Dictionary Learning for Medical Image Segmentation

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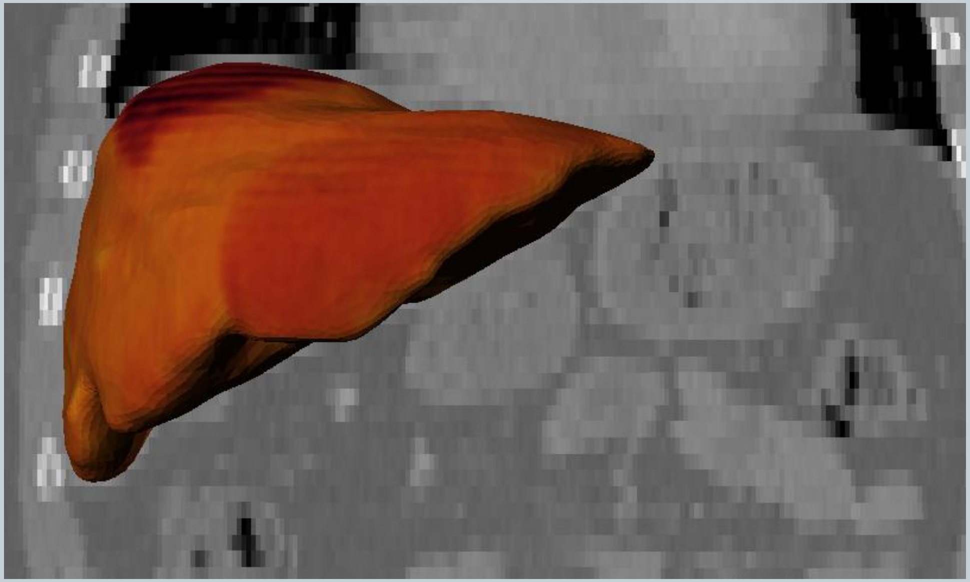
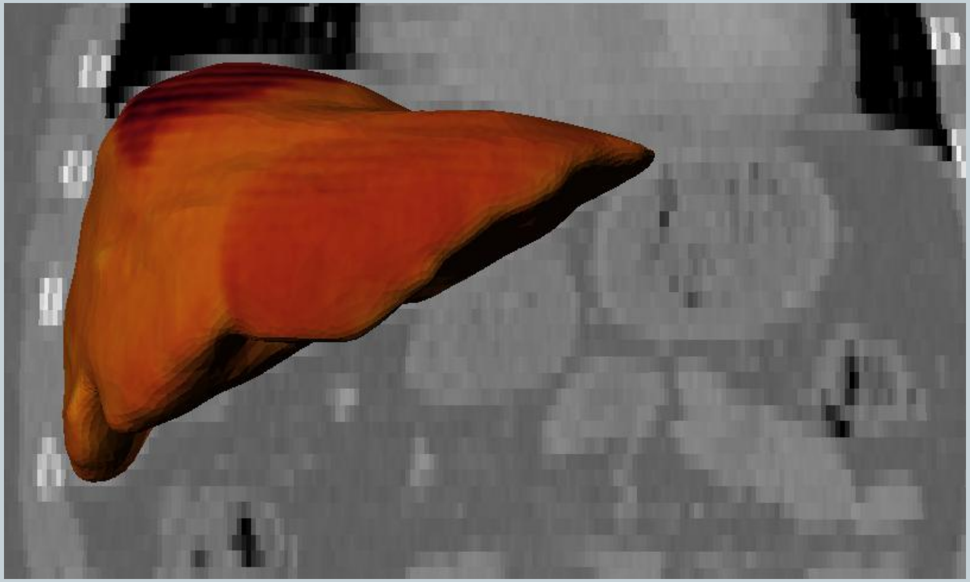
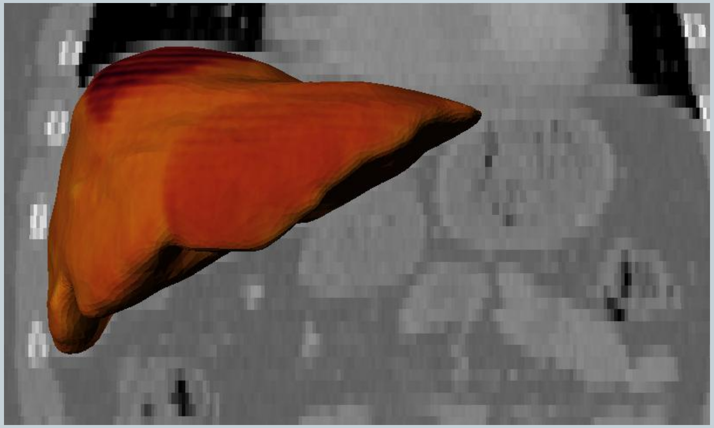
- Medical Image Segmentation

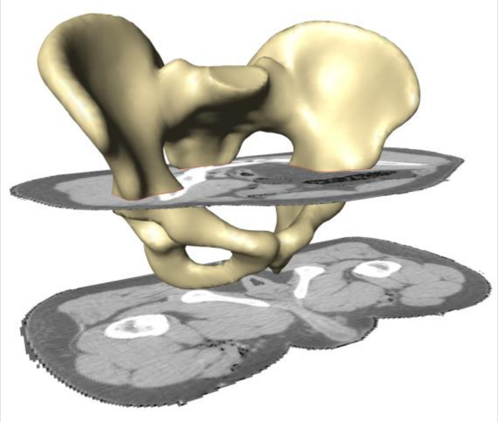


- Medical Image Segmentation
  - Fully automatic

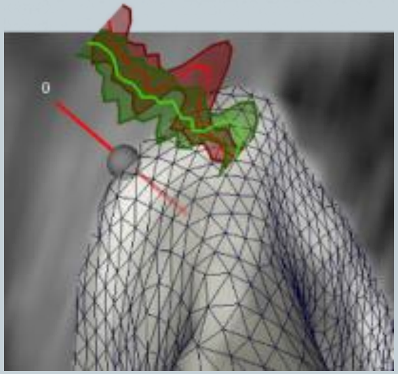


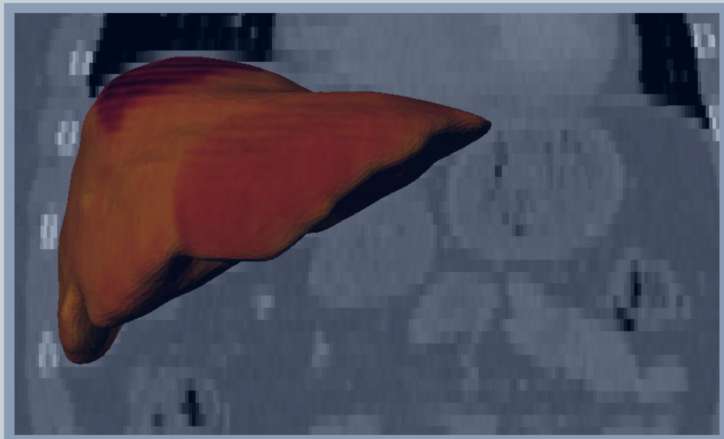
- Medical Image Segmentation
  - Fully automatic
  - Arbitrary 3D anatomy and modality

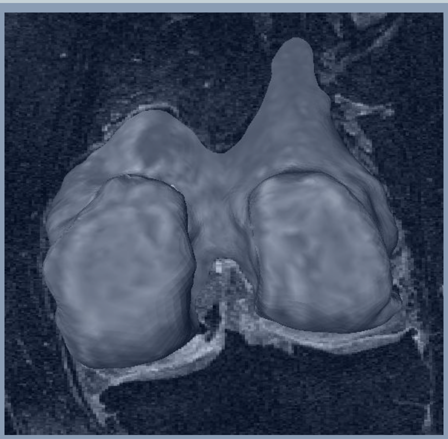


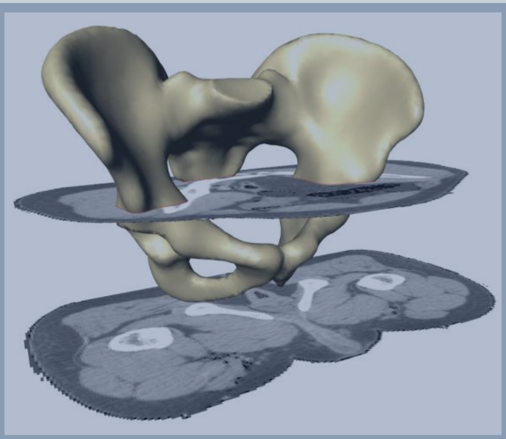


- Medical Image Segmentation
  - Fully automatic
  - Arbitrary 3D anatomy and modality
- Deformable model



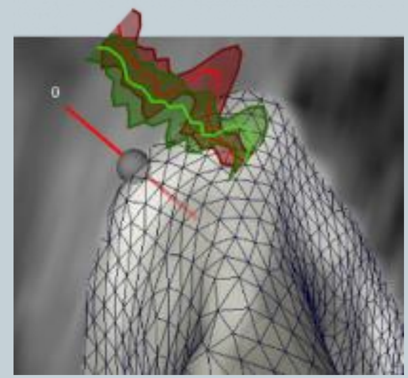


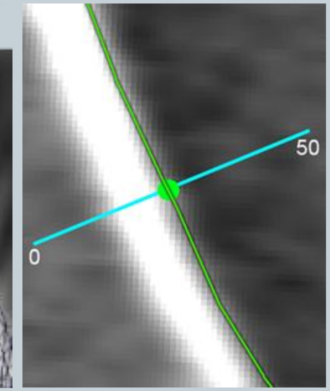


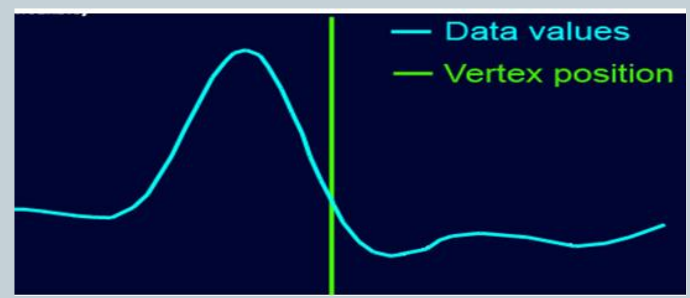


Deformable Model Recipe

Deformable Model
- Appearance model
- Geometric Regularizer







Deformable Model Recipe

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- Appearance model
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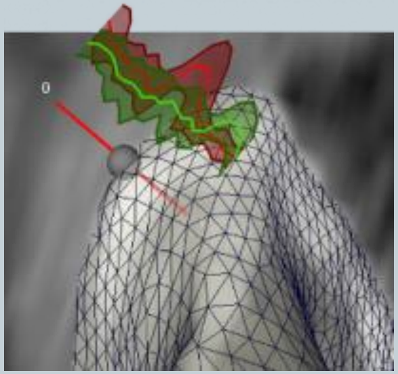
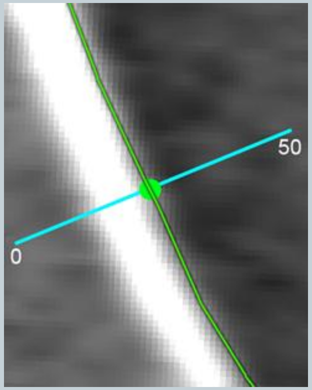
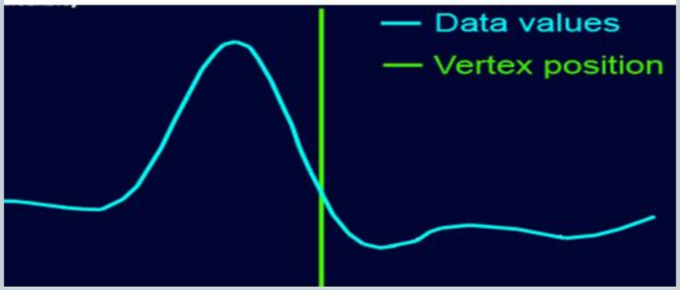




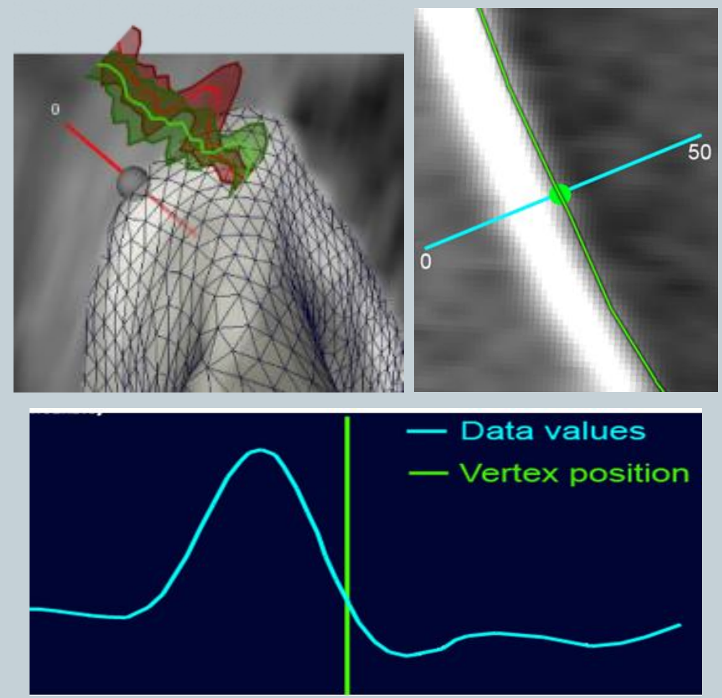


Deformable Model Focus

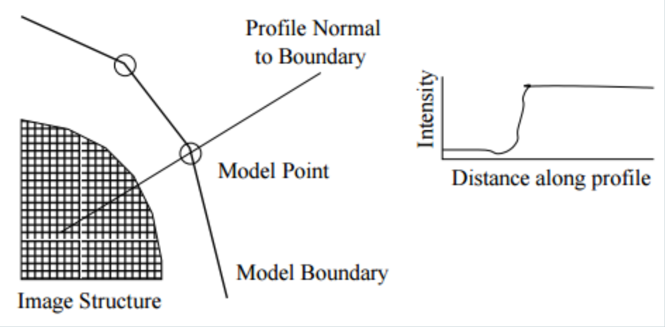
Deformable Model

- Appearance model
- ~~Geometric Regularizer~~

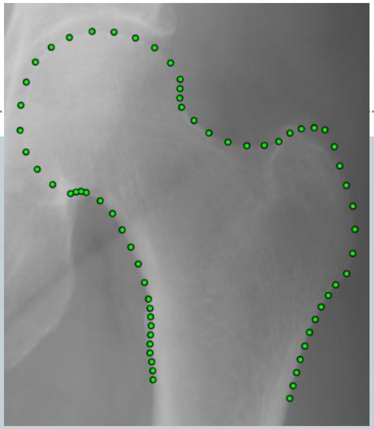
•**Main focus:** Systematic approach of generating appearance model



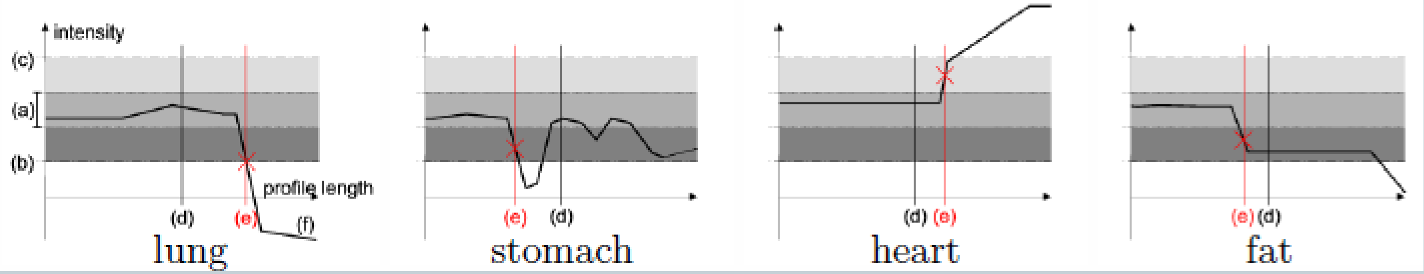
Related Work



Cootes et al., Image Proc. and Analysis 2000 ("PCA")

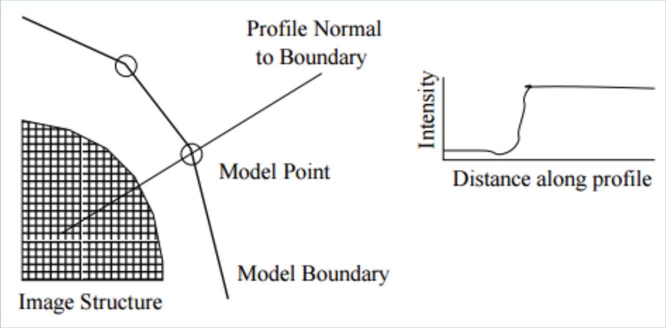


Lindner et al., TMI13



Kainmüller et al. *MICCAI Workshop 3D Segmentation* 2007

Related Work



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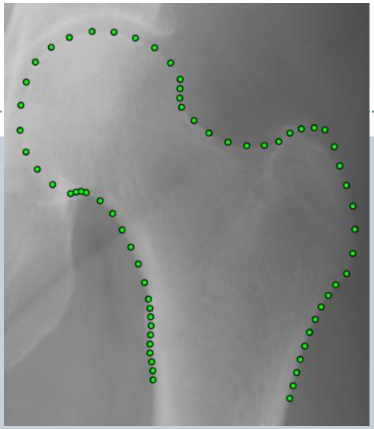

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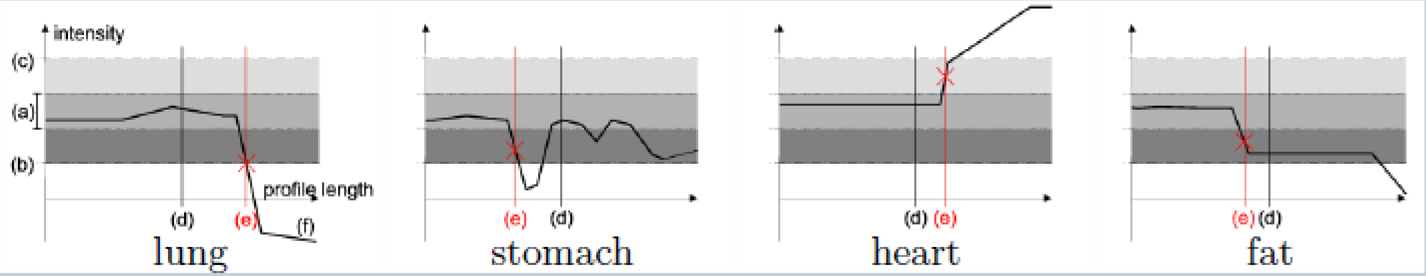


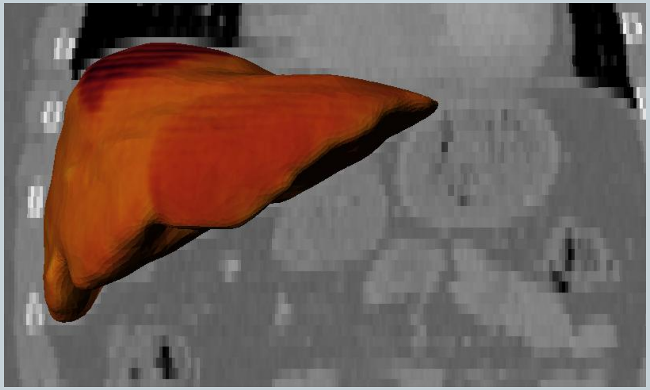
Kainmüller et al. *MICCAI Workshop 3D Segmentation* 2007

Dictionary Learning:

- Learn generic appearance model during training
- Efficient sparse representation during testing

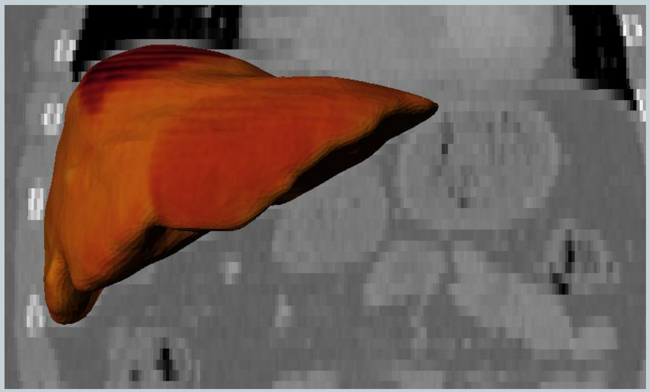
Contribution

- General 3D Segmentation

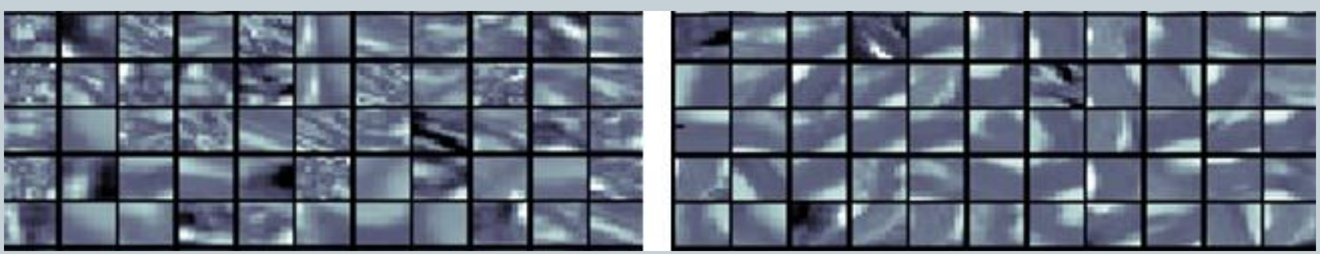


Contribution

- General 3D Segmentation

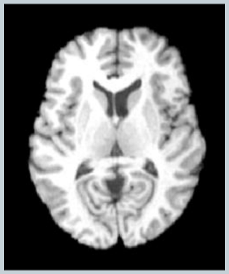
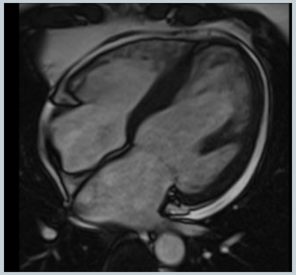


- Joint Dictionary Learning (JDL)

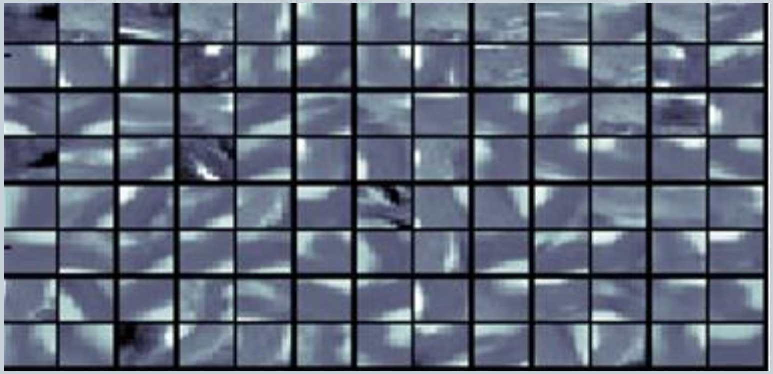


Dictionary Learning

- Image Representation
  - Image level: High variability, low redundancy

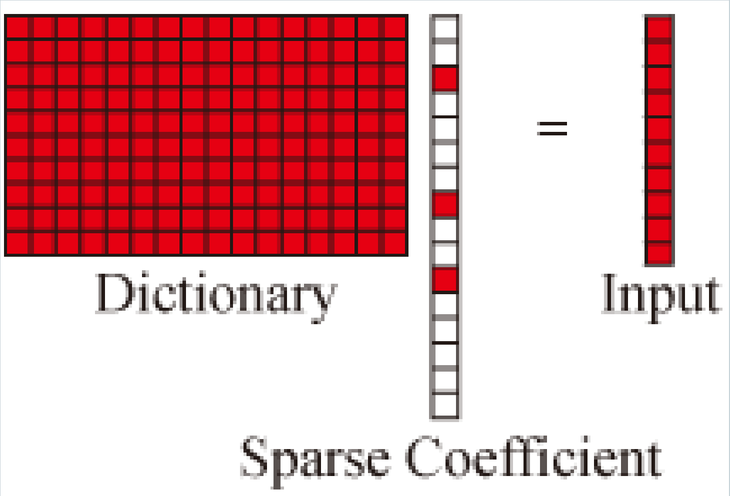




  - Patch level: Low variability, high redundancy



Dictionary Learning

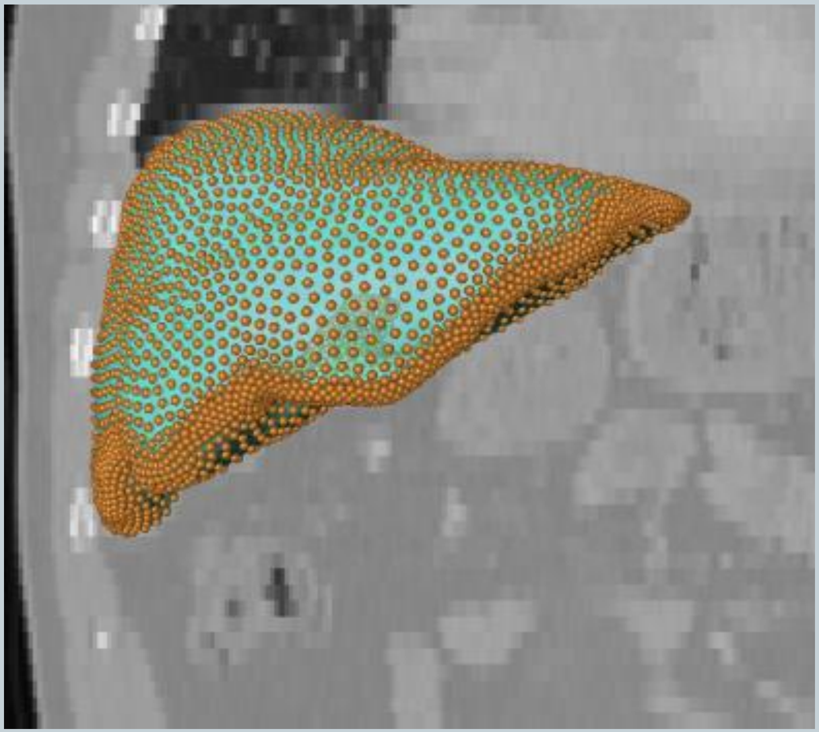
- Represent image patches using an over-complete dictionary



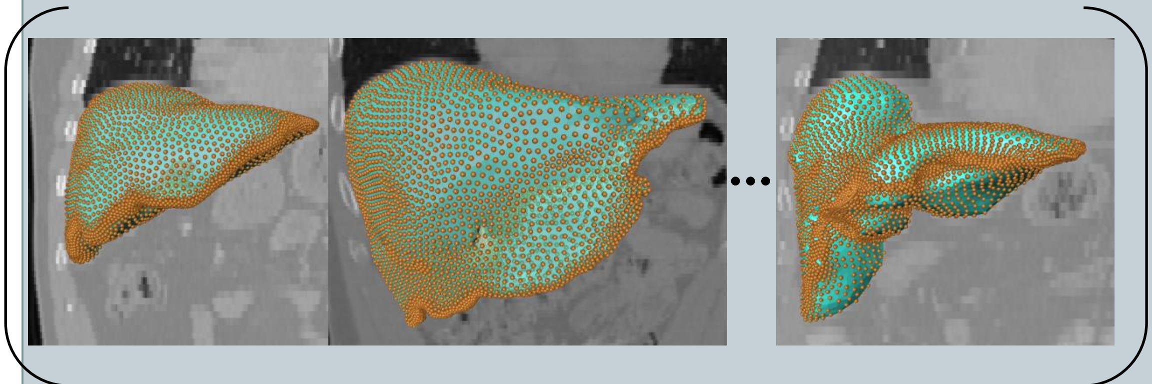
- Recon. patch: sparse combination of atoms of Dictionary

http://ranger.uta.edu/~huang/R_Cervigram.htm

Training



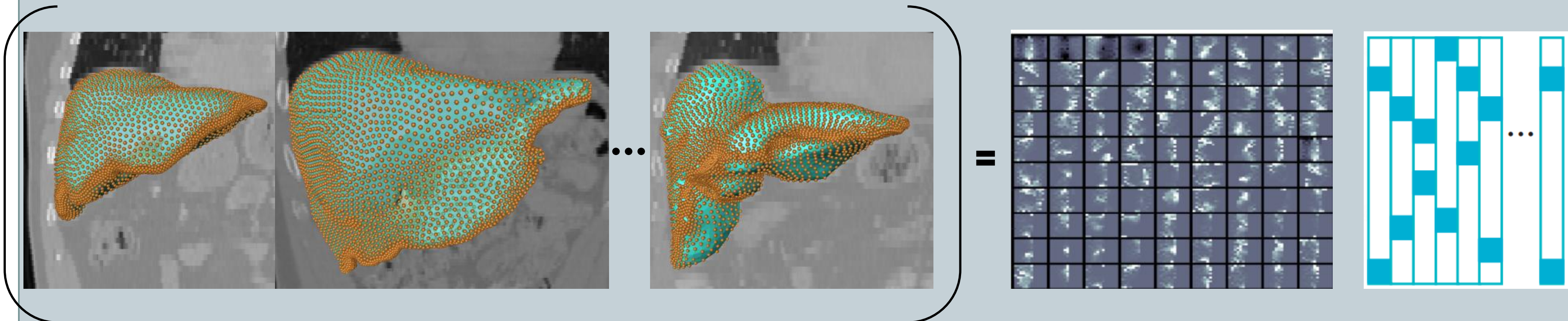
Training



Samples with intensity features

Rotation Inv. HOG

Training

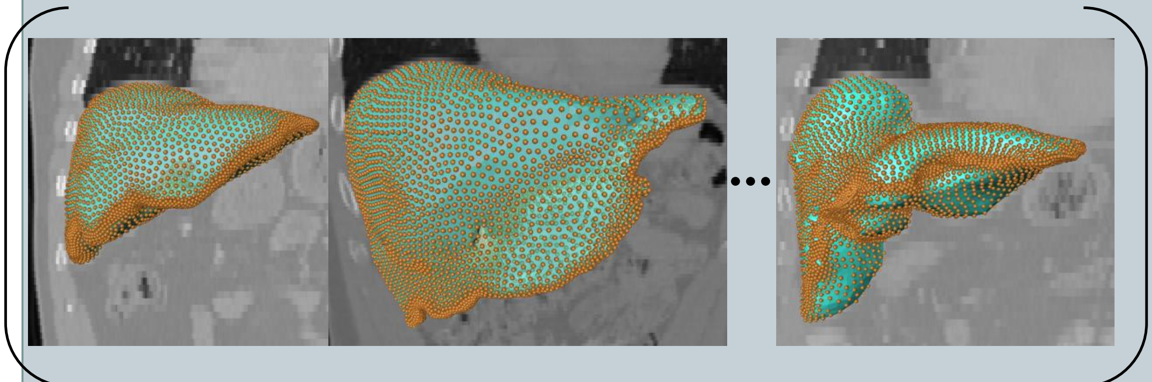


Samples with intensity features

FG Dictionary

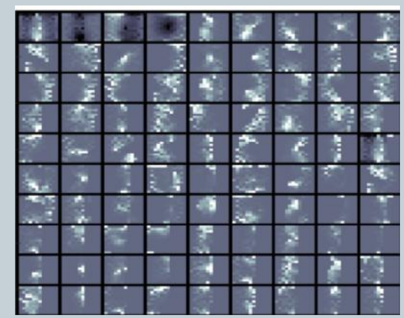
Sparse Rep

Training

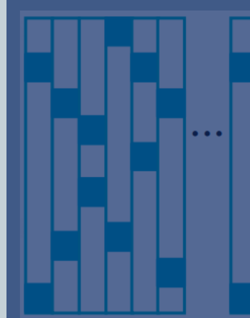


Samples with intensity features

=

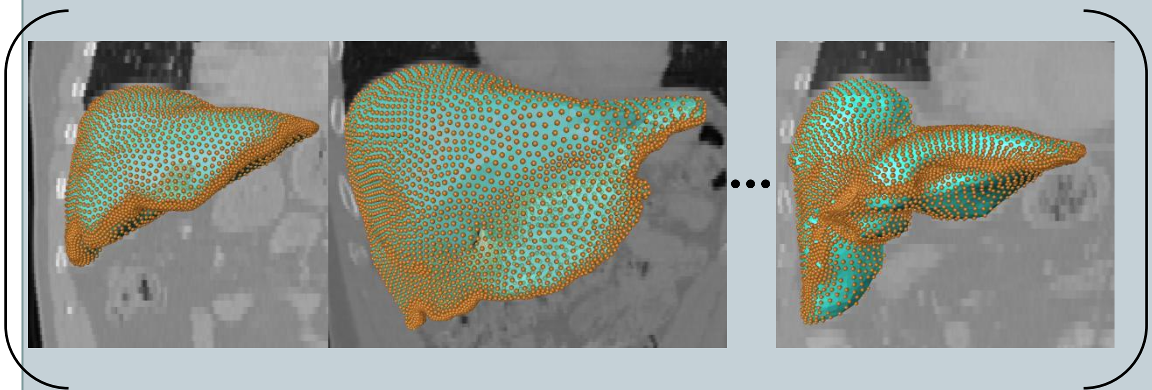


FG Dictionary

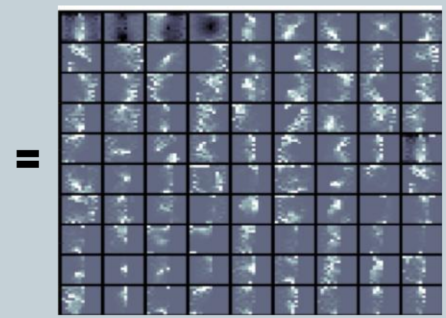


Sparse Rep

Training



Samples with intensity features



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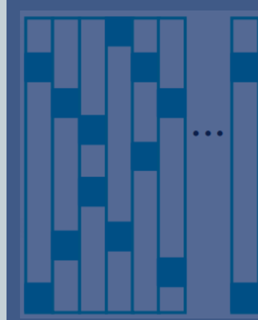
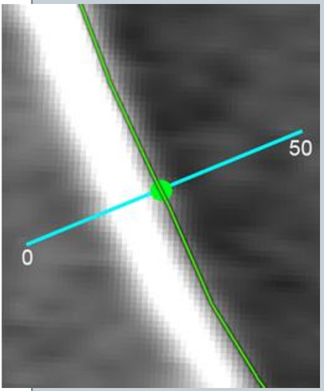


Sparse Rep

Similarly, Background Dictionary is generated

Cost Function Calculation



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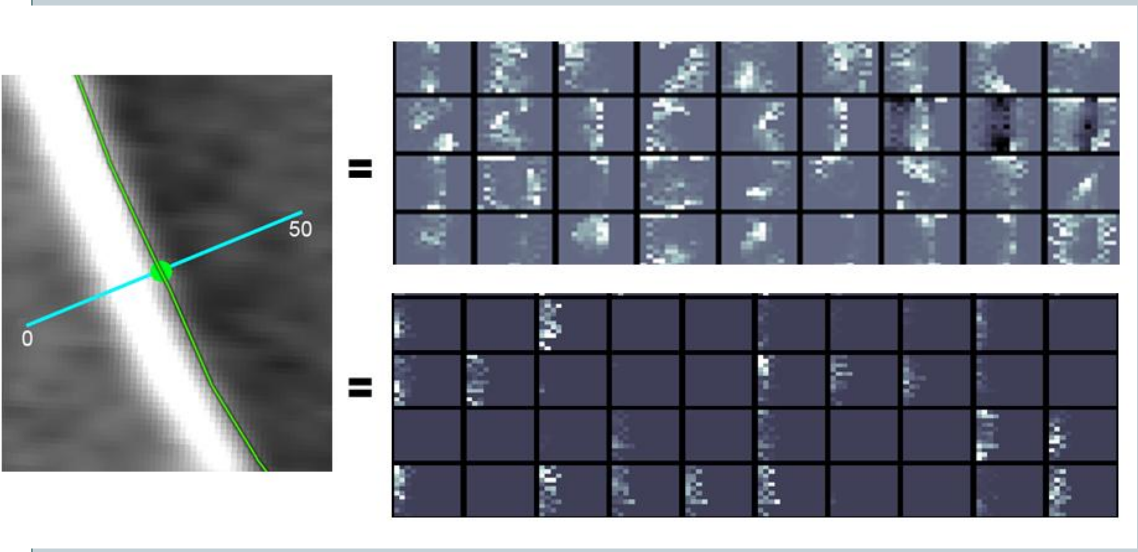

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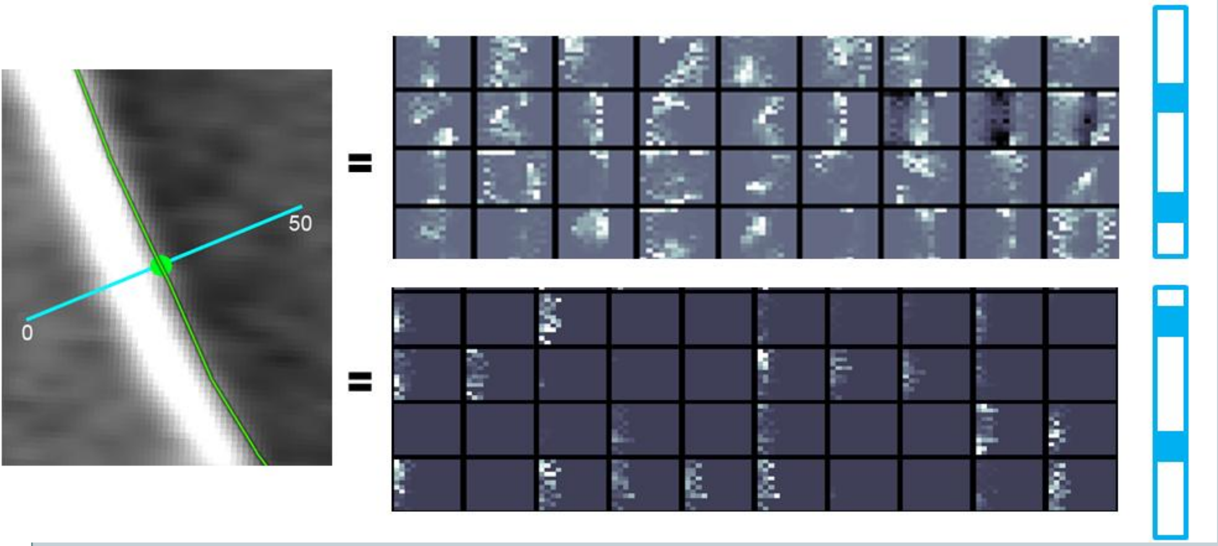

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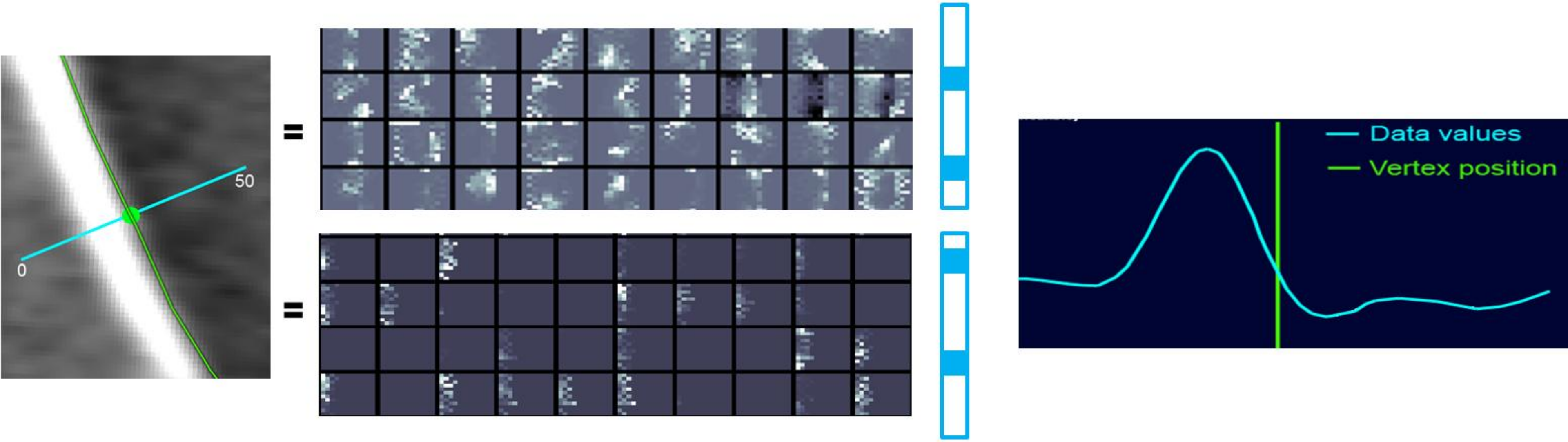

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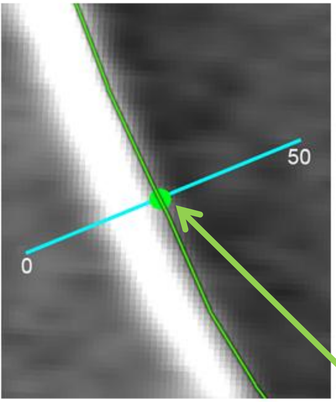
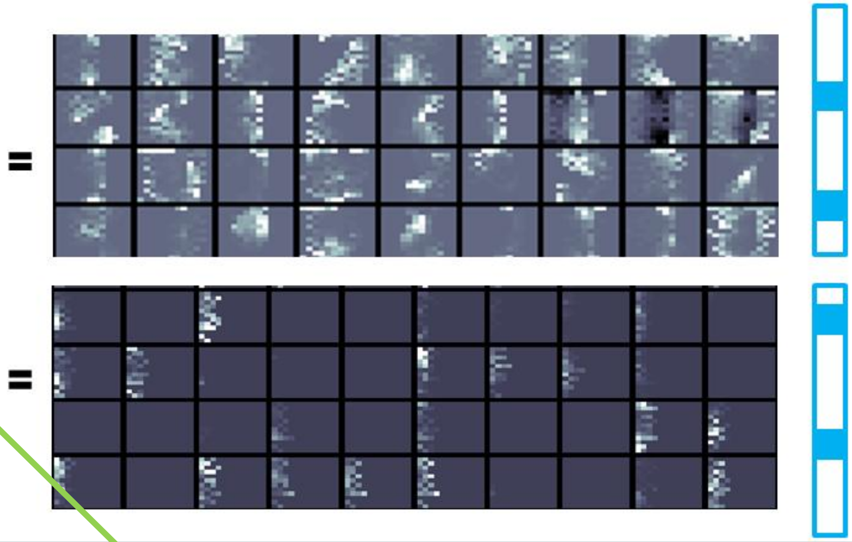
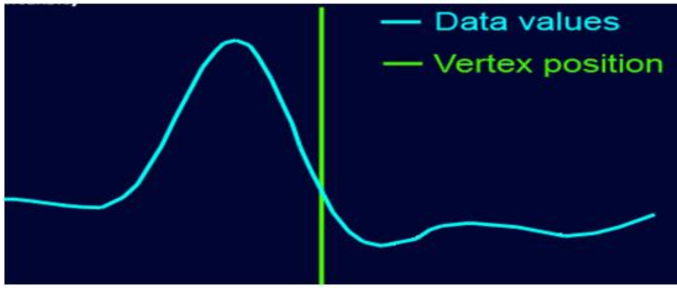
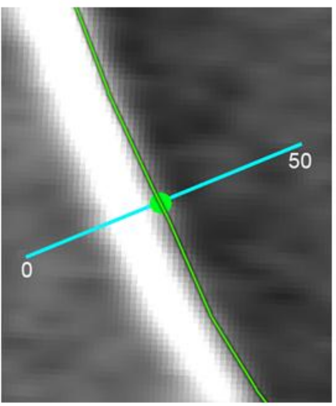


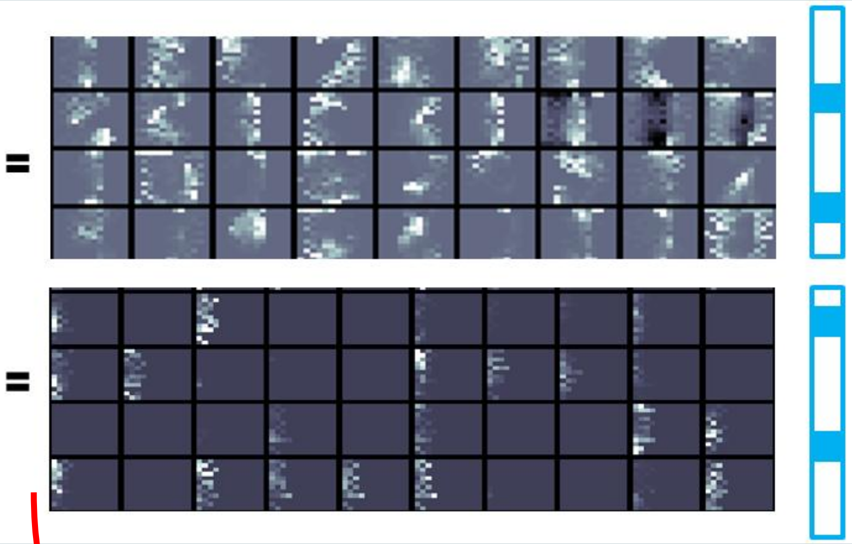


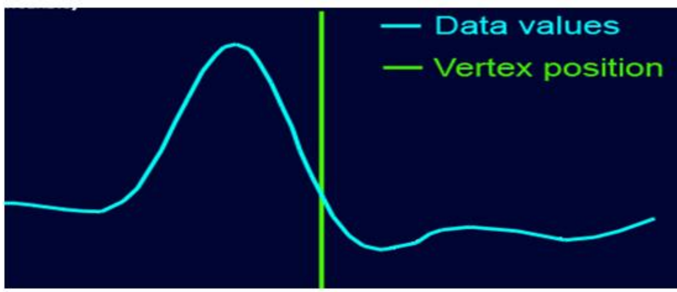


$$R^{C}_{l,p} = \|y^{T}_{l,p} - D^{C}\hat{x}^{C}_{l,p}\|_2^2$$

Cost Function Calculation

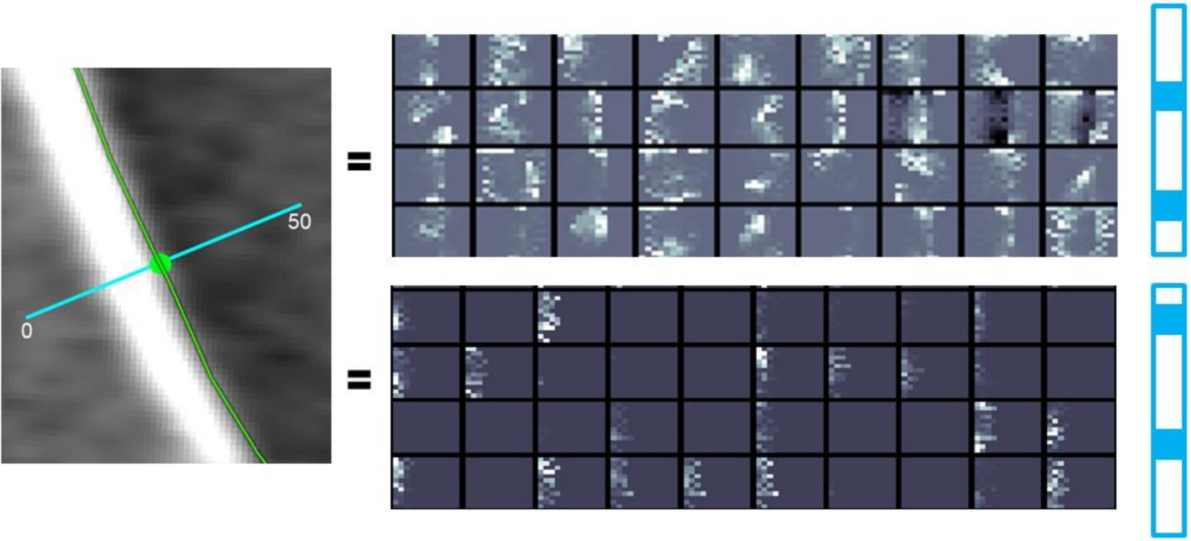


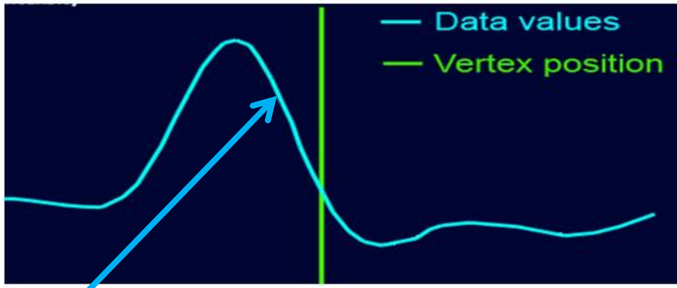




$$R_{l,p}^{C} = \|y_{l,p}^{T} - D^{C}\hat{x}_{l,p}^{C}\|_2^2$$

Cost Function Calculation

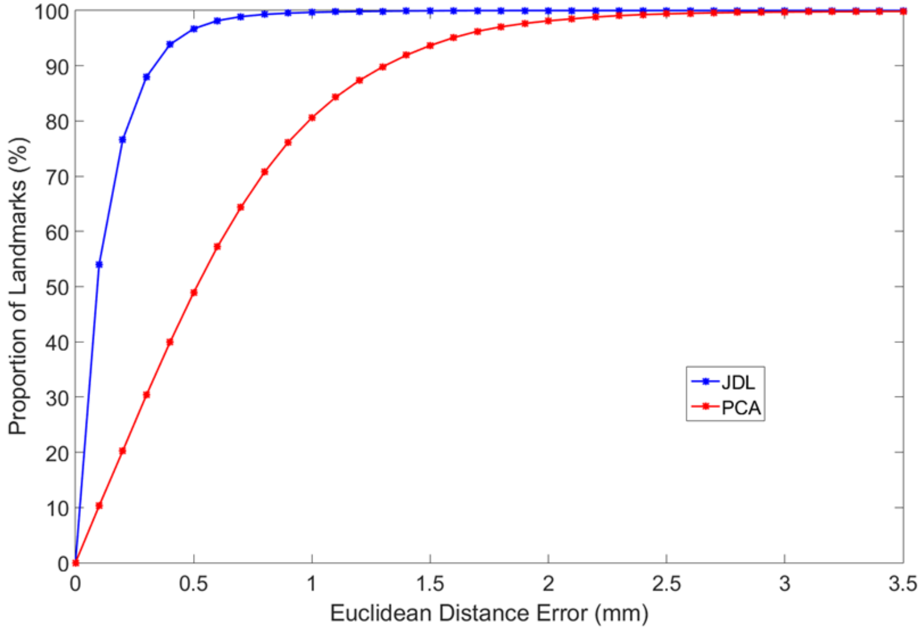


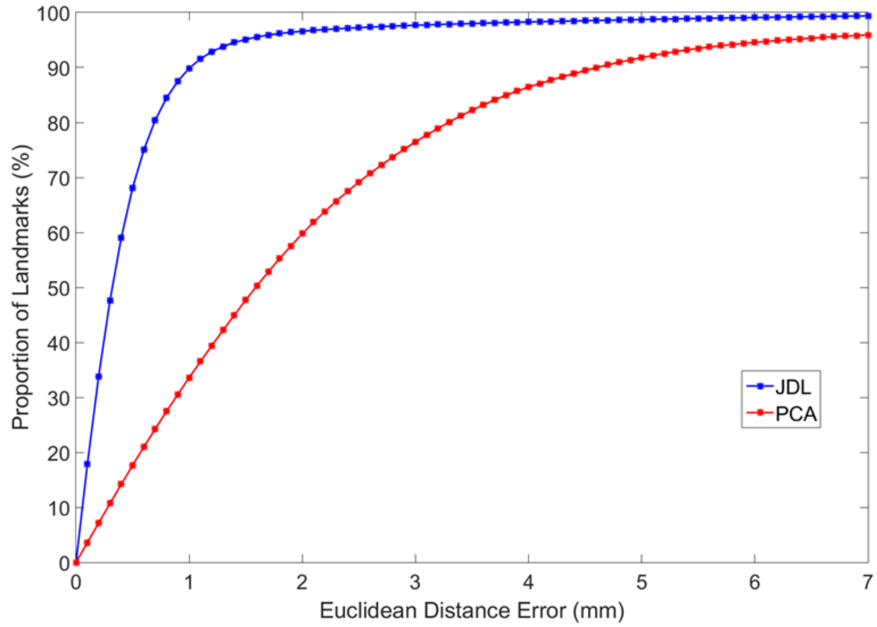


$$P_{l,p} = \lambda(1 - R^{B}_{l,p}) + (1 - \lambda)R^{F}_{l,p}$$

Results

Local search. NO Regularization.

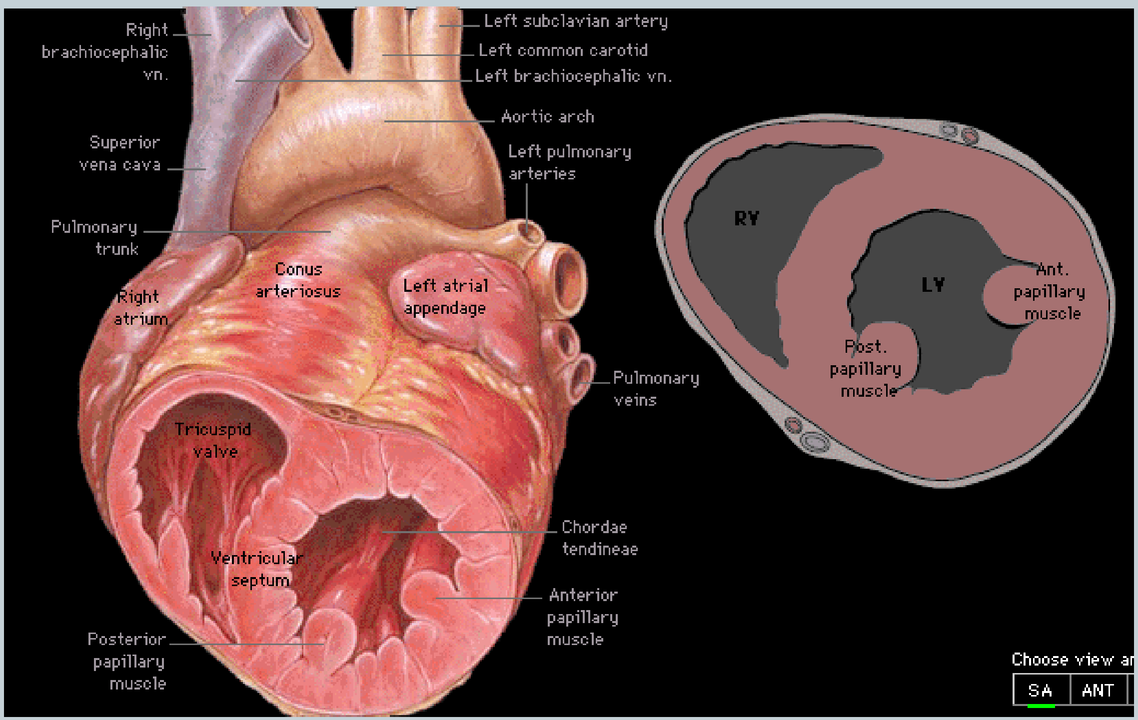




Liver CT

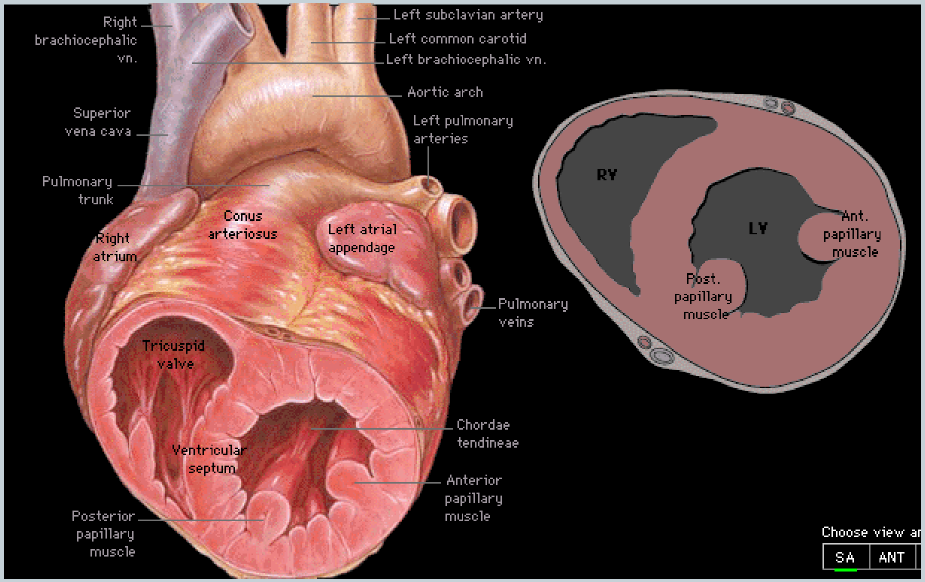
Femur MR

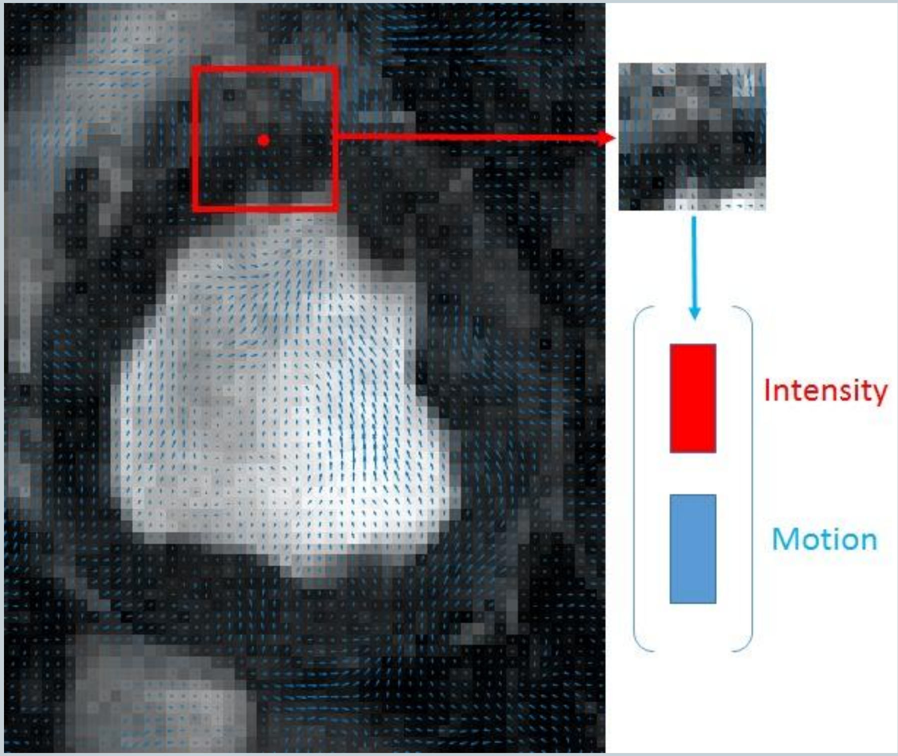
Cardiac Image Segmentation



Cardiac Image Segmentation

- Sparse modeling
  - Appearance
  - Motion



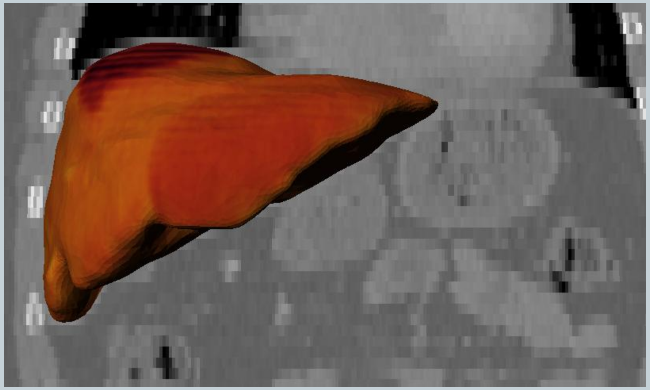


Results

DICE COEFFICIENT (MEAN $\pm$ STD) FOR SEGMENTATION ACCURACY IN %.

Methods	Baseline Standard CINE	Baseline CP-BOLD	Ischemia Standard CINE	Ischemia CP-BOLD
Atlas-based methods				
dDemons [6]	60 ± 8	55 ± 8	56 ± 6	49 ± 7
FFD-MI [20]	60 ± 3	54 ± 8	54 ± 8	45 ± 6
Supervised classifier-based methods				
ACRF	57 ± 3	25 ± 2	52 ± 3	21 ± 2
TACRF	65 ± 2	29 ± 3	59 ± 1	24 ± 2
Dictionary-based methods				
DDLS [7]	71 ± 2	32 ± 3	66 ± 3	23 ± 4
RDDL [39]	42 ± 15	50 ± 20	48 ± 13	61 ± 12
MSDDL [9]	75 ± 3	75 ± 2	75 ± 2	71 ± 2
UMSS [10]	62 ± 20	71 ± 10	65 ± 14	66 ± 11
Proposed	77 ± 10	77 ± 9	74 ± 7	74 ± 6

Summary and Future Work



- General model-based 3D segmentation
  - Across anatomies and modalities
- Benefits of Joint Dictionary Learning
  - Traditional PCA-based learning
  - 2D RFRV
- Localized error prone areas
  - Separate/ better strategy
- Experiments on other datasets

Thank You

Questions?

Training Algo

Algorithm 1 Joint Dictionary Learning (JDL)

Input: Training patches for background and the landmarks: Y^B and Y^F
Output: Dictionaries for background and the landmarks: D^B and D^F

1: **for** C={B,F} **do**
2: Compute Y^C
3: Learn dictionaries with K-SVD algorithm

$$\underset{D^C, X^C}{\text{minimize}} \|Y^C - D^C X^C\|_2^2 \quad \text{s. t.} \quad \|X_i^C\|_0 \leq S$$

4: **end for**

Cost Function Calculation

Algorithm 2 Cost Function Calculation (CFC)

Input: Testing patches along profile of current landmark locations: $\{Y_{l,p}^{T}\}_{l=1}^{L}$, Learnt Shape Model, Dictionaries for background and the landmarks: D^B and D^F

Output: Predicted Landmark location

1: **for** $l = 1...L$ **do**
2:     **for** p = each location on the profile of current Landmark l **do**
3:         **for** C={B,F} **do**
4:             Compute $Y_{l,p}^{T}$
5:             $R_{l,p}^{C} = \|y_{l,p}^{T} - D^{C}\hat{x}_{l,p}^{C}\|_2^2$
6:         **end for**
7:           $P_{l,p} = \lambda(1 - R_{l,p}^{B}) + (1-\lambda)R_{l,p}^{F}$
8:     **end for**
9: **end for**

Rotation Invariant - HOG

- Sample boxes aligned w.r.t. the surface normal
  - Training: Foreground patches can encode the boundary appearance and background patches can encode the completely inside/ outside info
  - Testing: optimization along normal profile ensures that both foreground and background agrees on final position.
- Rotation problem is resolved y the RI-HOG features
  - Any other sophisticated feature and sampling strategy will suffice