Fast Shape-Based Nearest-Neighbor Search for Brain MRIs using Hierarchical Feature Matching

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CONTRIBUTIONS

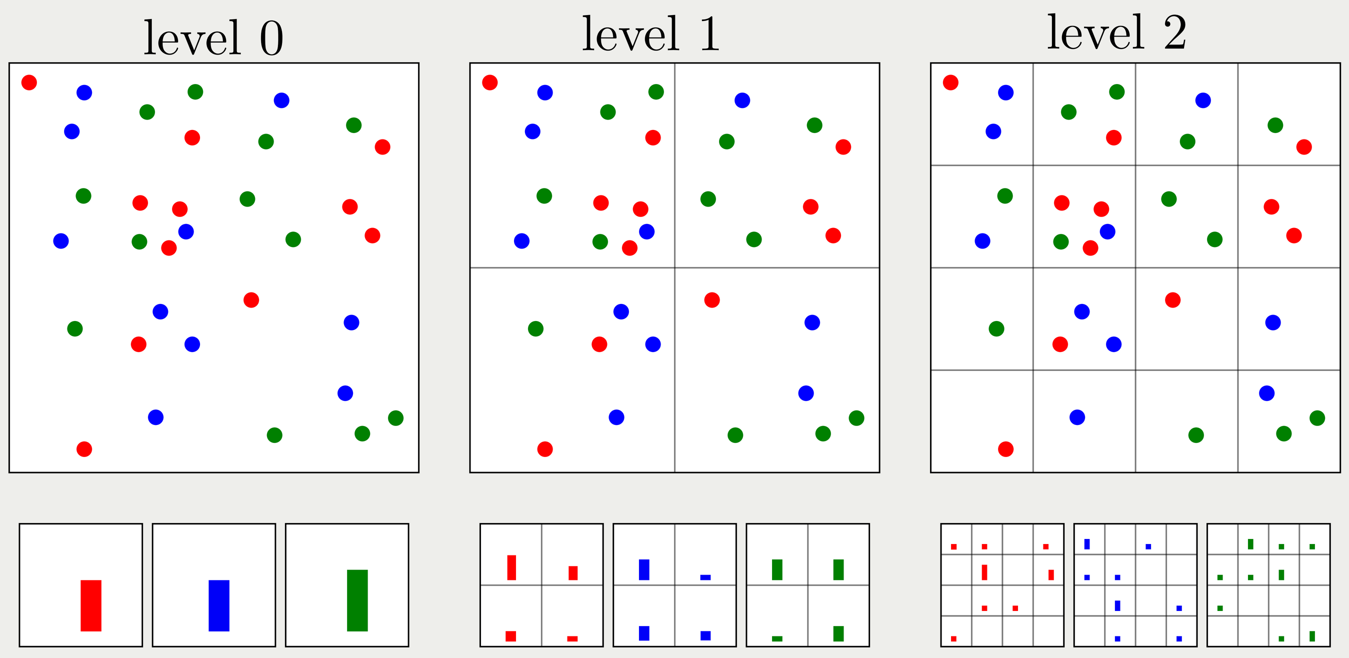
- Proposed a fast *spatial pyramid matching* (SPM)[1] based method for quantifying shape similarities/differences between pairs of brain MR Images.
- Demonstrated the effectiveness of the proposed method, by comparing with the registration based distance metrics, in k nearest neighbor (k-NN) search for brain MR Images.
- Applied this method to *multiatlases* based brain tissue segmentation.

METHODOLOGY

- Image pre-processing: intensity and spatial normalization, edge-preserving filtering.
- Feature extraction: collect orientation+curvature feature vectors on canny edges.
- Codebook generation: apply k-mean clustering in feature space, the clustering centers consist of the codebook.
- Label assignment: assign hard/soft labels to feature vectors.
- SPM similarity computation.

SPATIAL PYRAMID MATCHING (SPM)

Each labeled feature map is represented as a multilevel histogram called spatial pyramid. Features in two different pyramids are 'matched' if they lie in the same bin at a specific level in the pyramid.



Given two images *A* and *B*, if denote their spatial pyramid at level l as h_A^l and h_B^l, the number of matches is given by the *histogram intersection*:

$$I(h_A^l, h_B^l) = \sum_{i=1}^{M_l} \min(h_A^l(i), h_B^l(i))$$

The number of new matches occuring at level $l < L$ is $N_l = I(h_A^l, h_B^l) - I(h_A^{l+1}, h_B^{l+1})$, and for level *L*, is $N_L = I(h_A^L, h_B^L)$

Similarity between *A* and *B* is then measured using pyramid matching kernel (PMK):

$$\kappa(A,B) = \sum_{l=1}^{L} w_l N_l = I(h_A^L, h_B^L) + \sum_{l=0}^{L-1} \frac{1}{2^{L-l}} (I(h_A^l, h_B^l) - I(h_A^{l+1}, h_B^{l+1})),$$

where $w_l = 1/(2^{L-l})$ decreases exponentially with level coarseness, for the finest level, $w_L = 1$

To ensure a maximum PMK similarity, it is normalized as: $\tilde{\kappa}(A,B) = \kappa(A,B)/\sqrt{\kappa(A,A)\kappa(B,B)}$

PERFORMANCE EVALUATION

- Effectiveness

SPM is compared to elastic registration[2] and diffeomorphic registration (LDDMM)[3] for k-NN selection of brain MRIs. Considering a training set of brain images $\mathcal{B} = \{B_1, \cdots, B_M\}$ and a test set $\mathcal{A} = \{A_1, \cdots, A_N\}$. For image A_i, let the k-NN found by SPM and reference method (elastic registration or diffeomorphic registration) be $\eta_S(A_i, k)$ and $\eta_R(A_i, k)$, the evaluation metrics are:

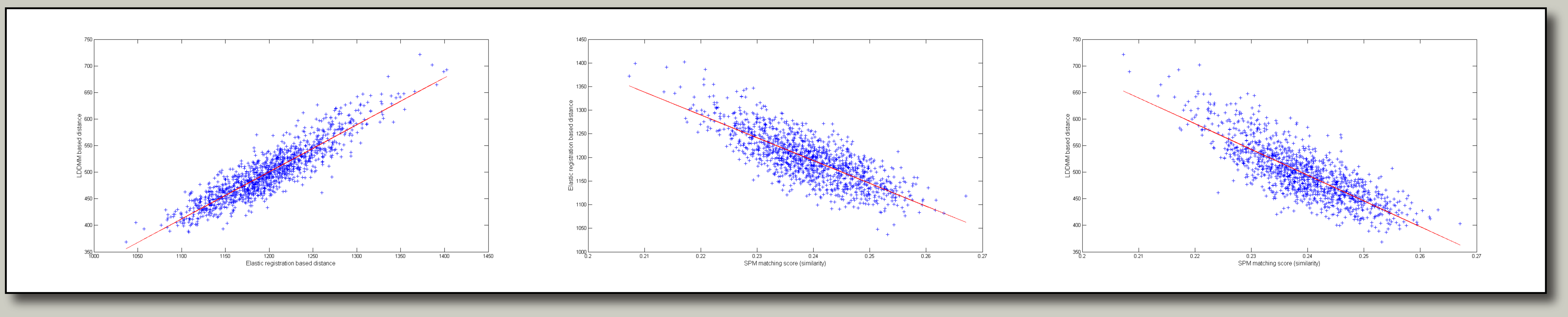
1. Accuracy: $\pi = (1/N) \sum_{i=1}^{N} |\eta_R(A_i,k) \cap \eta_S(A_i,k)| / |\eta_R(A_i,k)|$
2. ϵ -ball radius ratio: $\gamma = (1/N) \sum_{i=1}^{N} [\max_{B \in \eta_S(A_i,k^*)} d_R(A_i,B)] / [\max_{B \in \eta_R(A_i,k)} d_R(A_i,B)]$
3. Dice Overlap: $Dice = (2|A \cap G|)/(|A| + |G|)$

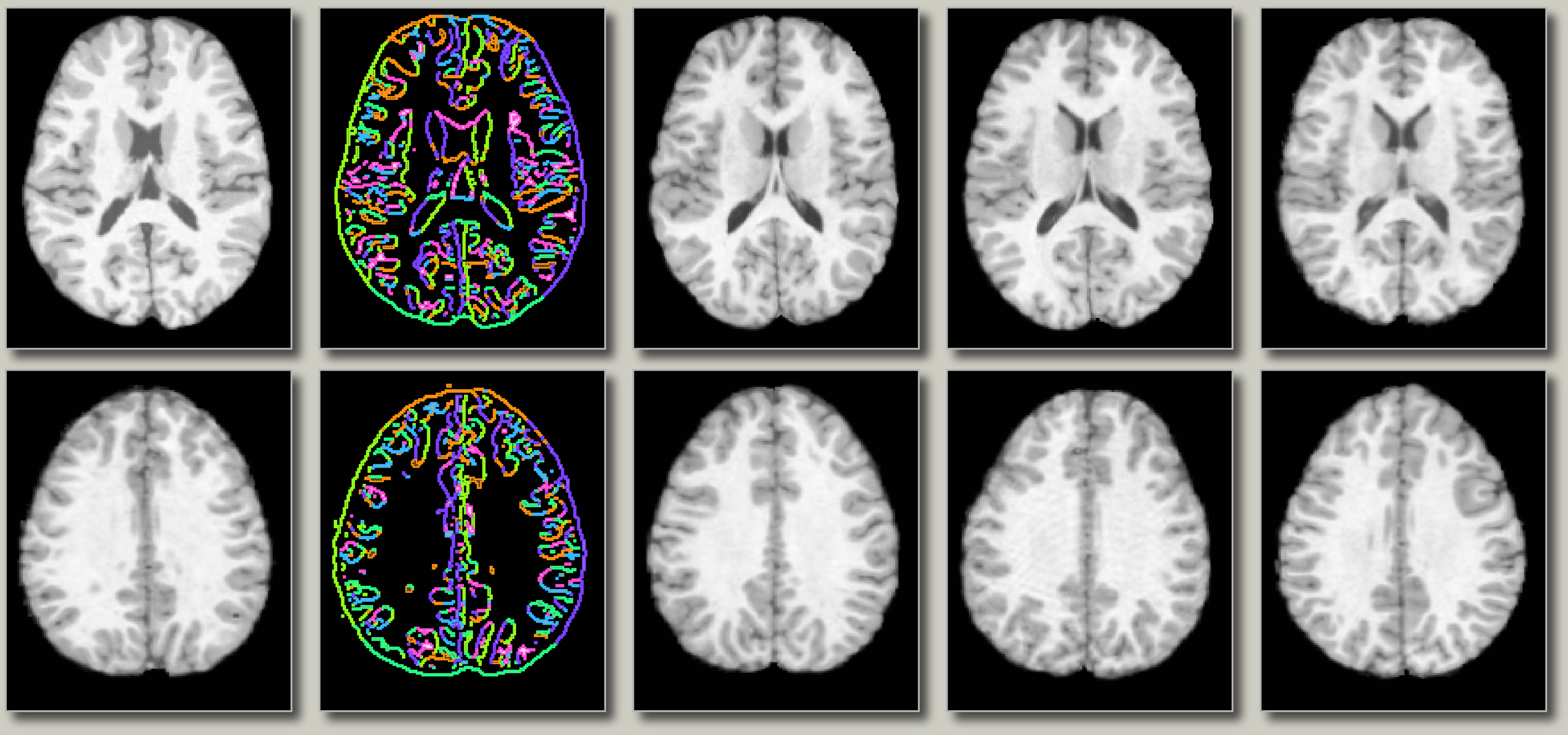
- Computational complexity

linear in the point-set cardinality, number of pyramid levels, and number of codes.

RESULTS

Plots of linear regression



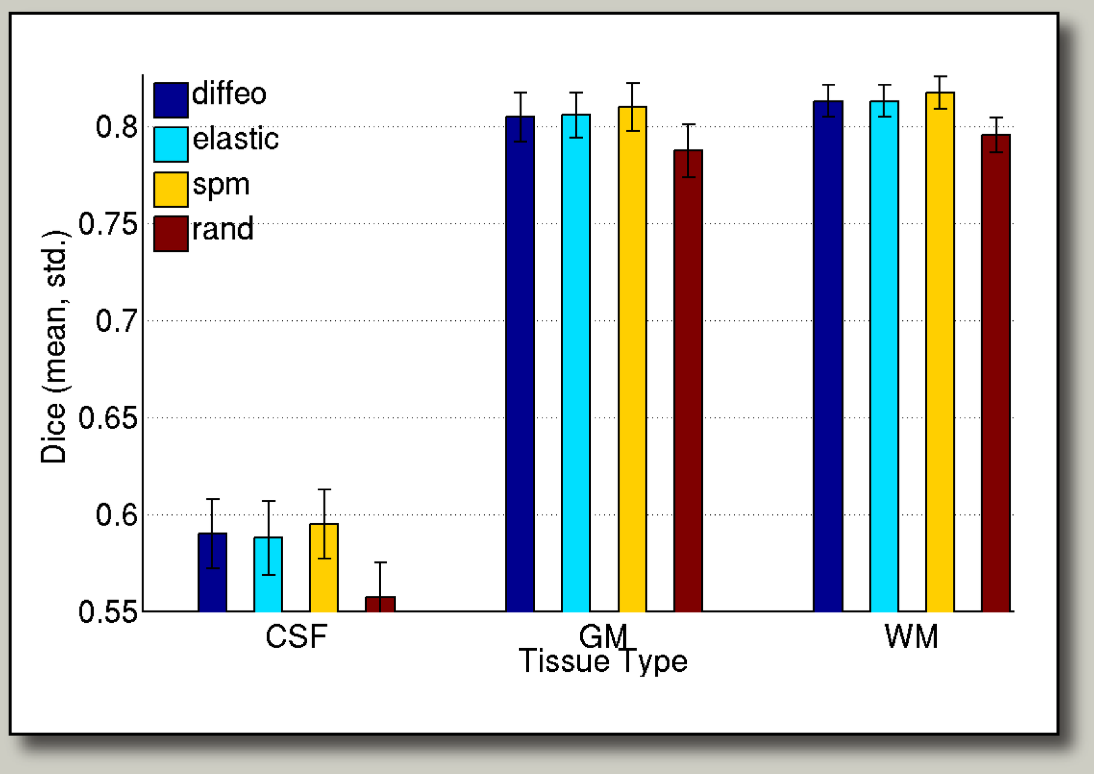


k-NN Accuracy

	$Diff_1$	$Diff_2$	$Elas_1$	$Elas_2$	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



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