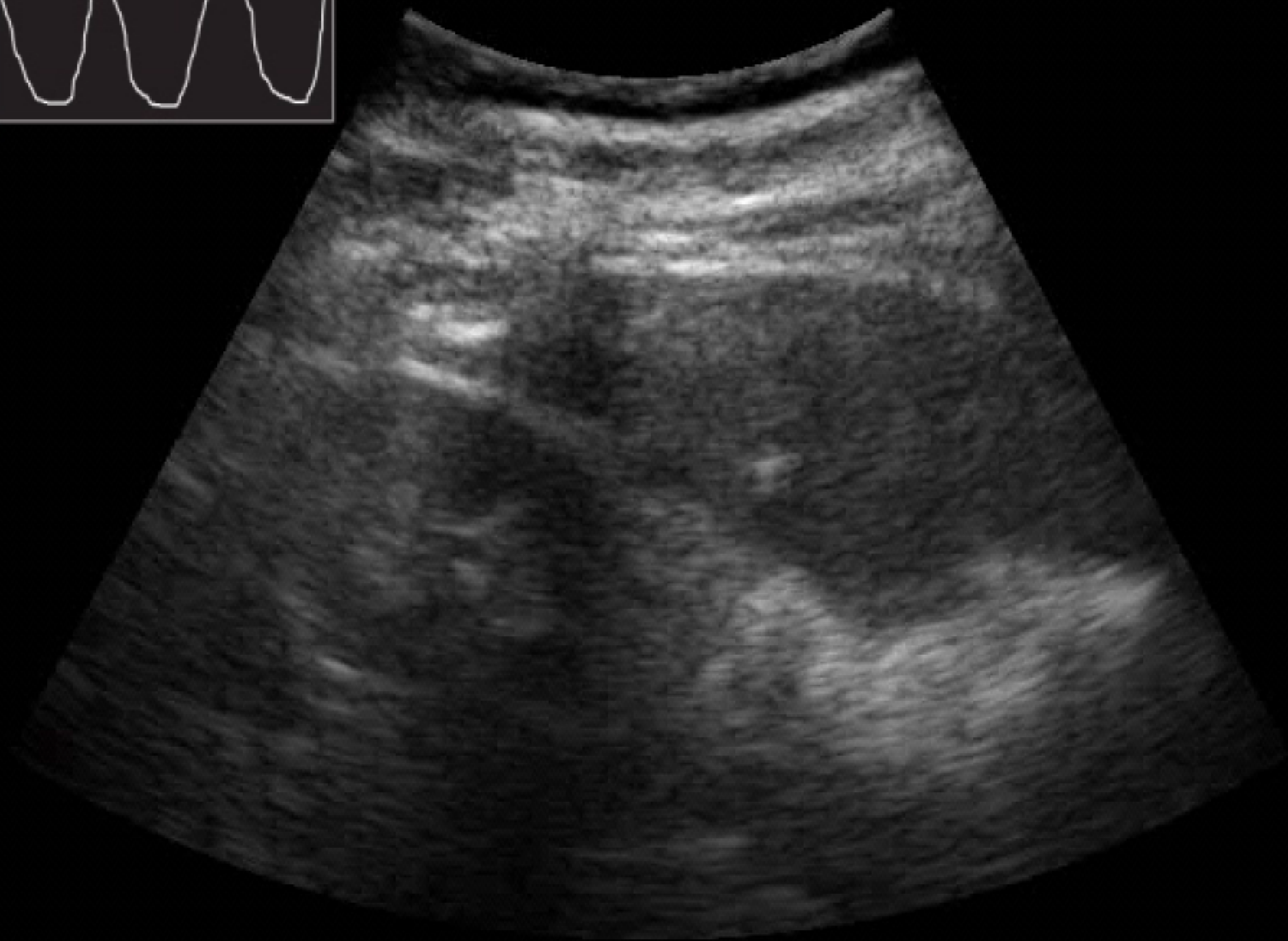
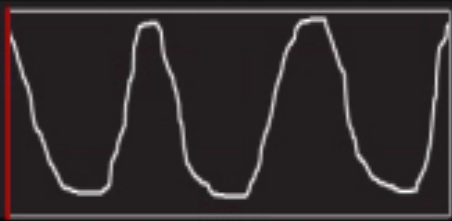
Ambient space:	$640 \times 480 \times 0.25 = 76,800$
Nearest neighbors:	14
Manifold dimension:	1
Heat weights on graph:	$e^{-\frac{(x_i - x_j)^2}{\sigma}}$

Breathing Gating Laplacian Eigenmaps (2D Ultrasound)

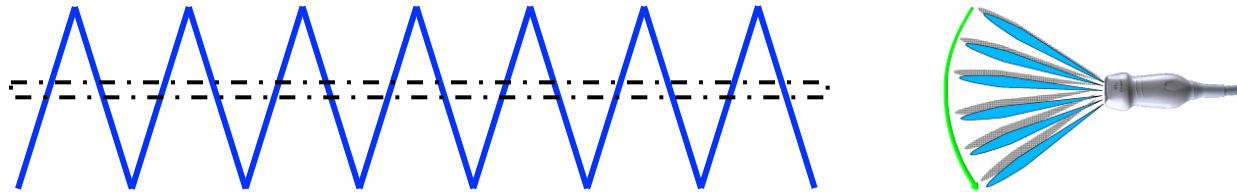


Correlation Coeff: 95.8 %

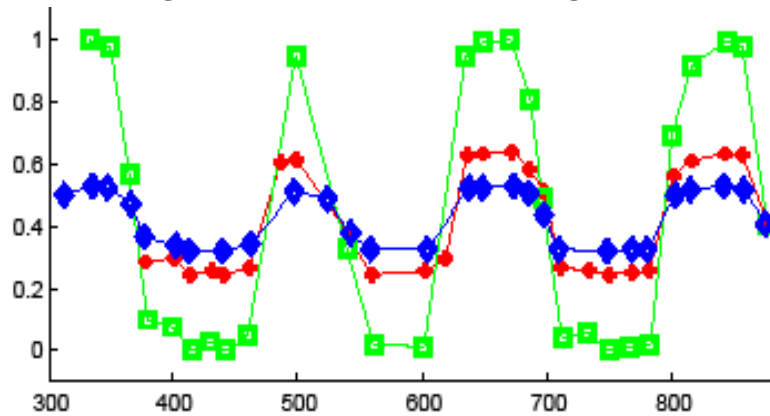




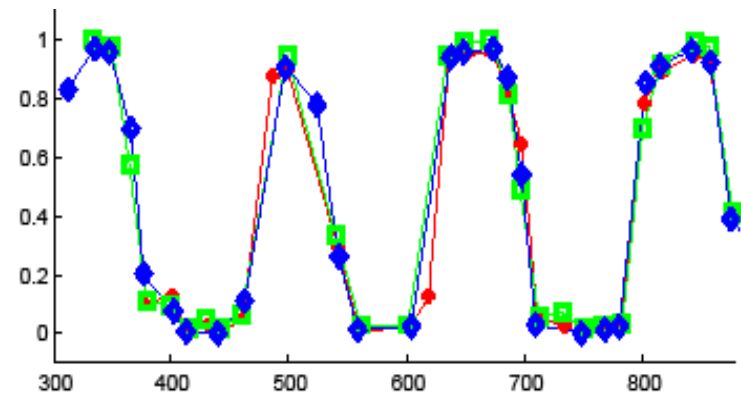
Consistent 4D breathing estimation



Unaligned local breathing curves

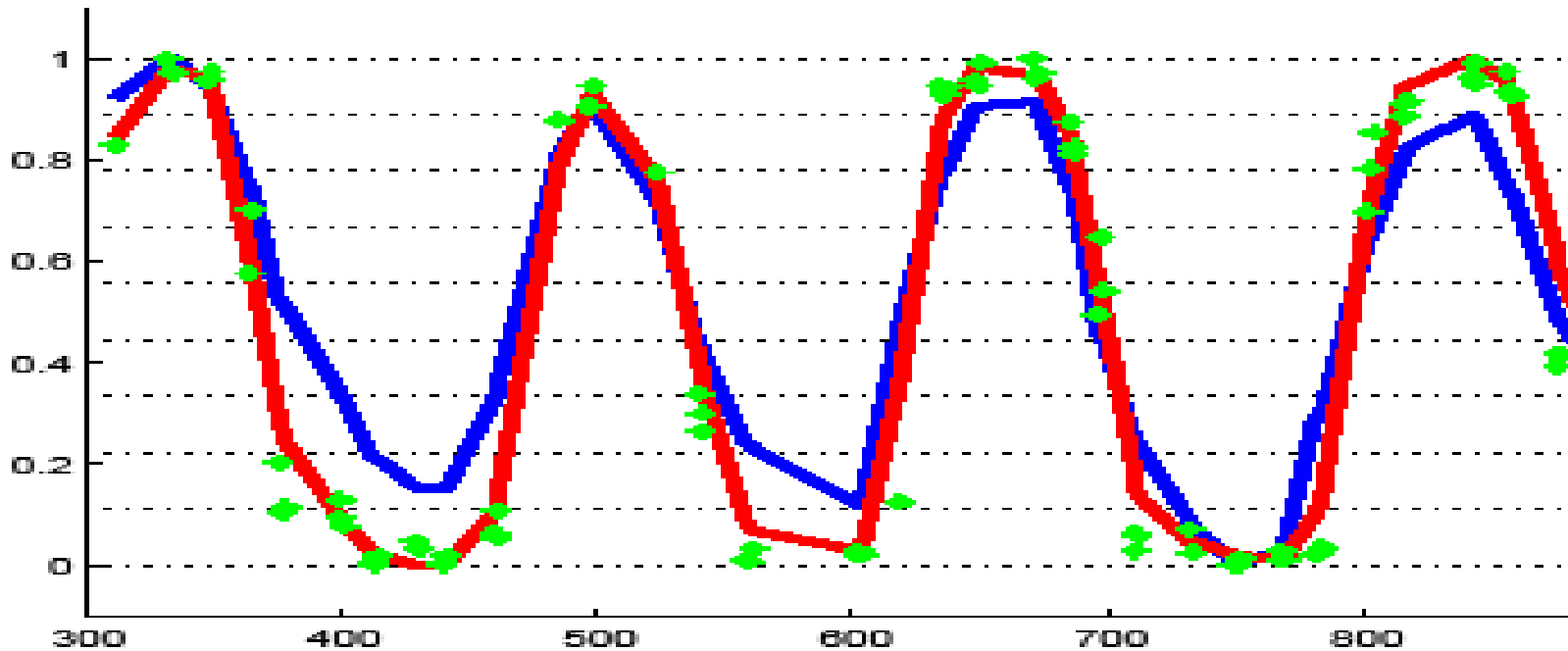
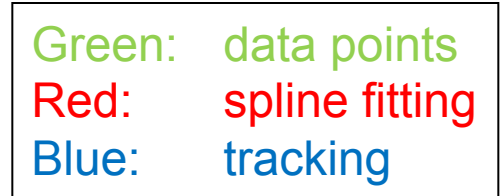


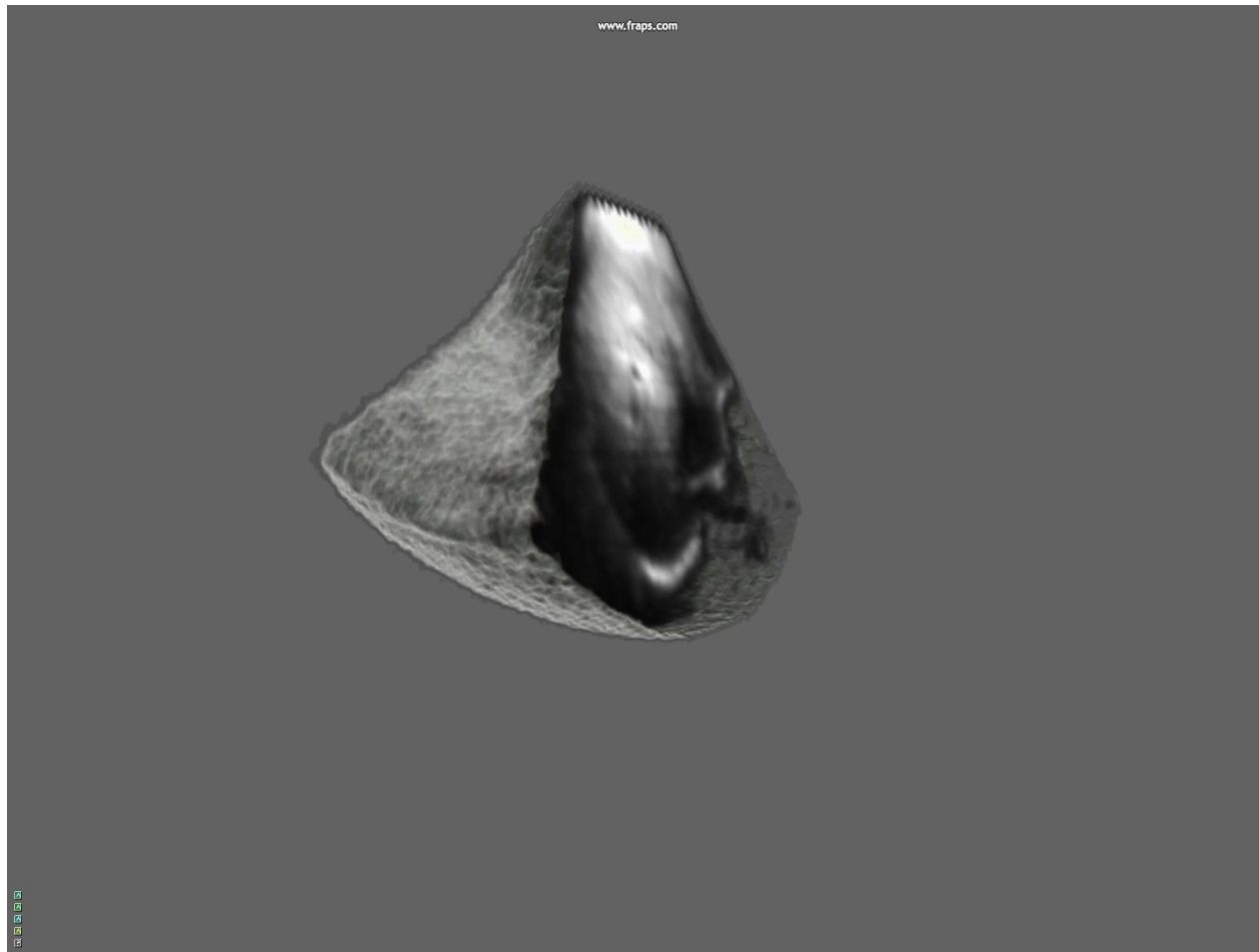
Aligned local breathing curves



Consistent 4D breathing estimation

- Robust curve fitting
- Compound volume for each dotted region





Correlation with external tracking

2D Correlation	
liver1	95.4
liver2	94.4
liver3	93.6
kidney	97.3

Table 1: 2D

3D Correlation	
liver 30°	94.3
liver 45°	95.8
liver 60°	96.8
kidney 45°	94.4

Table 2: 3D

Discussion

- Acquisition from same location
 - Analyzed motion trajectories by tracking wobbler
 - Good results of experiments
 - Usable in practice
- Retrospective gating
- Extension to breathing gating on MRI
 - M. Yigitsoy, C. Wachinger, N. Navab, *Manifold learning for image-based breathing gating in MRI*, SPIE Medical Imaging, 2011

END

To contact Christian Wachinger:
wachinge@in.tum.de