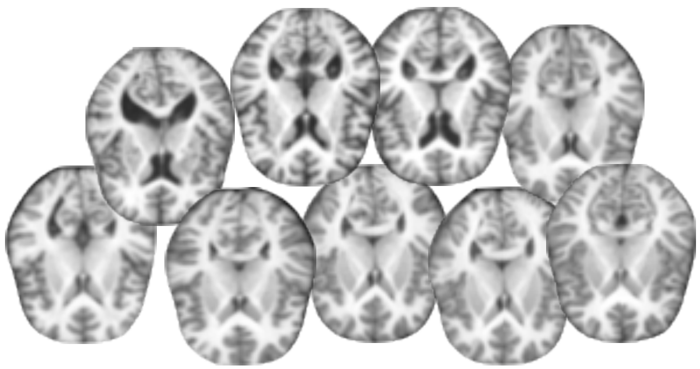
Hierarchical Feature Matching for Shape Analysis

Ross Whitaker

BIRS - Aug 2011

Some Recent Work

- Suppose we have lots of examples (images/ shapes)
  - 100s - 1000s



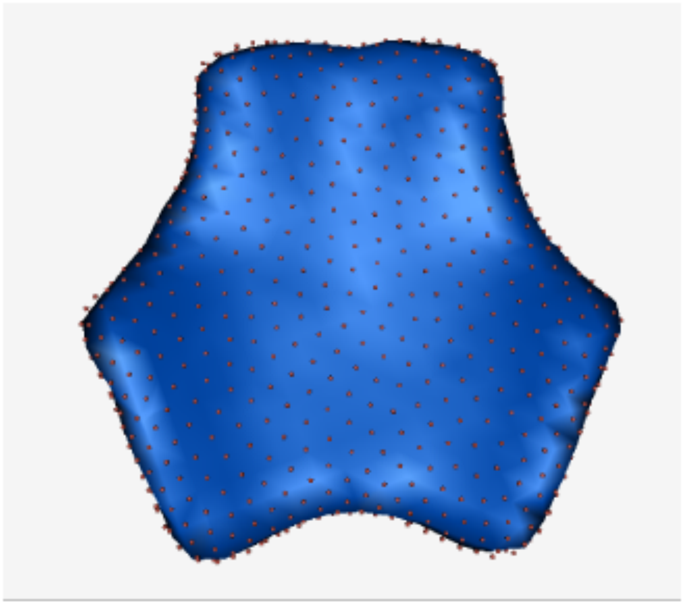
- Opportunities
  - Possibly <u>learn</u> important shape characteristics
  - Chance of finding similar shapes as needed
- Challenges
  - Making systematic use of so much data
  - Quickly finding what you want

The Talk I Had Planned

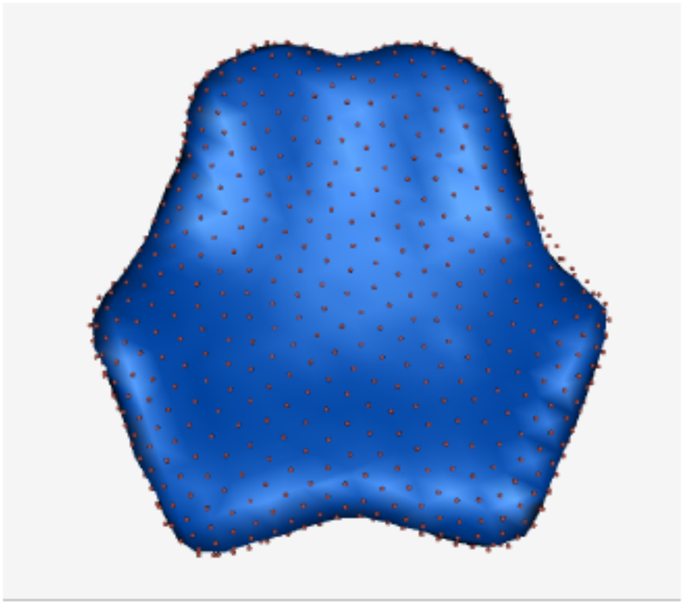
1. Statistics of ensembles for shape correspondence (Cates, Datar)
2. Learning manifolds of large collections of brain images (Gerber)
3. Hierarchical feature-based shape matching for fast neighbor lookup (Zhu)

This Talk

Ensemble-Based Shape Correspondence

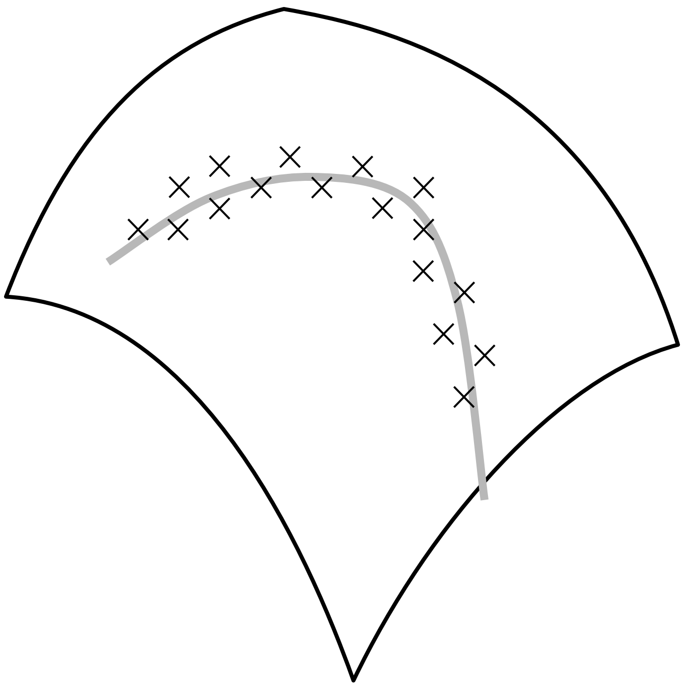


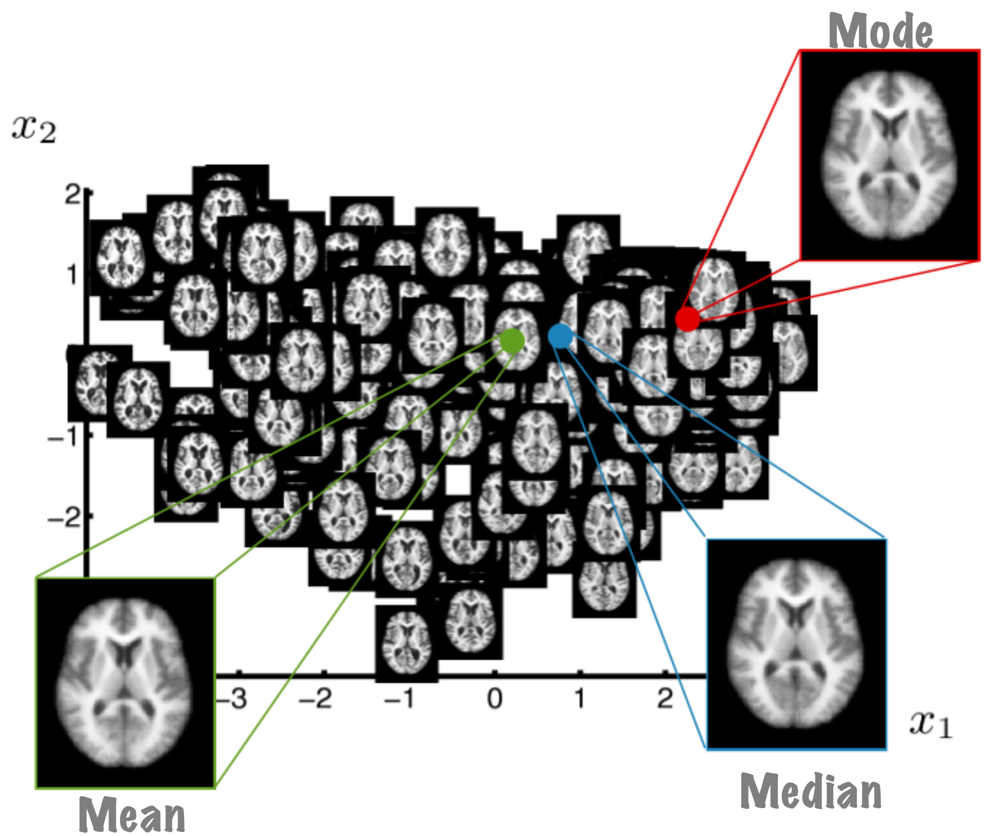
Mean shape: LacZ -/-



Wild Type

Learned Manifolds of Brain Images





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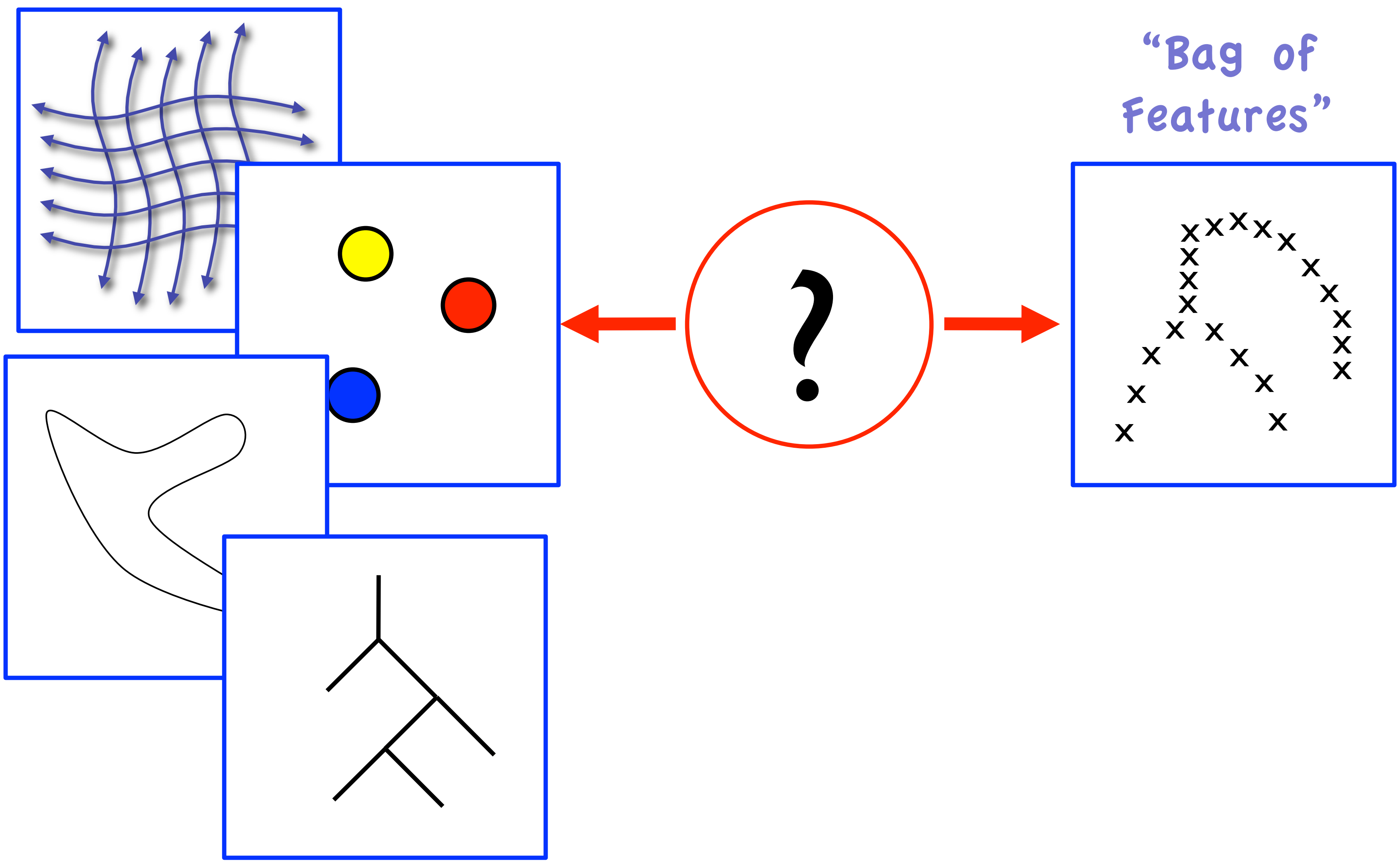
Some Observations

- Shape analysis hinges on "correspondence"
- Shapes similar => correspondence easy
  - Shapes very different => hard (optimization)
- Ensembles help with correspondence
  - Statistical models regularize/constrain problem
  - Rely on nearest neighbors in shape space
- Roadblocks to analysis
  - Getting data into the correct "framework"
  - Optimizations and lack of generality

Shape Representations

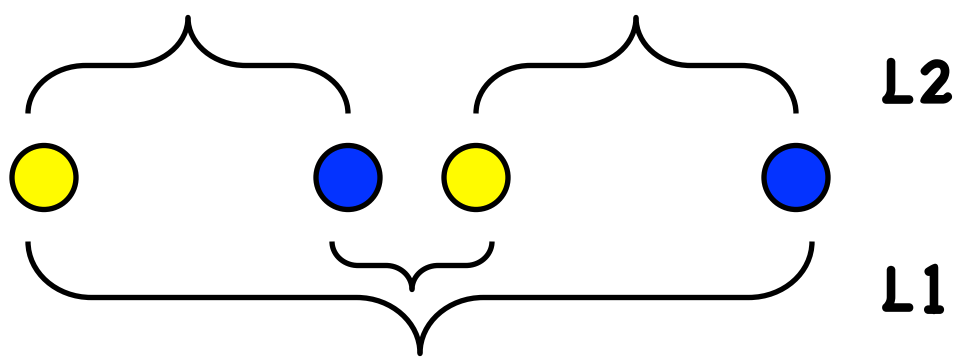


Bipartite Matching

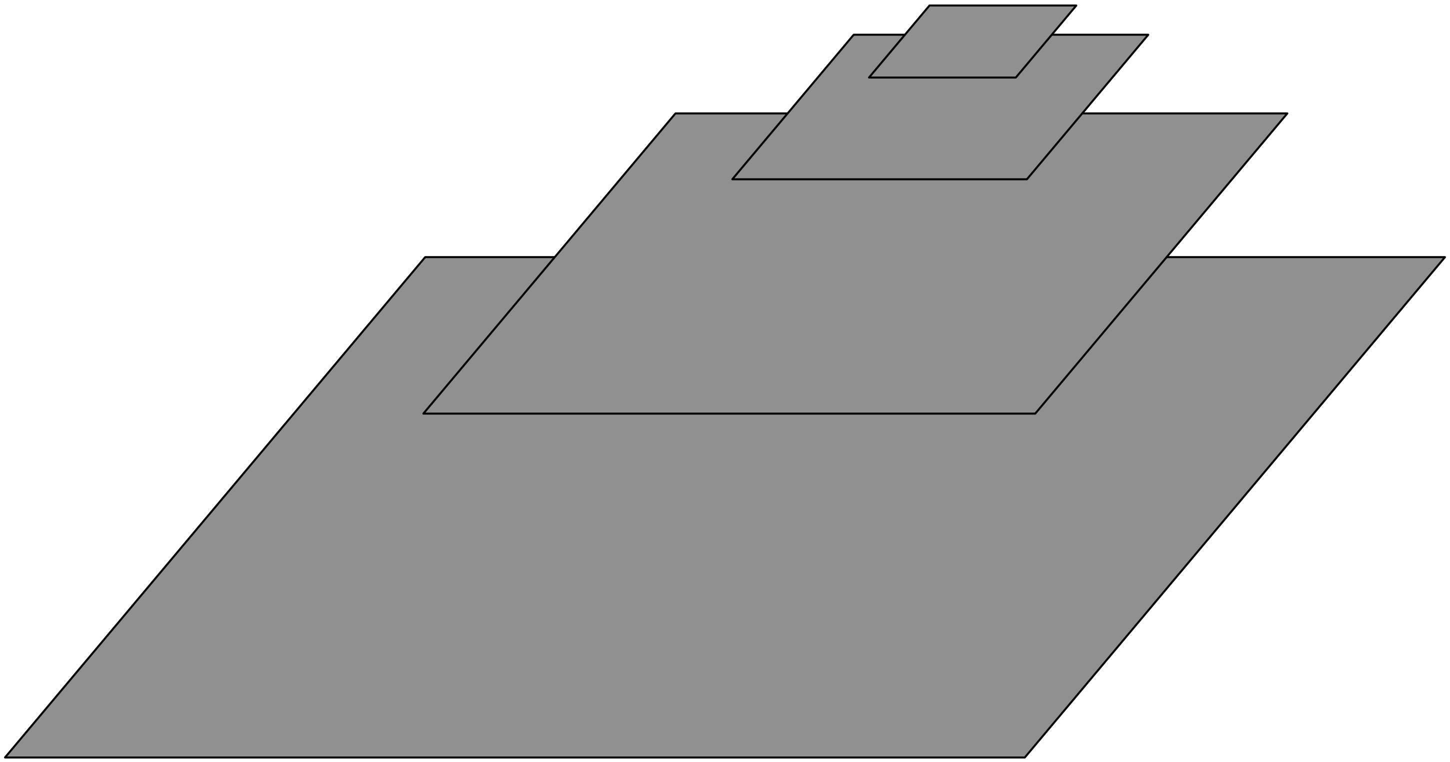
- Find the matches that minimize L1 norm

$$C(X, Y) = \min_{\pi}(|X - \pi Y|)$$

- L1 is agnostic about certain correspondences



Pyramid Matching



Pyramid Matching

- Form a multiresolution set of histograms (of features)

$$\Psi(\mathbf{X}) = [H_0(\mathbf{X}), \ldots, H_{L-1}(\mathbf{X})]$$

- Pyramid match distance/similarity

$$\mathcal{P}_\Delta\left(\Psi(\mathbf{Y}), \Psi(\mathbf{Z})\right) = \sum_{i=0}^{L-1} w_i N_i$$

- N_i is number of matches at each level

$$\mathcal{I}(\mathbf{A}, \mathbf{B}) = \sum_{j=1}^{r} \min\left(\mathbf{A}^{(j)}, \mathbf{B}^{(j)}\right) \qquad N_i = \mathcal{I}\left(H_i(\mathbf{Y}), H_i(\mathbf{Z})\right) - \mathcal{I}\left(H_{i-1}(\mathbf{Y}), H_{i-1}(\mathbf{Z})\right)$$

- Cost/distance vs similarity

$$w_i = d2^i \qquad w_i = \frac{1}{d2^i}$$

Pyramid Matching

- Form a multiresolution set of histograms (of feature sets A and B)

$$H(A) = [h_1(A), h_2(A), \ldots, h_L(A)]$$
$$H(B) = [h_1(B), h_2(B), \ldots, h_L(B)]$$

Bin size $\frac{1}{d2^l}$

- Pyramid match distance/similarity

$$\kappa(A, B) = \sum_{l=1}^{L} w_l N_l$$

- N_i is number of matches at each level

$$N_l(A, B) = I_l(A, B) - I_{l-1}(A, B) \quad I_l(A, B) = \sum_{\text{bins i}} \min\left(h_l^{(i)}(A), h_l^{(i)}(B)\right)$$

- Cost/distance vs similarity

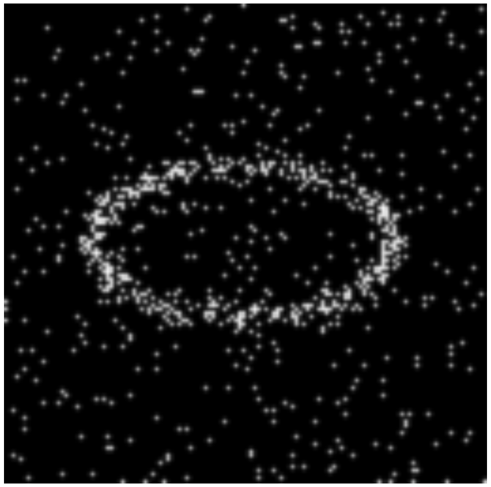
$$w_i = d2^i \quad w_i = \frac{1}{d2^i}$$

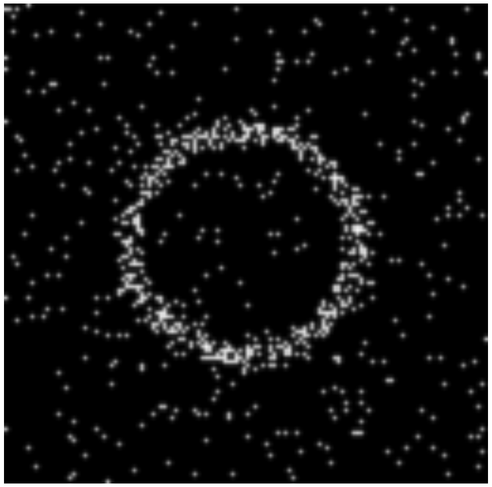
Pyramid Match Kernels
Grauman 2006

- The distance case approximates L1 (expected)
- Distance case -> metric
- Similarity case -> Mercer kernel
  - Also robust to outliers/mismatches
- Technicalities
  - How to deal with different numbers of features
  - Should be "normalized"
- Use x-y coordinates and coded features
  - SPM, Lazebnik 2006

Some Experiments

- Random points from circles/ellipses
- Up to 15% random points (mismatches)
- Kernels moderately robust (distinguish shapes)
- Distance less so…





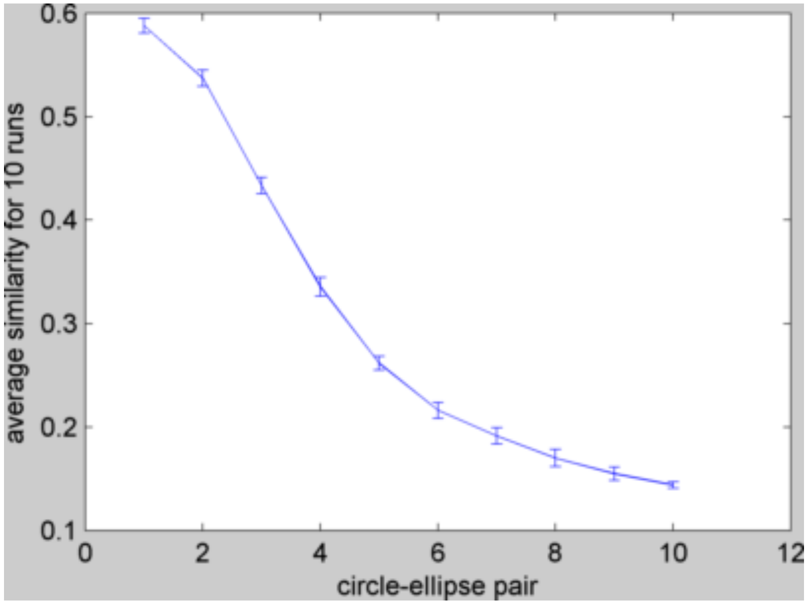
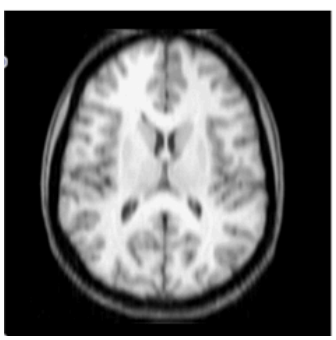
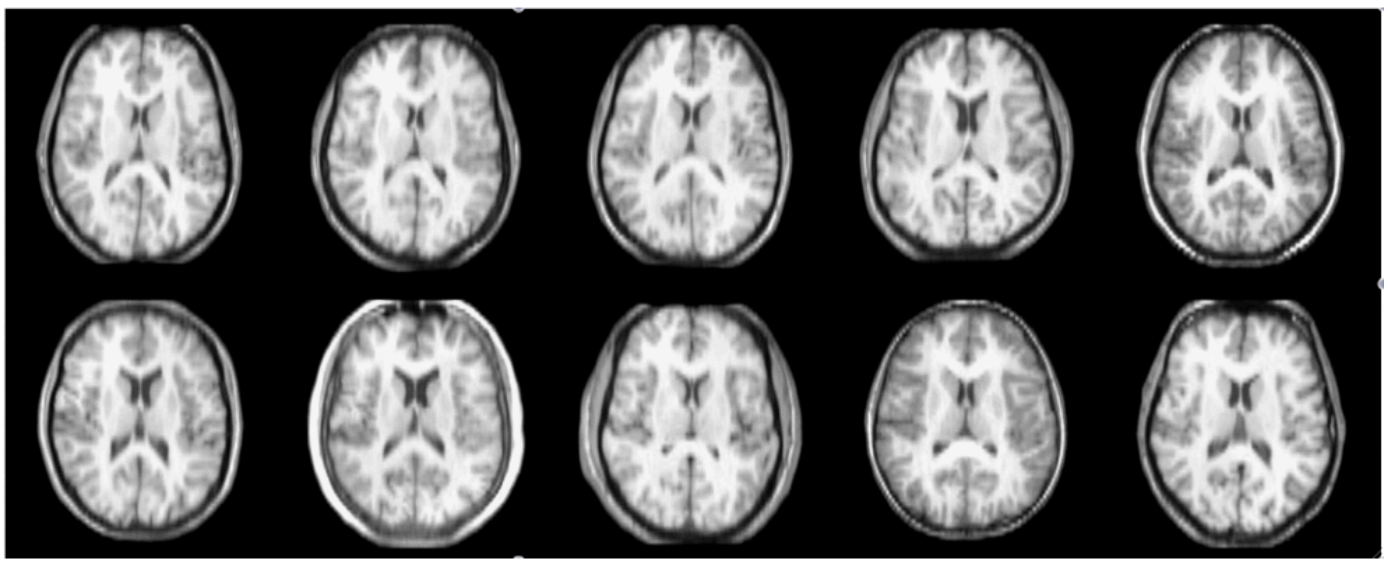


Image Segmentation
How to Choose a Template?

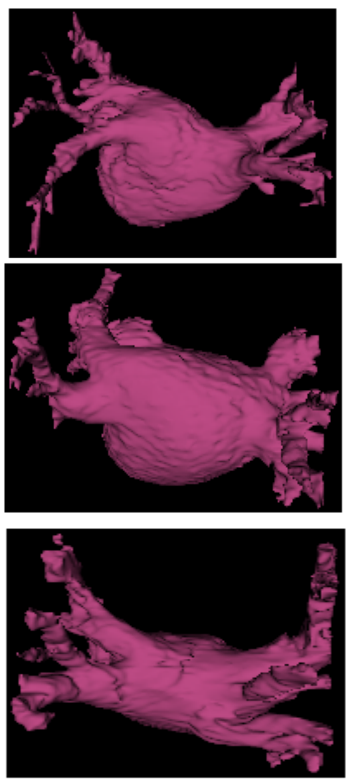
- Single individual? Not general
- Average of whole population? Too general
- Choose a set of segmented images that

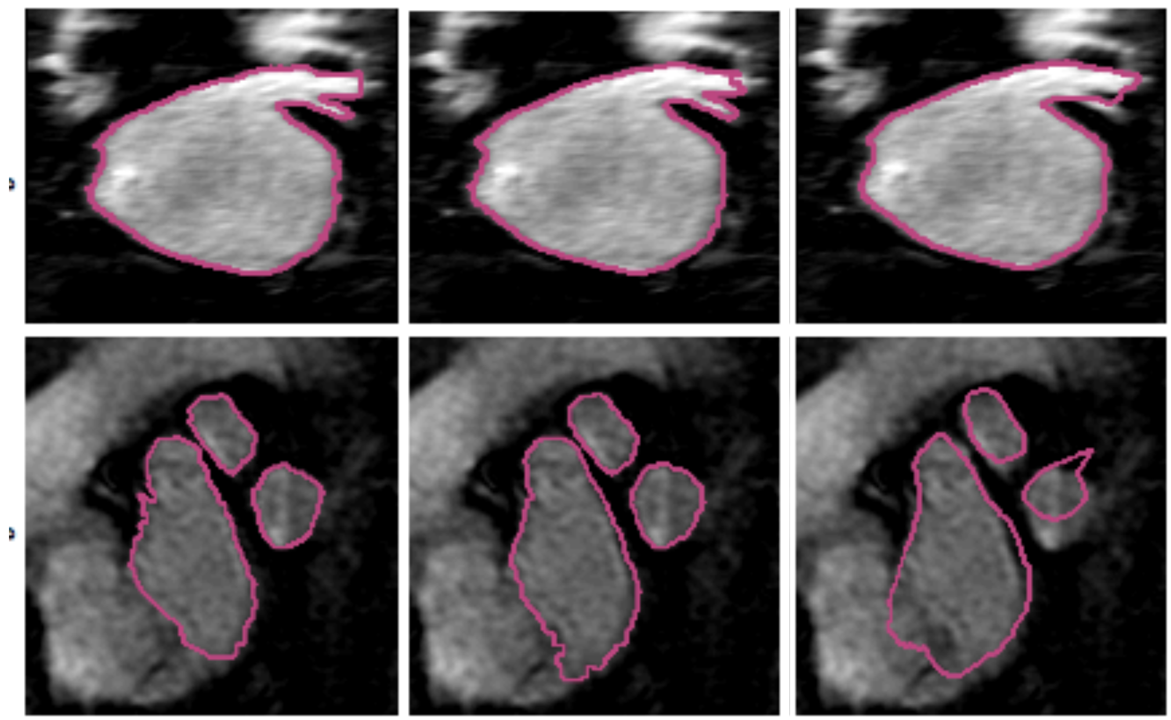




Choosing Similar Templates

- Nonparametric estimators on the space of objects [Depa, et al. 2010]



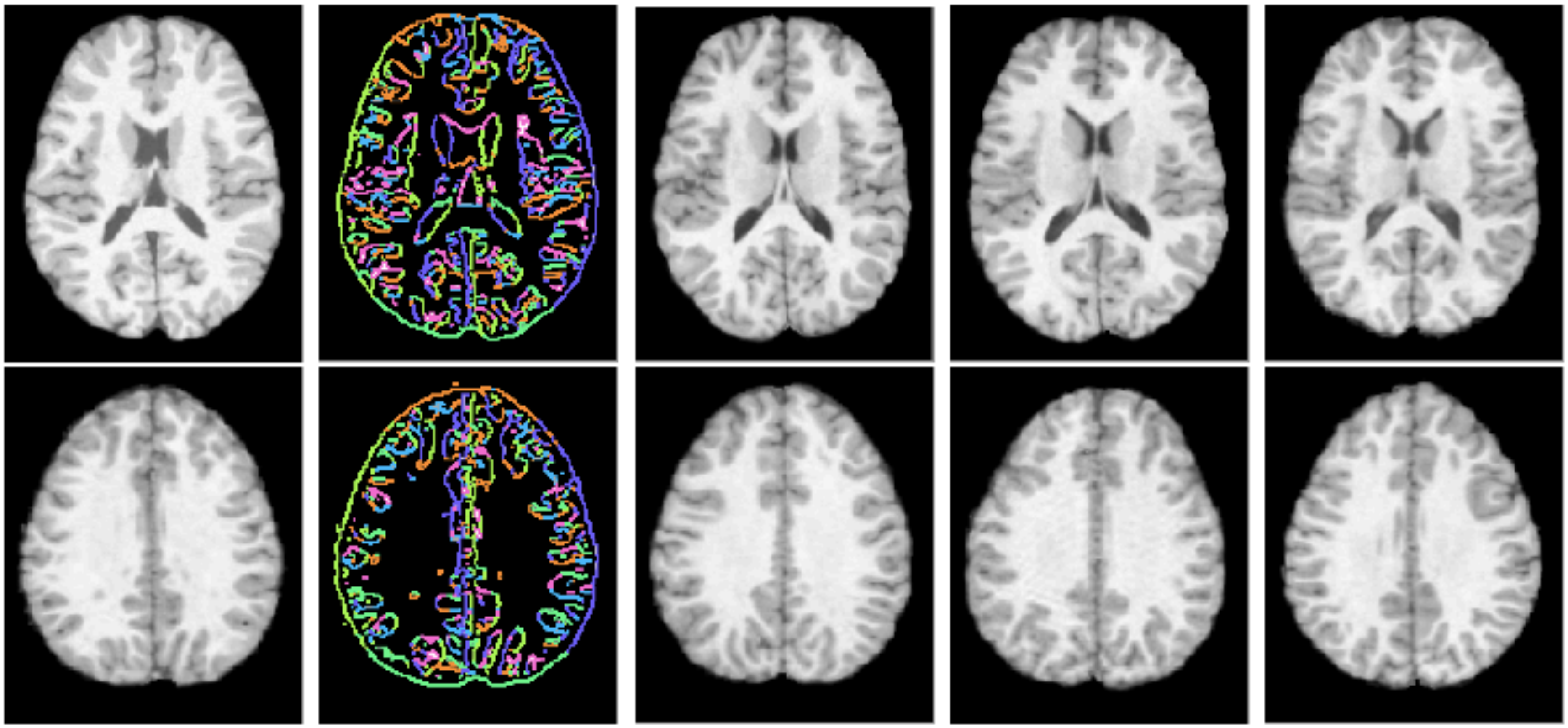


(a) expert (b) WV (d) AT

Challenge

- Given (potentially) thousands or millions of examples, how do we find the most similar images (shape)?
- Zhu, et al. , MICCAI 2011
  - Use spm as an approximate, fast shape "lookup" for very large sets of examples
  - Strategy: (i) Features (ii) Codebooks (iii) SPM for shape similarity

Nearest Neighbor Lookup (Brains)

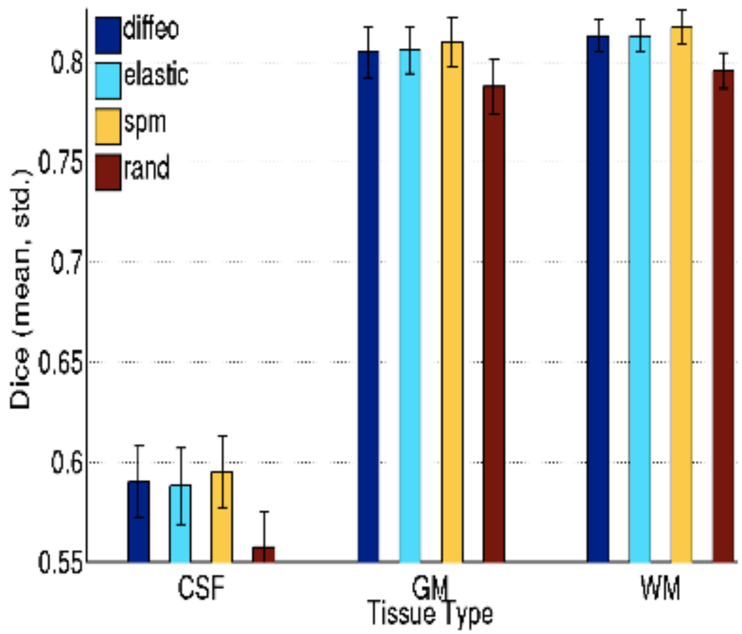


Nearest Neighbor Lookup Segmentation Performance

k-NN Accuracy	Diff$_1$	Diff$_2$	Elas$_1$	Elas$_2$	SPM$_1$	SPM$_6$	SPM$_{18}$
Diff$_1$	1	0.39	0.22	0.35	0.25	0.32	0.32
Diff$_2$		1	0.51	0.69	0.45	0.53	0.53
Elas$_1$			1	0.45	0.36	0.36	0.36
Elas$_2$				1	0.42	0.52	0.53
SPM$_1$					1	0.56	0.52
SPM$_6$						1	0.86
SPM$_{18}$							1

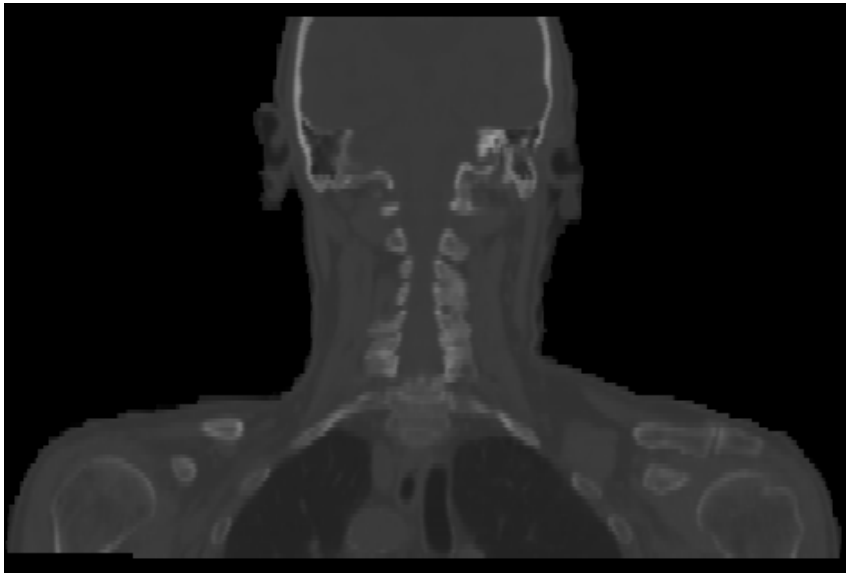
Average ϵ-Ball Radius Ratio	Diff$_1$	Diff$_2$	Elas$_1$	Elas$_2$	SPM$_1$	SPM$_6$	SPM$_{18}$
Diff$_1$	1	1.24	1.30	1.25	1.38	1.33	1.32
Diff$_2$	1.26	1	1.20	1.16	1.33	1.29	1.26
Elas$_1$	1.29	1.19	1	1.23	1.29	1.27	1.27
Elast$_2$	1.13	1.07	1.10	1	1.12	1.09	1.09

Tissue classification

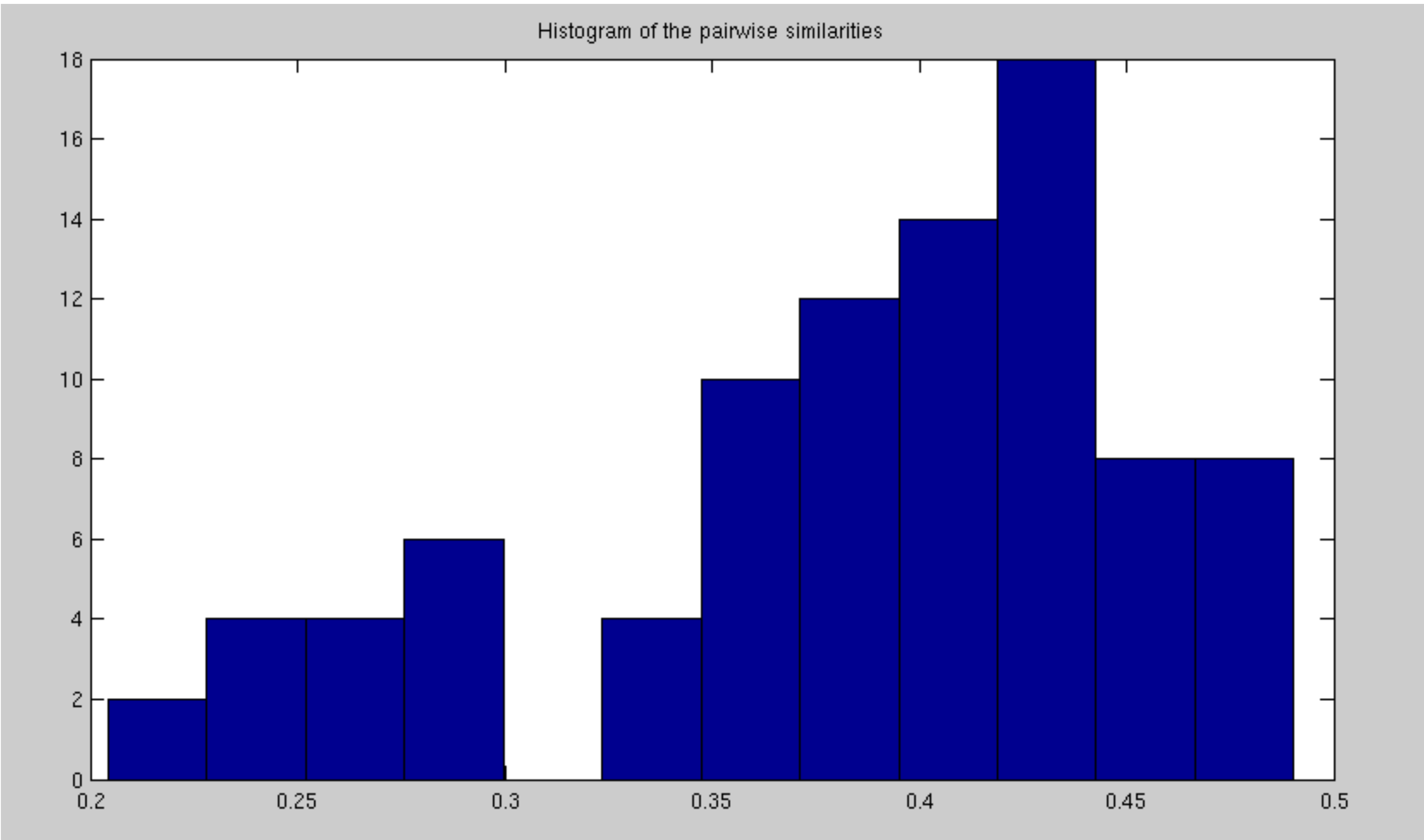


Another Example

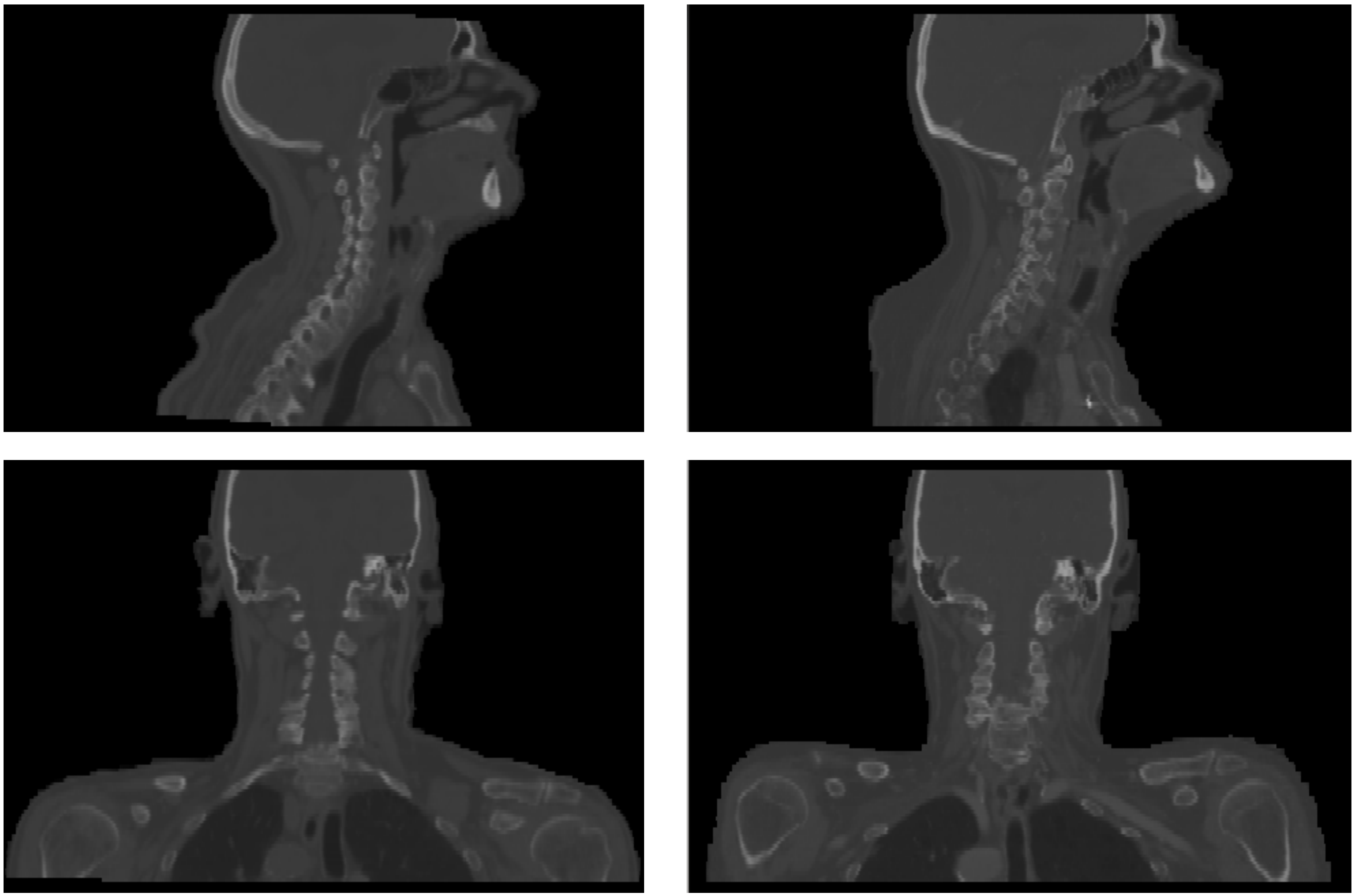
- Head/neck CT for radiation treatment
- Can we reuse old segmentations?
  - E.g. from large database



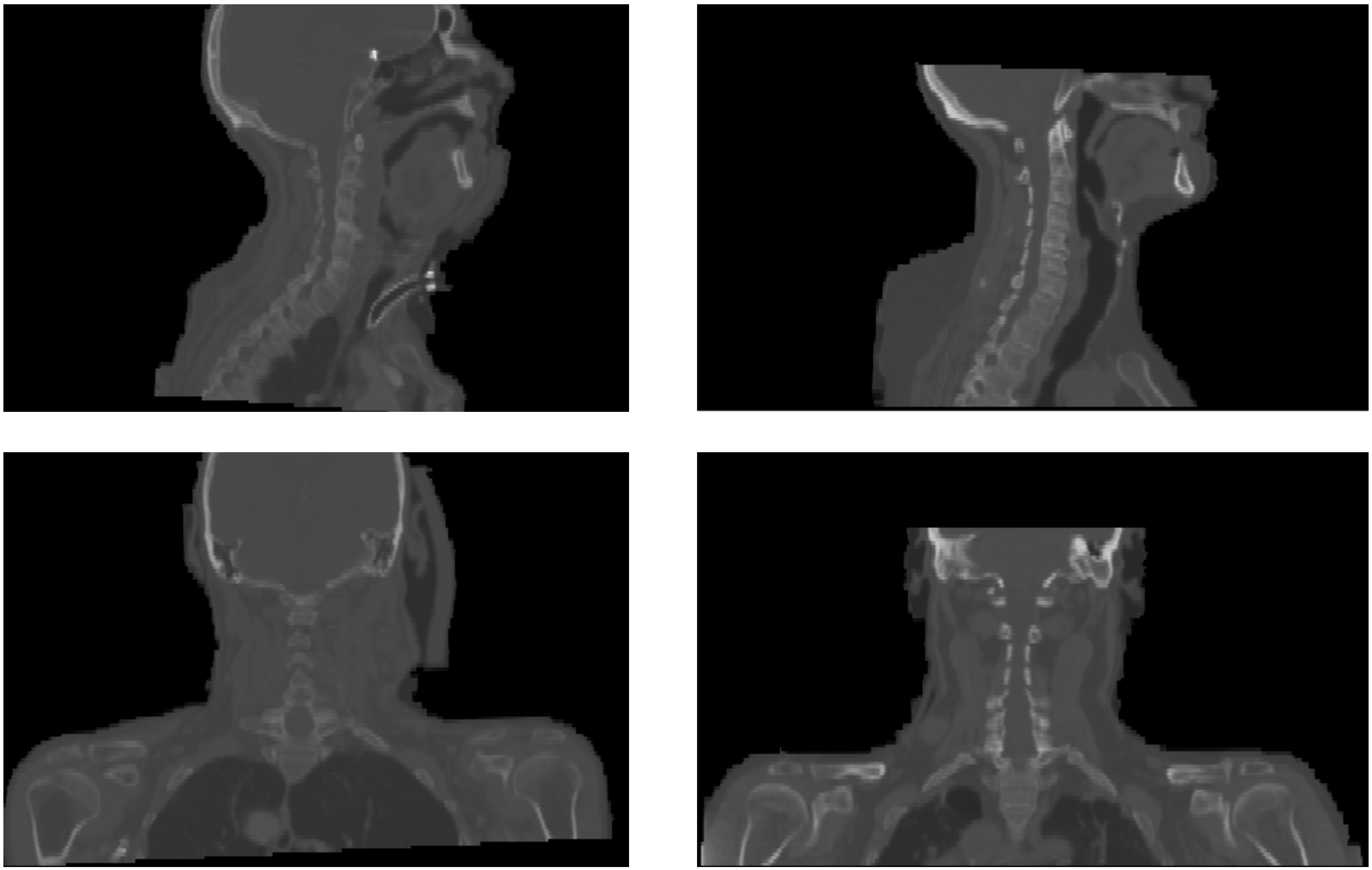
Experiment - 10 Scans



Good Match



Bad Match



Speed Is Important

- Floating point operations (est. for vol)
  - LDDM – 10^{13}
  - Elastic registration – 10^{11}
  - SPM – 10^{8}
- Can we do more with this representation?
  - E.g. statistics