A Latent Source Model for Patch-Based Image Segmentation



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Motivation

Patch-based segmentation methods popular now \rightarrow circumvent nonrigid registration for label fusion

 \rightarrow leverage fast approximate nearest-neighbor search

Goal: Develop theory to understand why these methods work

Patch-Based Segmentation

Point-wise Segmentation

Predict each pixel's label separately using patches

Generative Model for Each Patch

Each pixel has its own canonical patches in two bags

Center pixel: Center pixel: not liver liver

Randomly Add choose patch Gaussian from bags noise

Variants of the following nearest-neighbor algorithm:



There are many ways to improve this algorithm (weighted majority voting, feature descriptors, smoothing, etc.)

Contributions

New theoretical guarantee

 \rightarrow characterizes pixel mislabeling rate of nearest-neighbor, weighted majority voting patch-based segmentation



Theoretical Guarantee

Nearest-neighbor/weighted majority voting

Assume:

- Nearby pixels share enough canonical patches
- Canonical patches with opposite labels different enough

Then can make average pixel mislabeling rate (0 to 1) \rightarrow 0 with # training subjects = $\Theta(k \log k)$

 $k = \max \#$ canonical patches a pixel has

Interpretation

- # training subjects sufficient: enough to see all canonical patches per pixel
- error doesn't \rightarrow 0: assumptions don't hold across image

New probabilistic model for patch-based segmentation \rightarrow leads to new iterative algorithm with many existing patchbased methods as special cases

Key Ideas

Patches Cluster

In real images, what do plausible small patches look like?



Can cluster these into "canonical" patches!

 \rightarrow model image patches as noisy versions of few canonical patches ("latent sources" that generate patches)

Multi-point Segmentation

Predict label patches and merge label patch estimates

Probabilistic Model

Two additions to point-wise segmentation model:



Inference: ADMM Algorithm

Iterate between:

 Predict each label patch separately – parallelizable

Nearby Patches Appear Similar

Spatially nearby patches (within subject & across subjects) can be explained by same canonical patch



Two subjects (affinely aligned)

Shared canonical patch

 \rightarrow model nearby patches to share which canonical patches they are generated from

- (e.g., weighted majority voting) Merge label patches
- (uniform global prior \rightarrow average each pixel's label predictions)

Results

Average

label

images





ADMM

New

Weighted Nearest neighbor majority voting



New ADMM algorithm

Multi-point/in-painting



