Tissue-Specific Sparse Deconvolution *for* Low-Dose CT Perfusion

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P1-02

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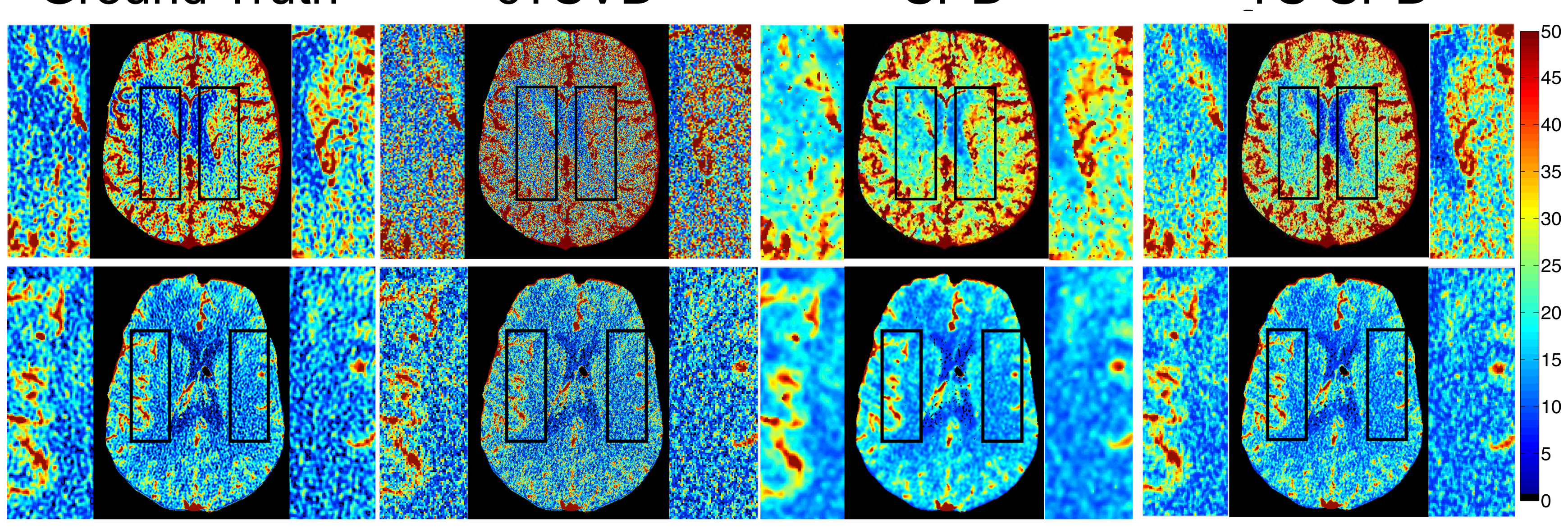
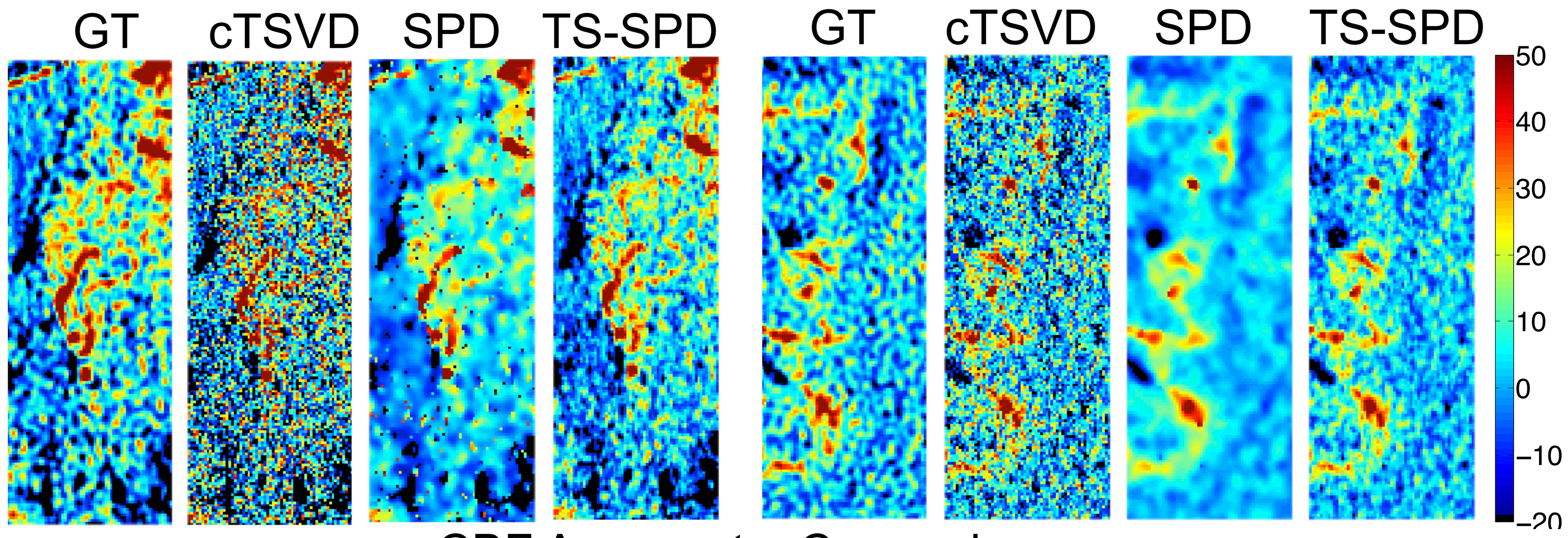
Visual Comparisons

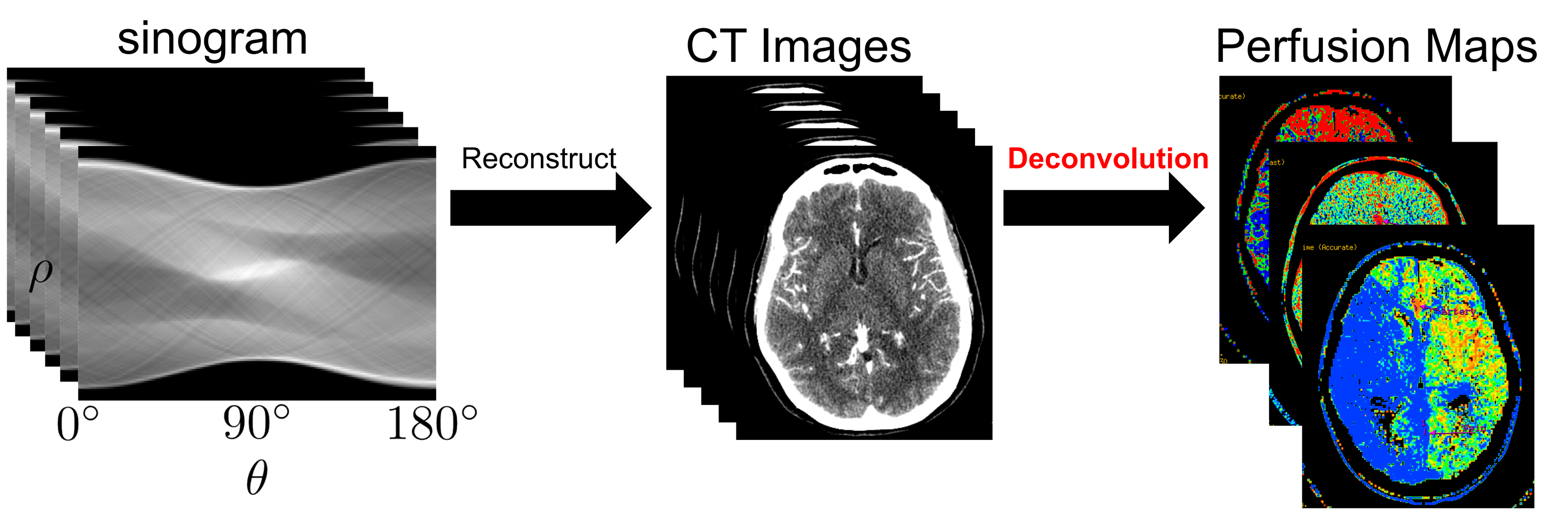


Low-dose CBF Estimation



CBF Asymmetry Comparison

Background

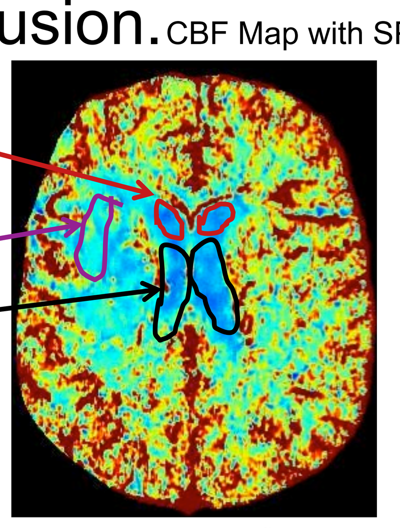


Deconvolution: Estimate perfusion parameters (cerebral blood flow, blood volume, mean transit time) from time-series CT images.

Motivations

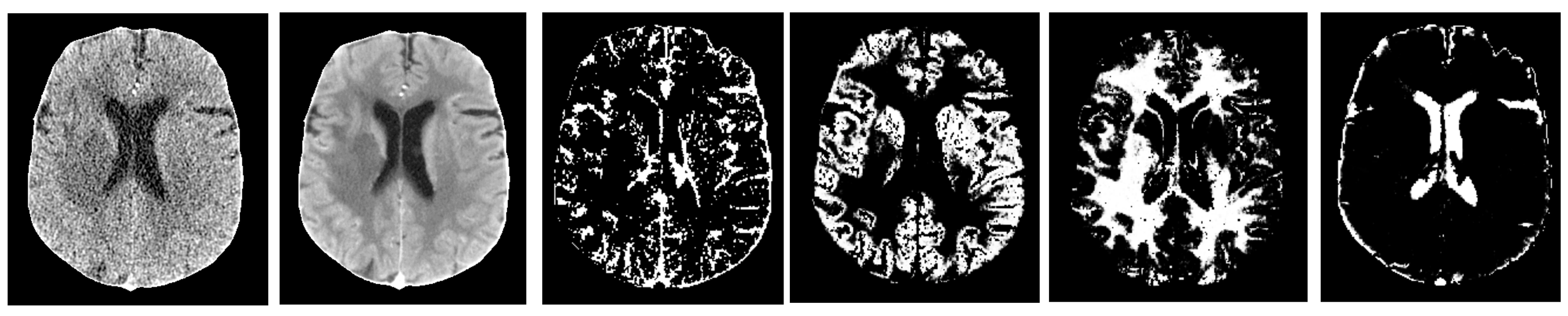
- **Our Goal:** Preserve the low-contrast tissue and subtle perfusion information in low-dose CT perfusion.
- **Current State of Art:** SPD
  - ❖ **Pros:**
    - Spatial-temporal, Data-driven
  - ❖ **Cons:**
    - Over-smooth low-contrast tissue (ischemic penumbra, infarct core, etc.)
- Can we treat the different tissue types respectively?

CBF Map with SPD



Method

- How to remove the noise and preserve the structural details of both high-contrast (vessels) and low-contrast (insula, thalamus) regions?
- Assumption: Different tissue types could be reconstructed from different dictionaries.
- A tissue-specific approach to sparse deconvolution
- **STEP 1**: Tissue Classification
  - Classify the voxels in CTP into four classes: vessel, gray matter (GM), white matter (WM) and cerebrospinal fluid (CSF).
  - Use Expectation-Maximization Segmentation (EMS) with contexture information incorporated by a MRF.



Method cont.

- **STEP 2**: Tissue-Specific Dictionaries Learning

$$\min_{\mathbf{D}^m, \mathbf{A}^m} \sum_{i=1}^{N} \|y_i^m - \mathbf{D}^m \alpha_i\|_2 + \mu_2 \|\alpha_i\|_1$$

m=vessel, GM, WM, CSF

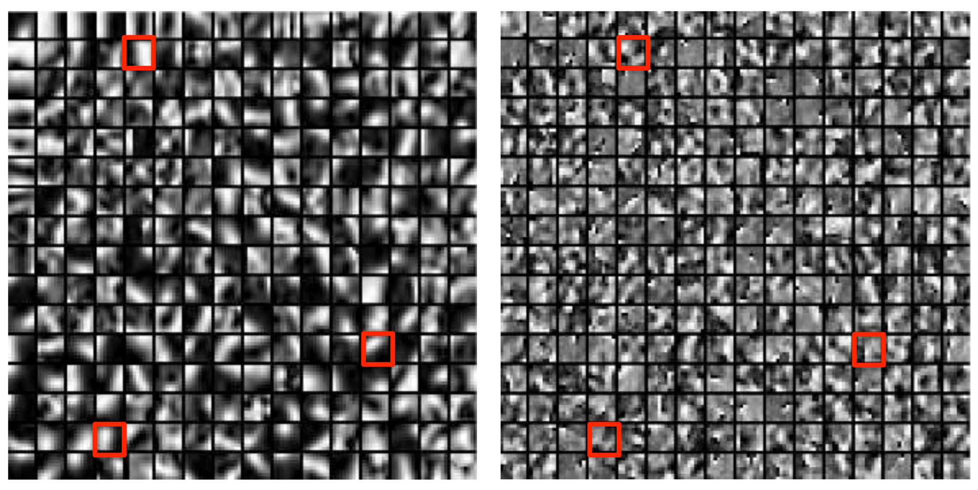
  - Patches with 50% or more pixels in class *i* are used for training dictionary D^i .
  - Use online dictionary learning.
- **STEP 3**: Weighted Sparse Deconvolution
  - Reconstruct the CBF map for each tissue class using the respective dictionary.

$$J = \mu_1 \|\mathbf{C}^m - \mathbf{C_a}\mathbf{R}^m\|_2^2 + \|f^m - \mathbf{D}^m \alpha\|_2^2 + \mu_2 \|\alpha\|_1$$

  - Weighted sum for each pixel based on the classification probability map. $\bar{f}_i = \sum_m w_i^m f_i^m$

Results

- Learned Dictionaries



- Ischemic/Normal Voxels Separation

$$d = (m_1 - m_2)/\sqrt{\sigma_1^2/n_1 + \sigma_2^2/n_2}$$

Method	Stroke	SAH	All data
cTSVD	42.71	46.03	49.91±5.12
KSVD-SPD	57.19	53.96	55.62±3.91
TS-SPD	**63.25**	**56.64**	**59.60±3.82**

- Clinical Evaluation: 10 CTP datasets. PSNR

PSNR	Brain			GM			WM		
	Stroke	SAH	All data	Stroke	SAH	All data	Stroke	SAH	All data
cTSVD	43.51	34.87	33.57	12.81	15.94	15.91	19.99	18.65	17.82
KSVD-SPD	45.80	37.11	34.91	17.53	18.08	17.88	22.80	19.75	19.41
TS-SPD	**47.84**	**38.38**	**36.65**	**18.92**	**19.66**	**19.91**	**25.02**	**22.56**	**22.28**

Take Home Messages

- Significantly improve the qualitative and quantitative fidelity to ground truth compared to global SPD.
- Preserve low-contrast, subtle structural information for improved diagnosis.
- Incorporate tissue-specific information into dictionaries.

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