

# A Practitioner's View on (Normalized) Mutual Information

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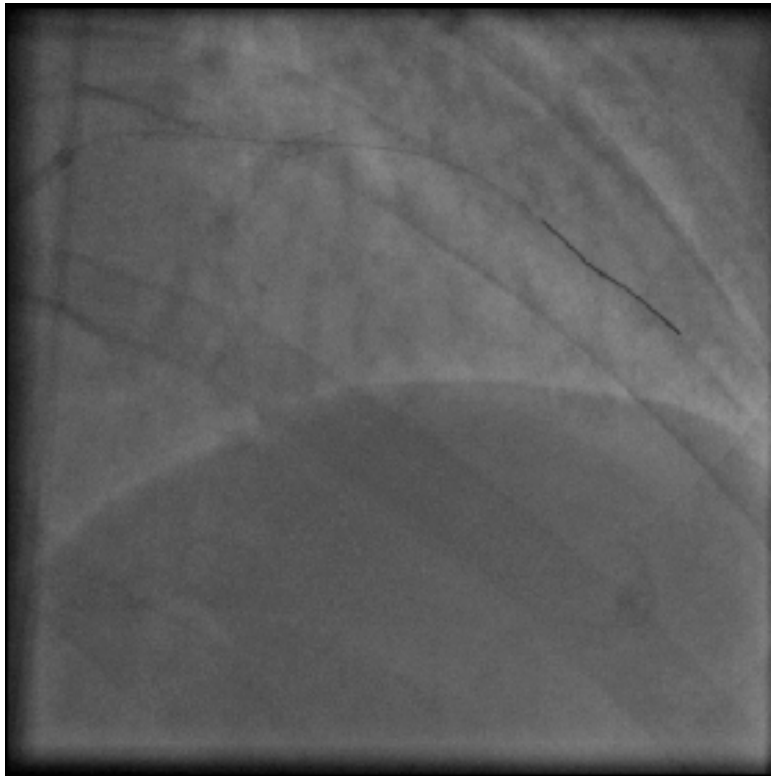
Erlangen-Nürnberg



# Overview

- Introduction
- Parzen Windowing
- Histogram Binning
- Jittering
- Conclusions

# Cardiac Imaging

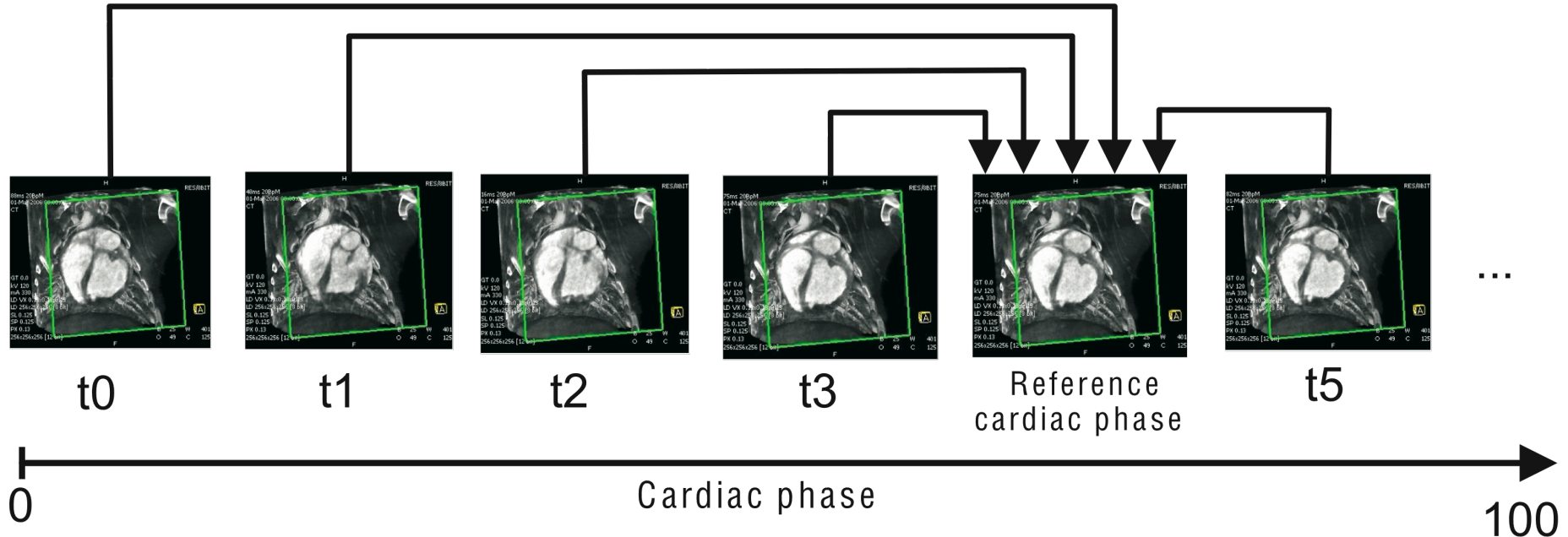


# Registration and Reconstruction

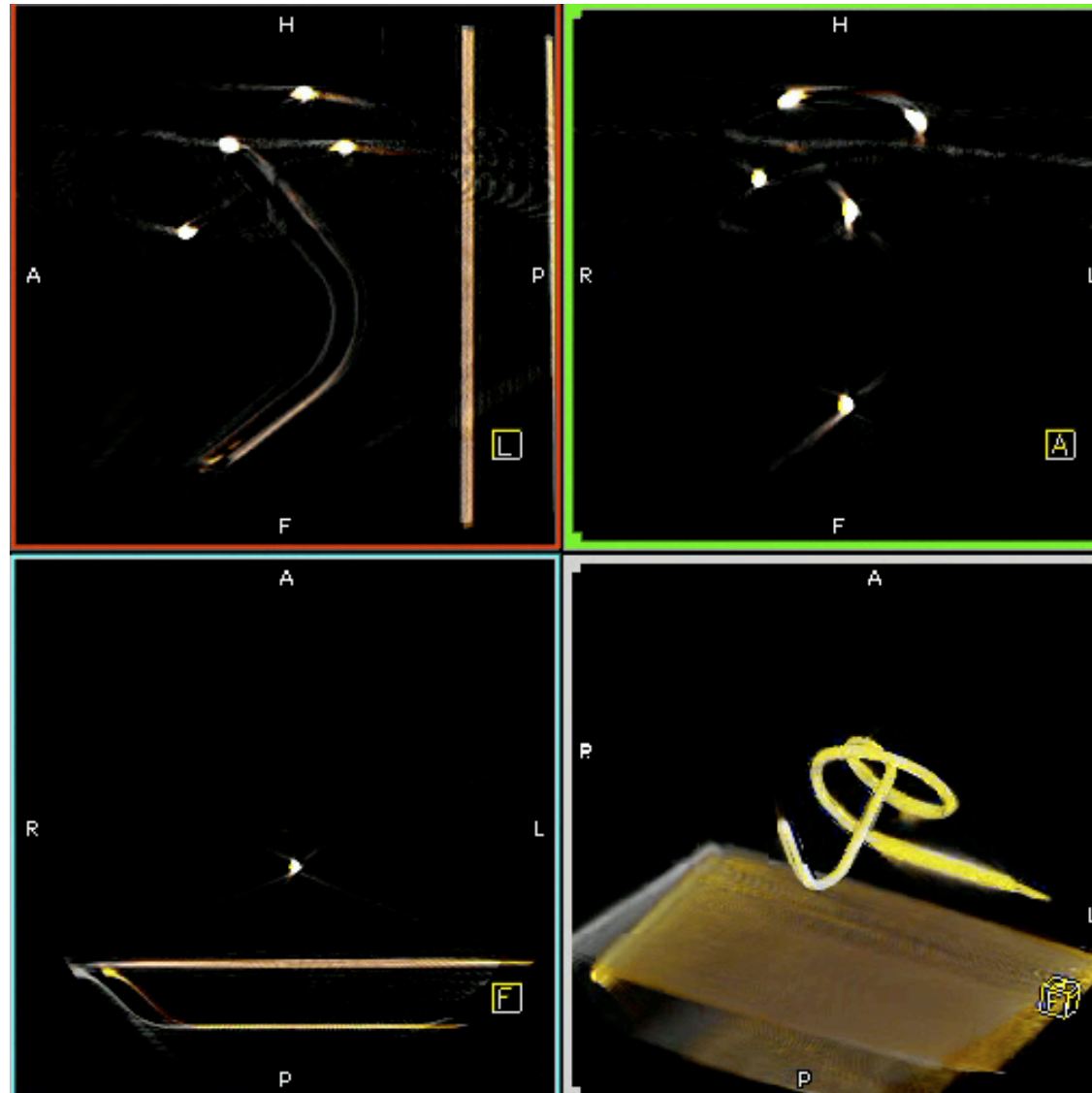


## ■ 3-D/3-D registration:

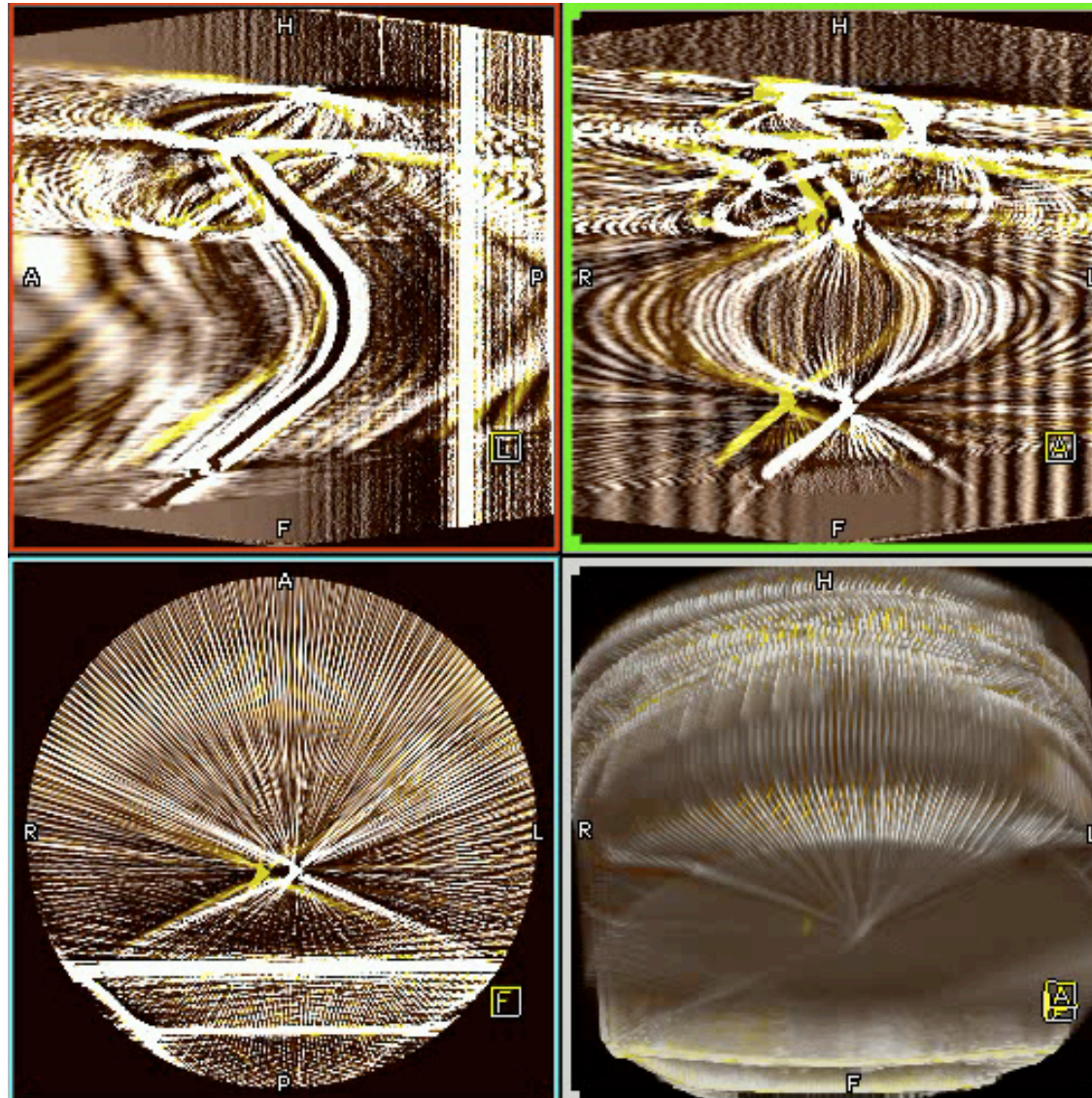
Reconstruct certain heart states, register 3-D volumes, interpolate deformation fields



# Interventional Imaging



# Interventional Imaging



# Goals of our work



- Multi-modality registration
- Highly efficient registration ( $< 5$  sec., CUDA)
- Parameter free and of clinical use
- Integration in the ITK/VTK framework
- Experimental evaluation using benchmark data sets (RIRE version 2.0: CT-MR, PET-MR, MR-MR)

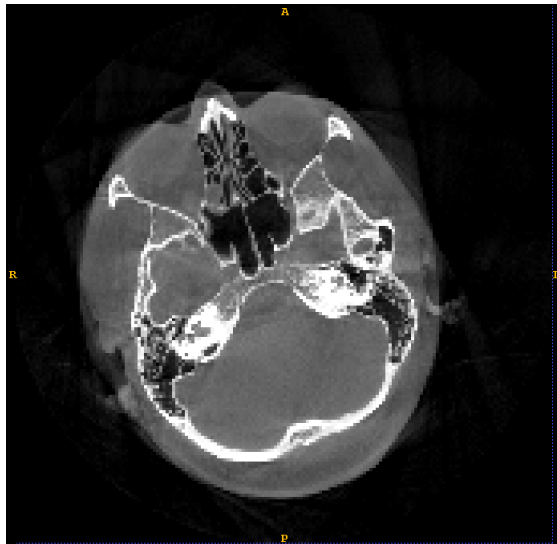


# Registration

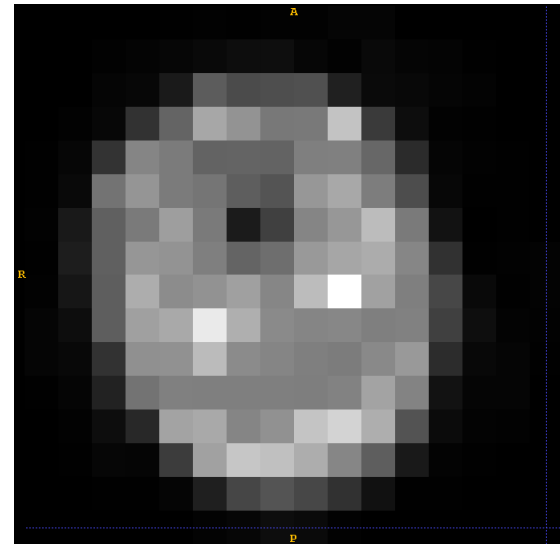


- Why another standard registration implementation?
  - Correct implementation of mathematical formulation
  - Numerically accurate multileveling (no drastical SNR reduction)
  - Statistical similarity measures
- Speed is achieved by subvoxel accurate registration on low resolution images
- High expectations on sublevel registrations

256x256



16x16





# (Normalized) Mutual Information



- Universally usable registration has to be multimodal
  - Mutual Information is currently state-of-the-art
- Statistical information degrades with lower resolution
- Numerical problems of MI in low resolution images known from literature



# Image Registration

- Normalized Mutual Information (NMI)

$$\mathcal{D}_{\text{NMI}}[R, T_{\Phi}] = -\frac{\mathcal{H}(R) + \mathcal{H}(T_{\Phi})}{\mathcal{H}(R, T_{\Phi})}$$

- Question:

How to always achieve good PDF estimates?

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# Parzen-Window Estimation



## ■ **Efficient discretization:**

- Discretization of pdf using histogram and Parzen estimator
- Kernel width estimation
- Number of bins and bin size
- Apply methods from signal theory

# Parzen-Window Estimation



## ■ Discrete Parzen-window estimator:

$$p_{\lambda,n}(x) = \frac{1}{n} \sum_{i=1}^n K_{\lambda}(x - x_i)$$

$$\hat{p}_{\lambda,n}(c_j) = \sum_{i=1}^b h_n(c_i) K_{\lambda}(c_j - c_i) = (h_n \star K_{\lambda})(c_j) \approx p_{\lambda,n}(c_j)$$

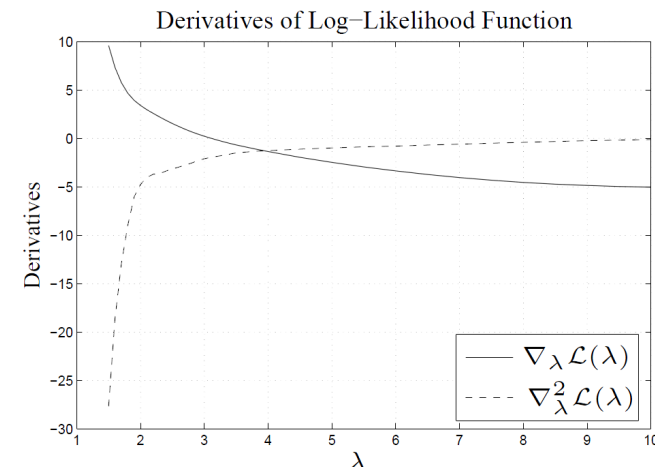
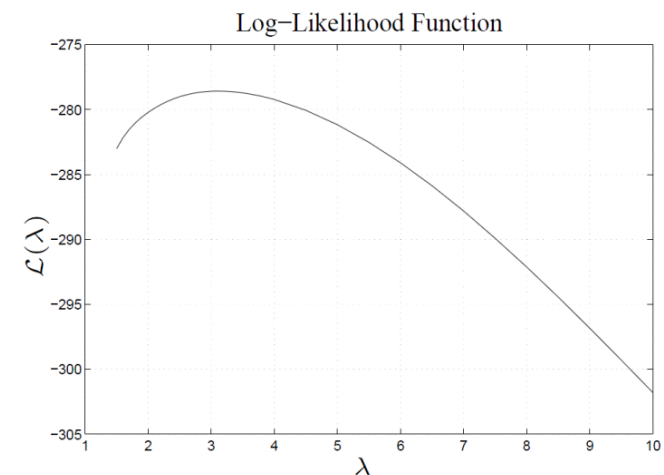
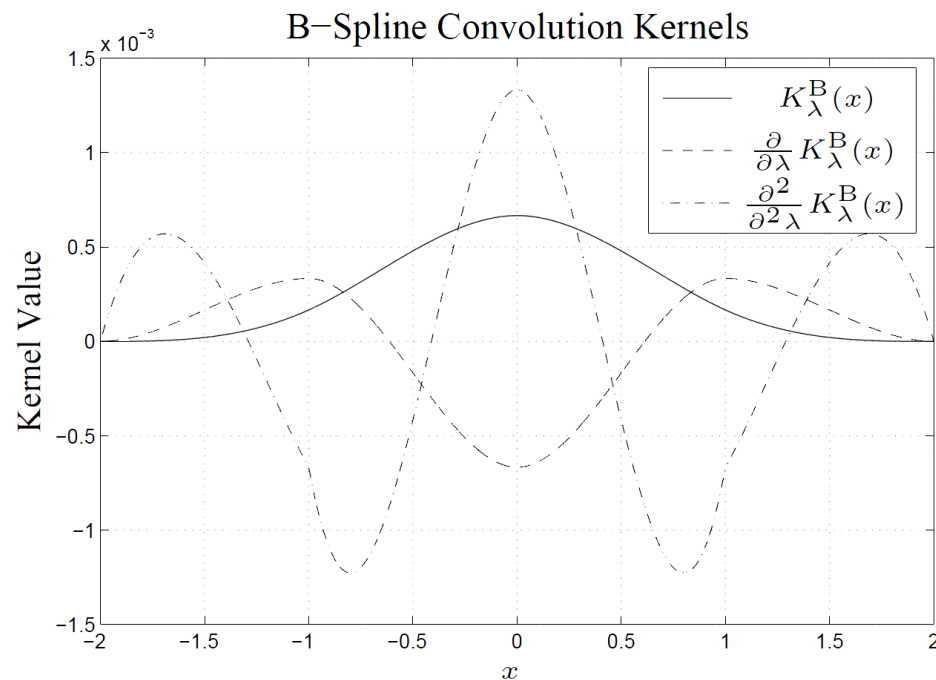
## ■ Kernel width estimation (LOO-CV):

$$\mathcal{L}(\lambda) = \sum_{j=1}^n \log \hat{p}_{\lambda,n-1}^j(x_j)$$
$$\hat{\lambda} = \underset{\lambda}{\operatorname{argmax}} \mathcal{L}(\lambda)$$

# Density Estimation



- Optimal kernel width determined by log-likelihood estimation based on a leave-one-out cross-validation
- Numerical optimization



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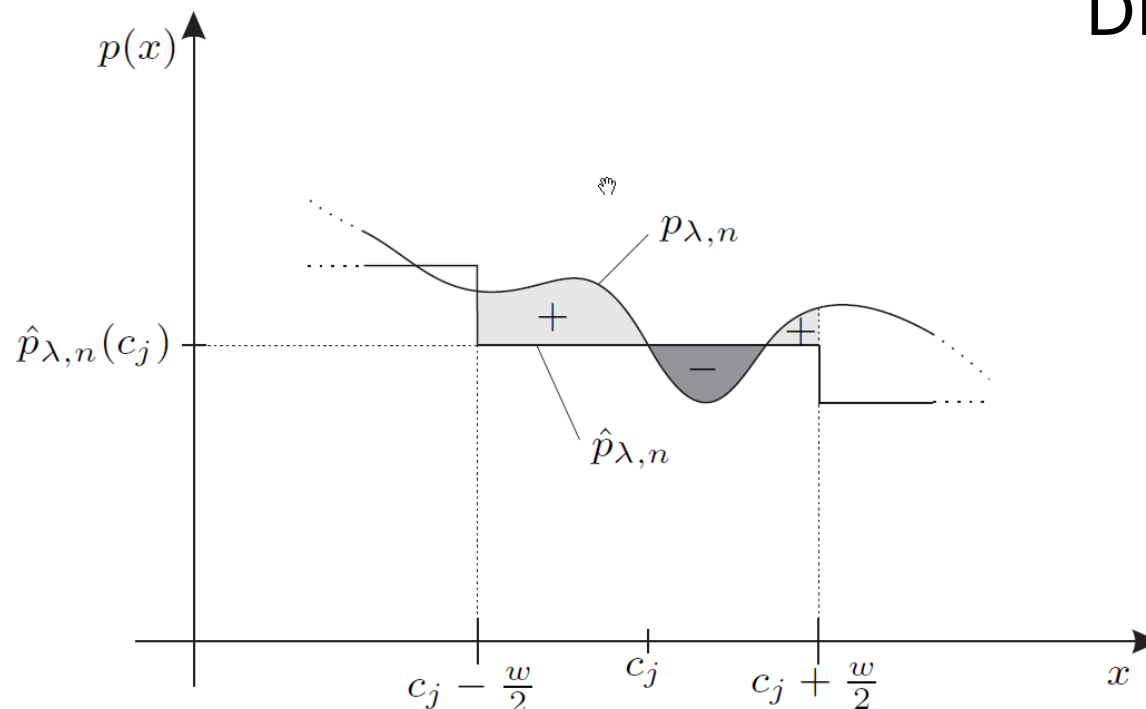
# Discrete PDF Representation



## ■ Discretization error:

$$e(c_j) = \int_{c_j - \frac{w}{2}}^{c_j + \frac{w}{2}} p_{\lambda,n}(x) \, dx - \underbrace{w \hat{p}_{\lambda,n}(c_j)}$$

Discrete estimator

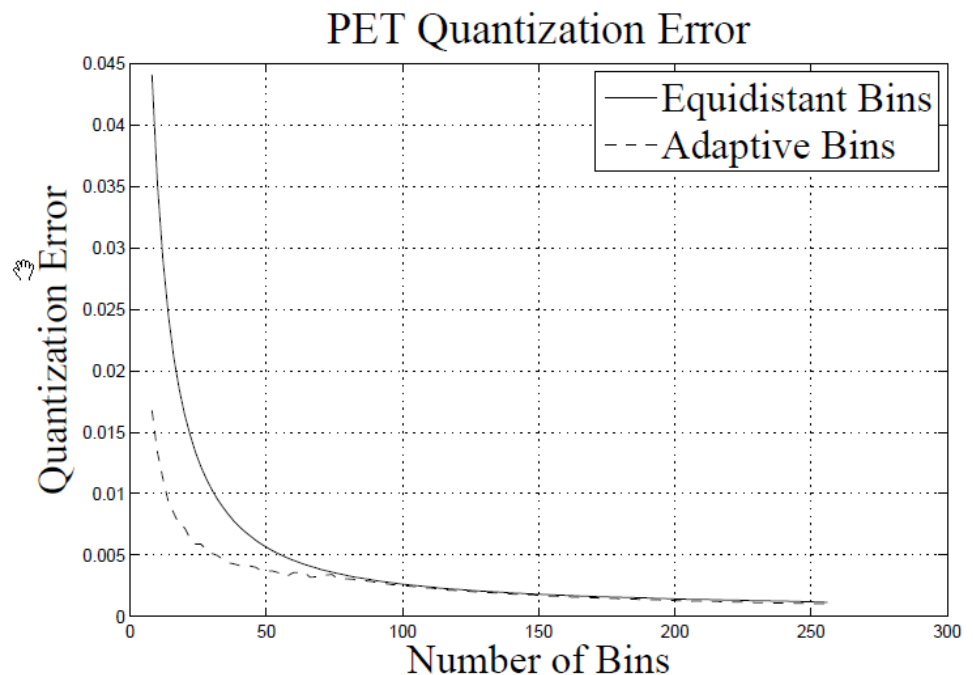
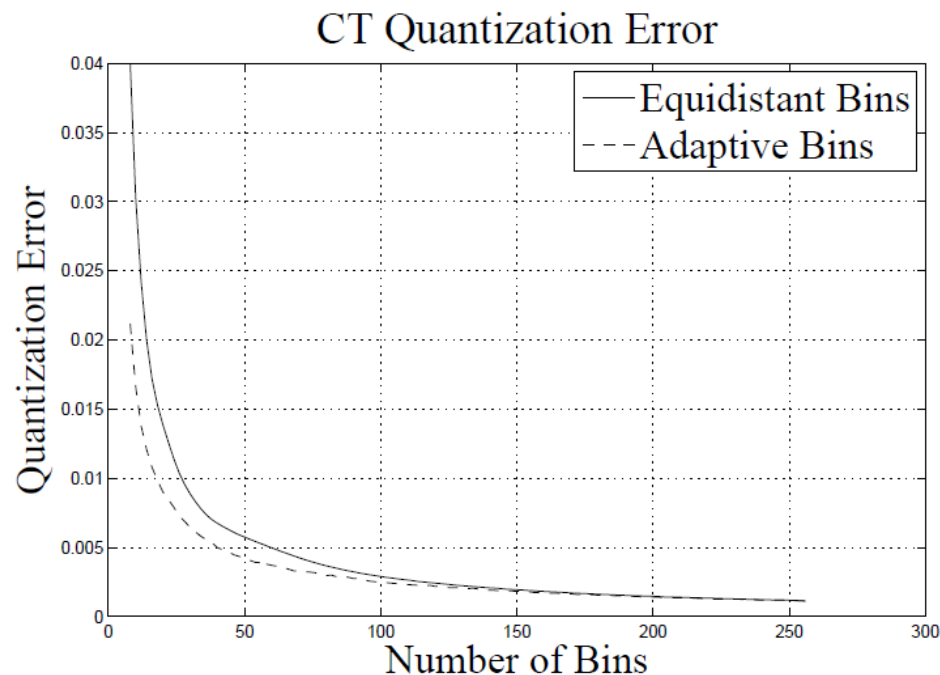


$$e = \sum_{j=1}^b e(c_j)$$

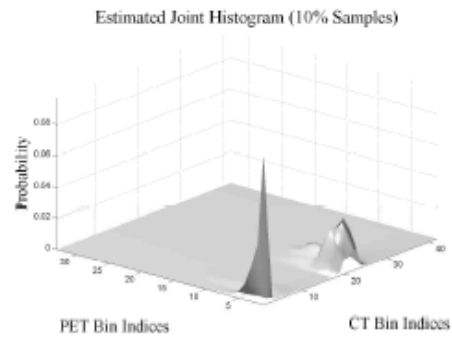
# Discrete PDF Representation



- Discretization error is minimized w.r.t. number of bins
- Tradeoff between accuracy and efficiency
- Error threshold of 0.5% yields good results

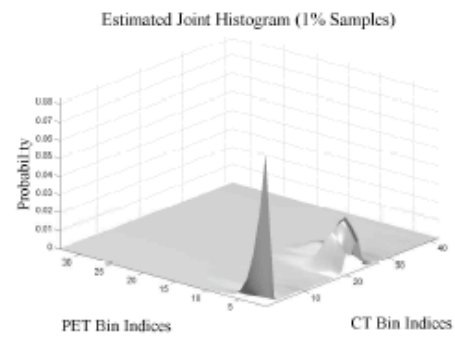


# Estimated PDF



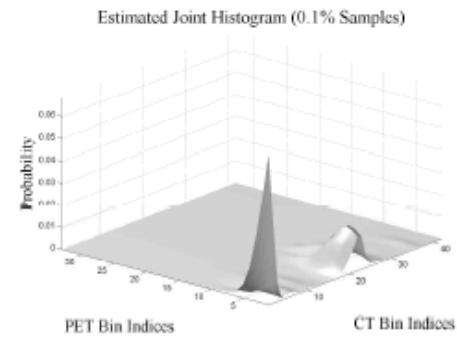
(a)

10%



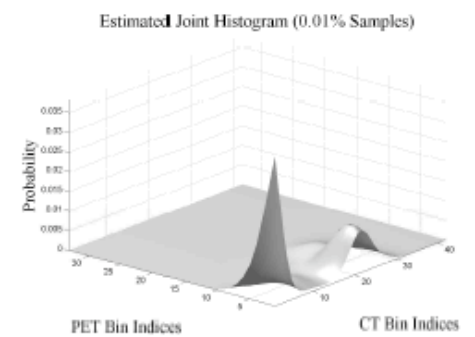
(b)

1%



(c)

0.1%



(d)

0.01%

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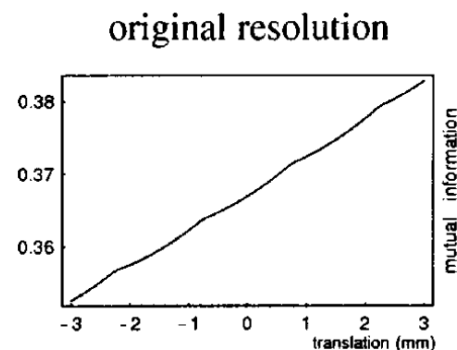
# Artifacts in Mutual Information

## ■ Problem:

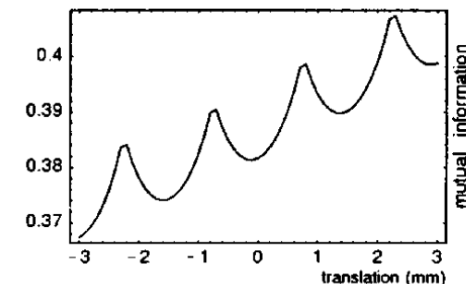
Interpolation has a high impact on local extrema due to grid aligning positions (common in medical images).

Effect is increased at lower resolutions.

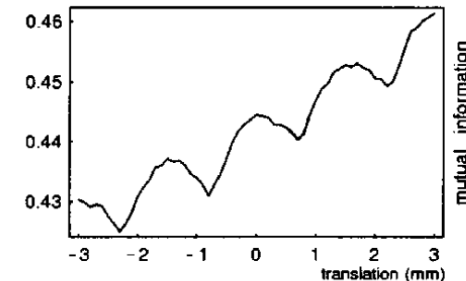
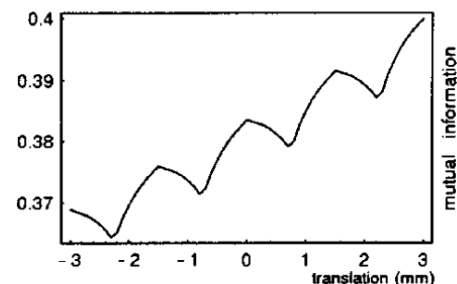
MRI to CT I,  
partial volume



downsampled



MRI to CT I,  
linear

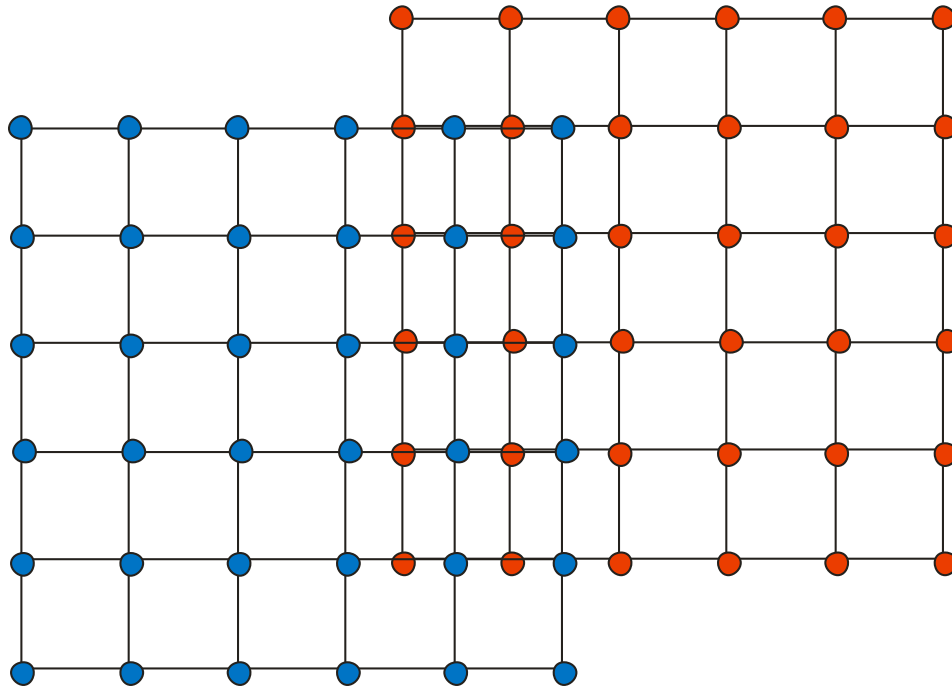




# Artifacts in Mutual Information

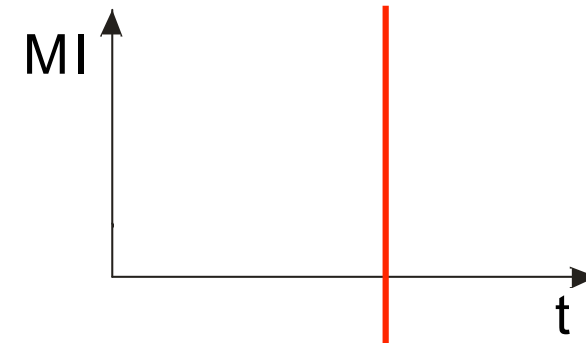
## Image Translation

- Reference Image
- Template Image

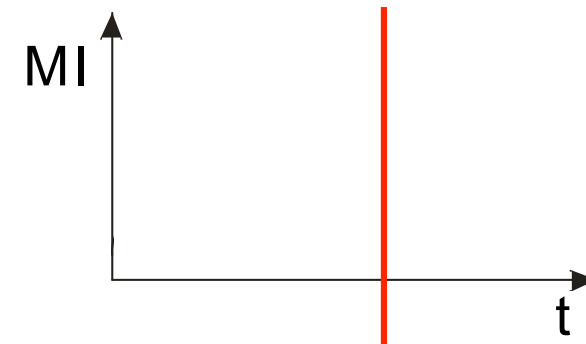


## MI Energy

Partial Volume Interpolation



Linear Interpolation

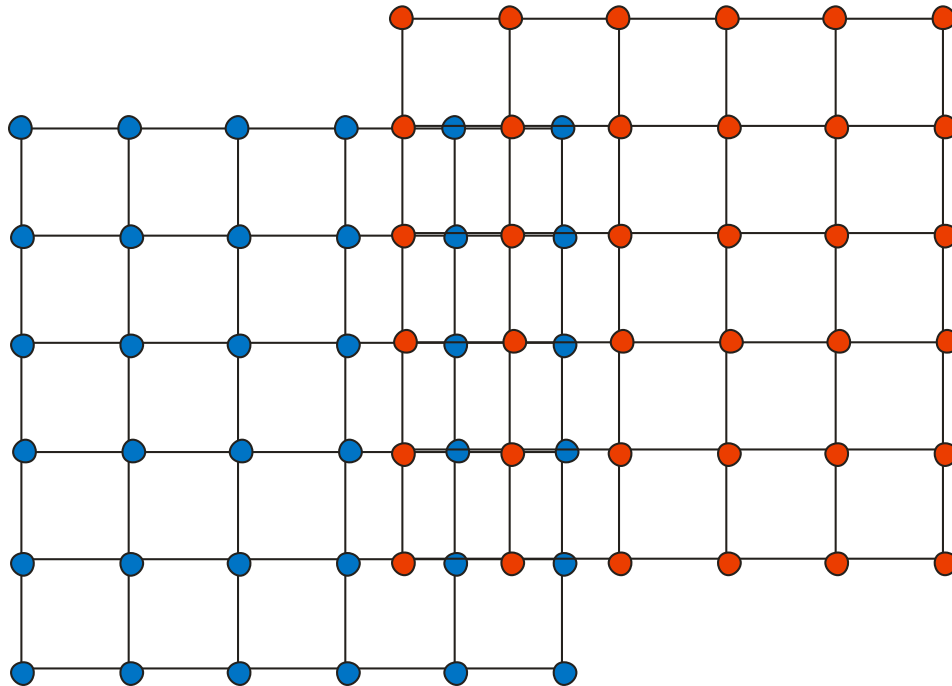




# Artifacts in Mutual Information

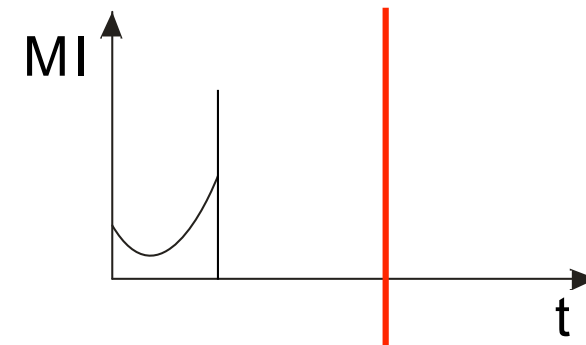
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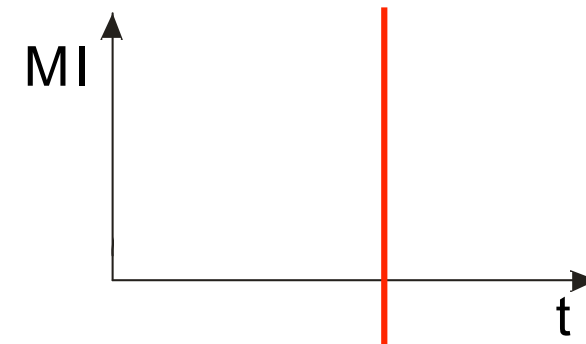


## MI Energy

Partial Volume Interpolation



Linear Interpolation



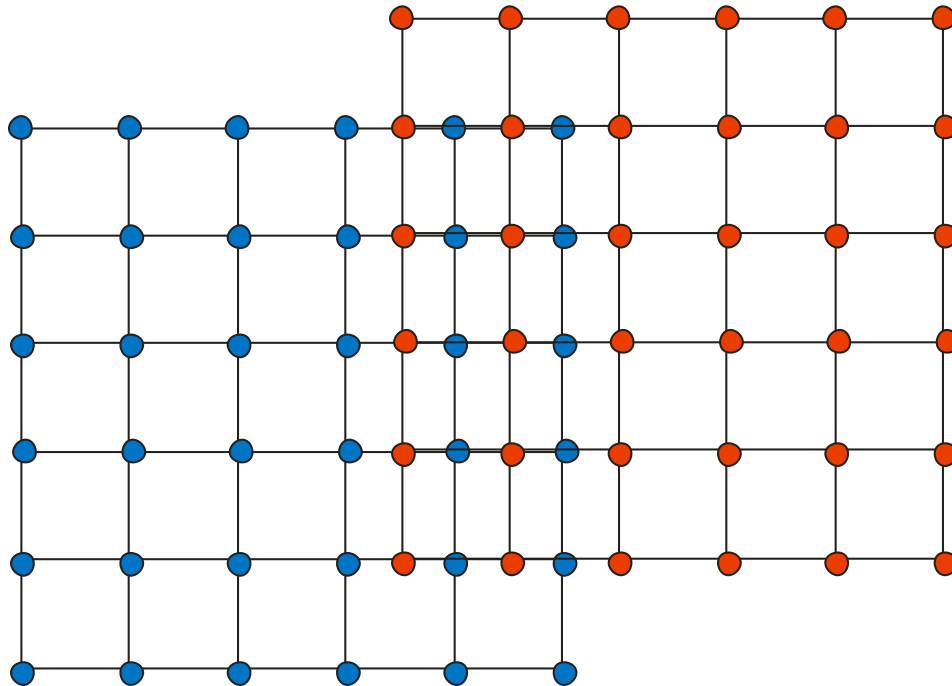




# Artifacts in Mutual Information

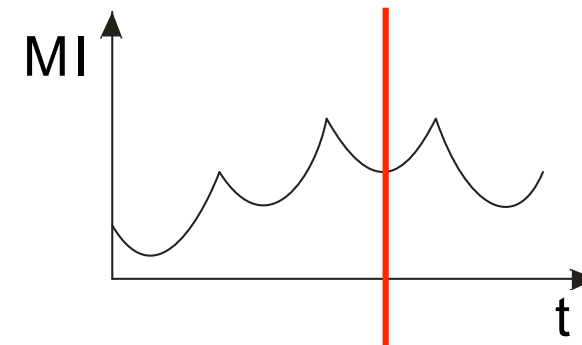
## Image Translation

- Reference Image
- Template Image

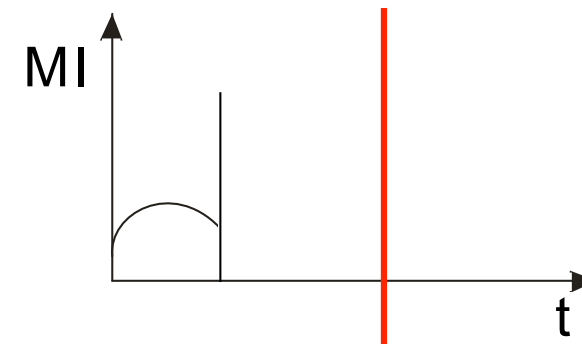


## MI Energy

Partial Volume Interpolation



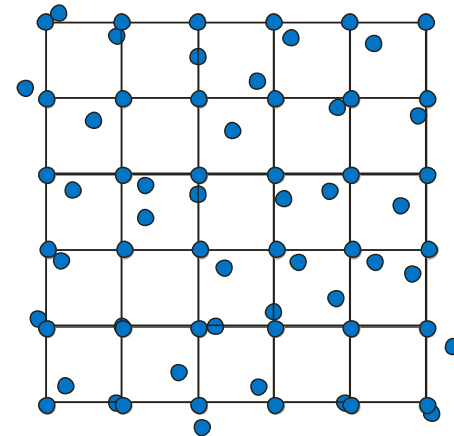
Linear Interpolation





# Improvements of Smoothness

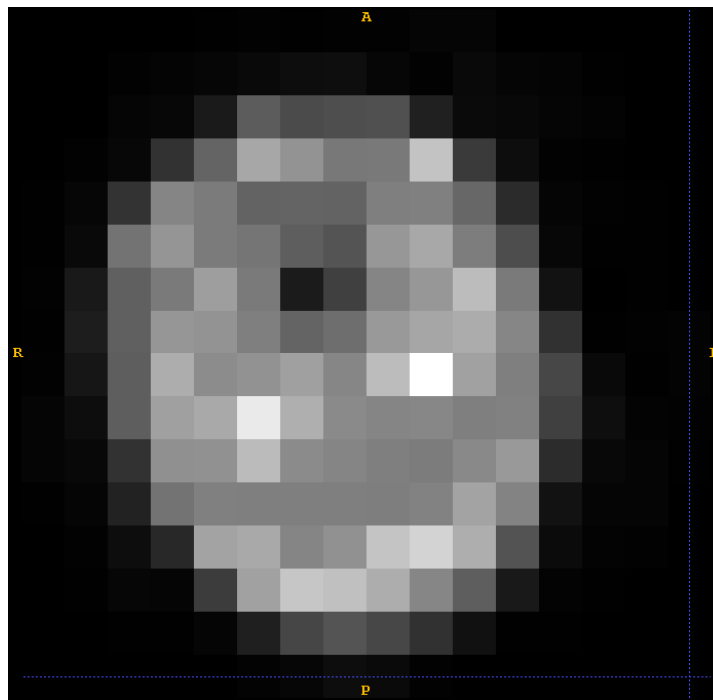
- Jittering
  - Implementation in ITKx
  - Using random generator to disturb positions of voxels



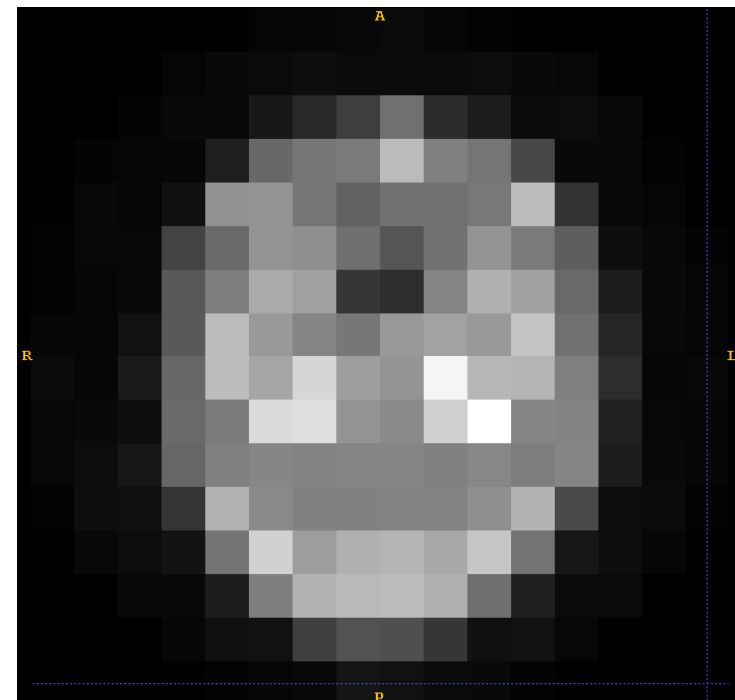


# Artifacts in Mutual Information

- The numerical results on the following slides are computed from a CT with a DynaCT registration
- Level 16 x 16 x 16
- Resolution: 15.56 x 15.56 x 12.16



CT

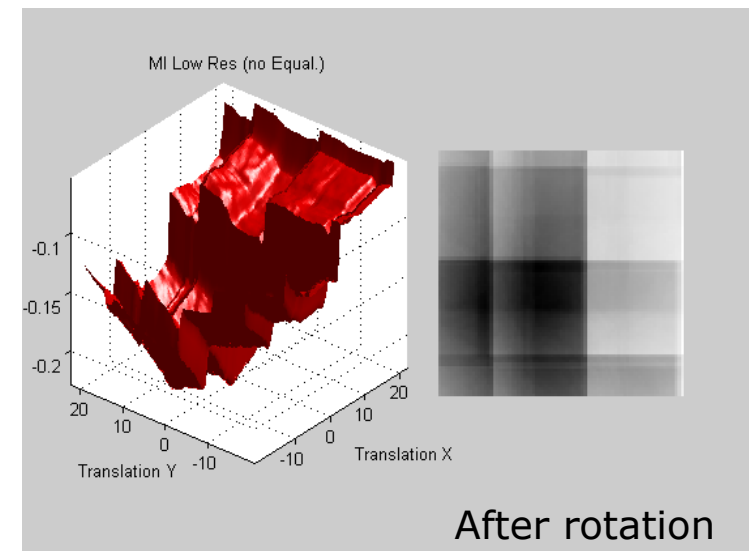
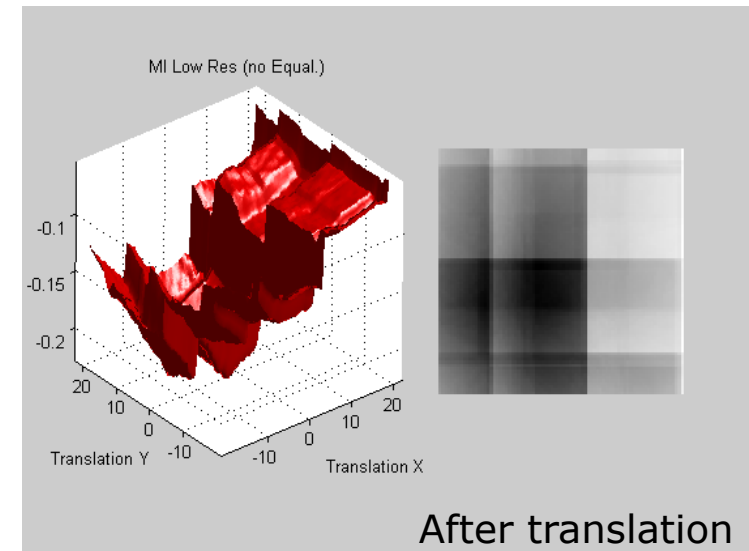
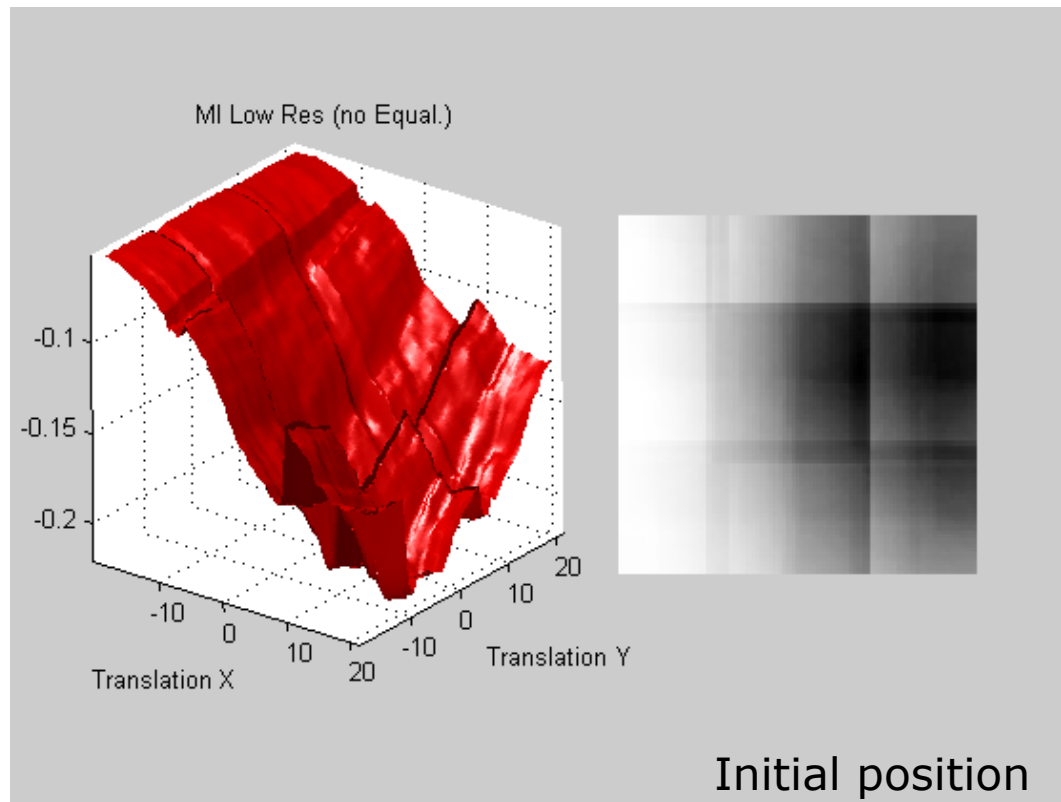


Dyna CT

# Numerical Results I



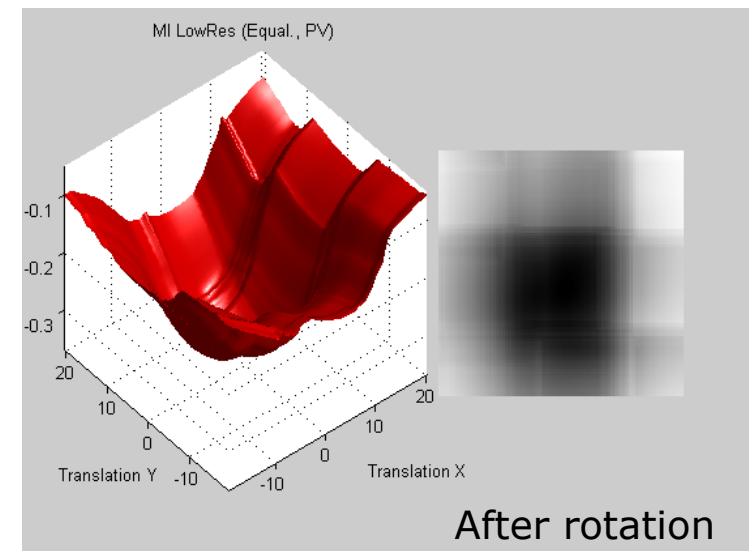
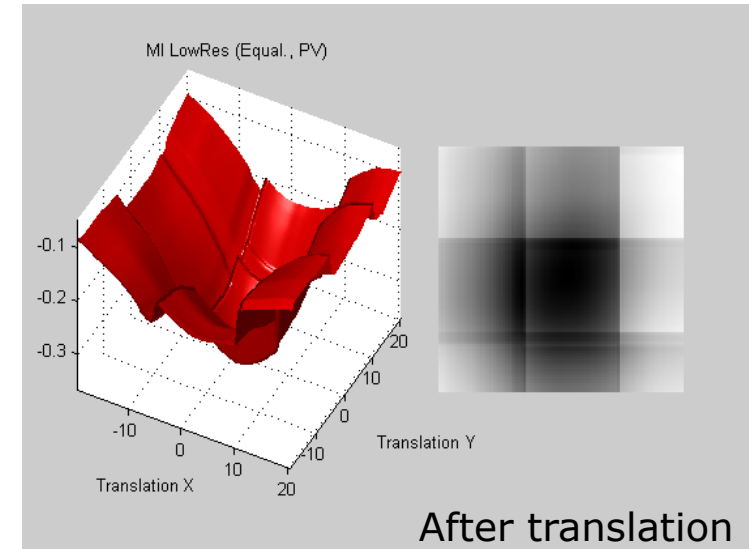
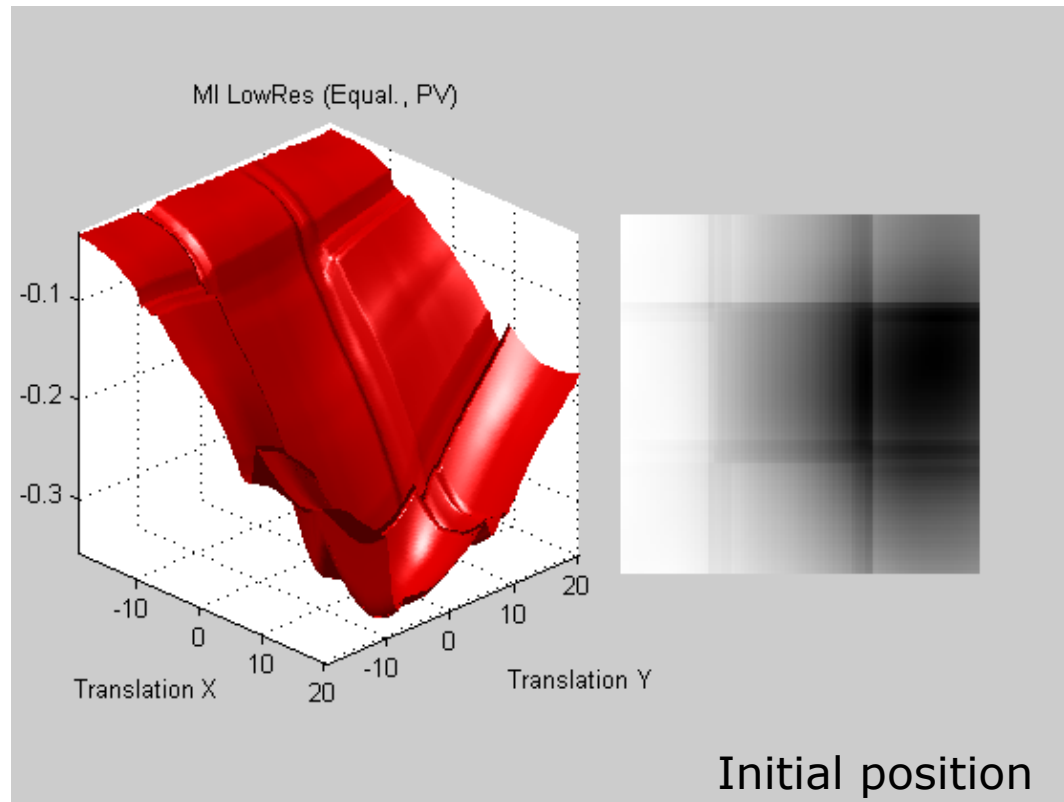
## ■ MI



# Numerical Results I



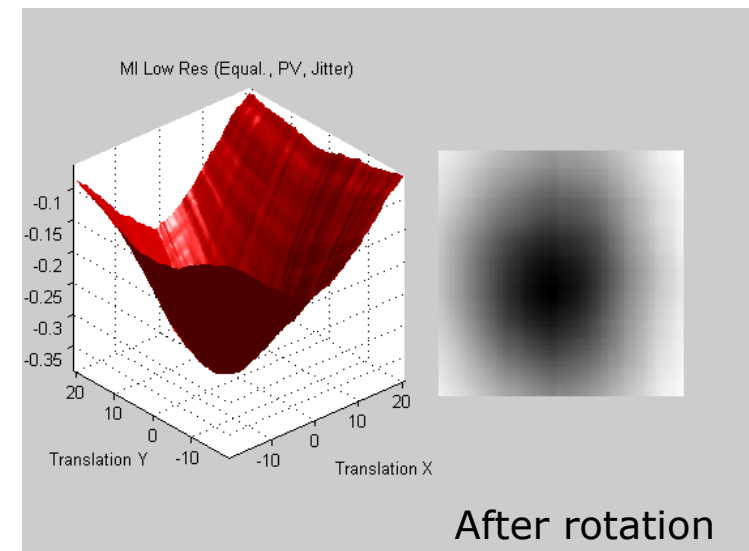
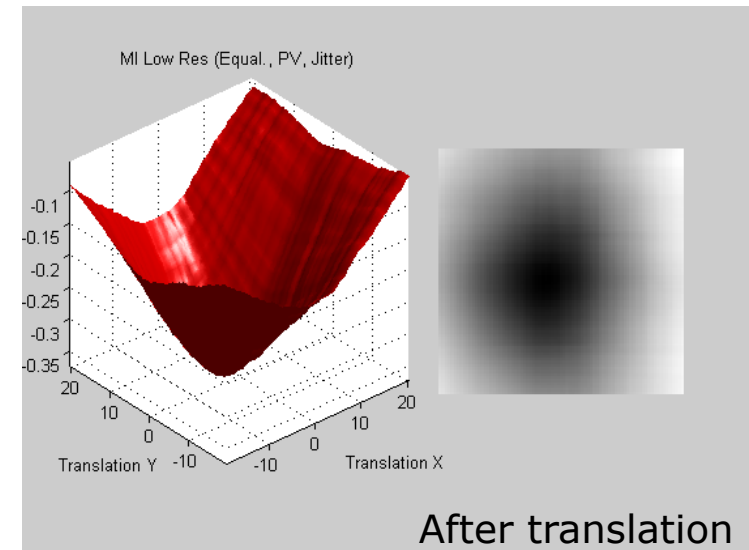
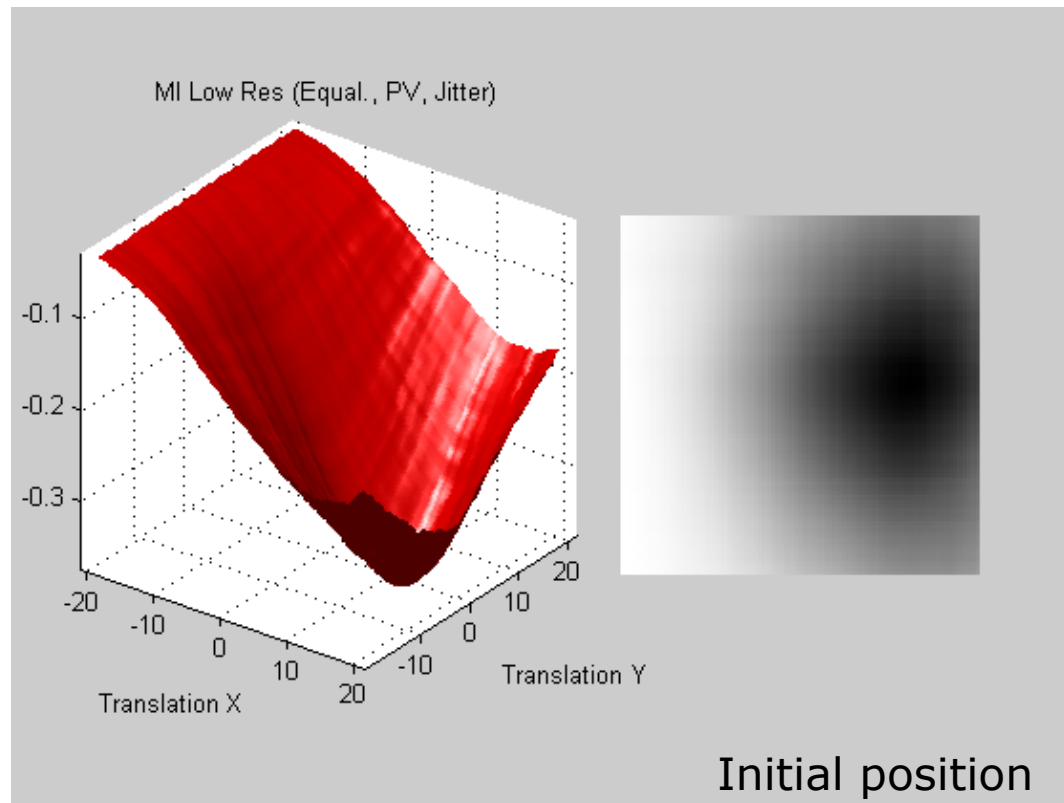
- MI with Histogram Equalization, Partial Volume interpolation



# Numerical Results I



- MI with Histogram Equalization, Partial Volume Interpolation, Jittering



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# Conclusions



- Non-parametric estimation of pdf's underestimated
- Empirical results on pdf's nice, but useless
- Resolve regularities by jittering
- Benchmark datasets