SuperPatchMatch: an Algorithm for Robust Correspondences using Superpixel Patches

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Abstract

Superpixels have become very popular in many computer vision applications but remain underexploited due to the decomposition irregularity. In this paper, we first introduce a novel structure, a superpixel-based patch, called SuperPatch. The proposed structure leads to a robust descriptor that includes the spatial information of the superpixel neighborhood. The SuperPatchMatch method is also introduced to generalize the PatchMatch algorithm to SuperPatches. Finally, we propose a framework for fast segmentation and labeling from an image library, and demonstrate the potential of our approach since we outperform, in terms of computational cost and accuracy, state-of-the-art methods based on learning.

SuperPatch

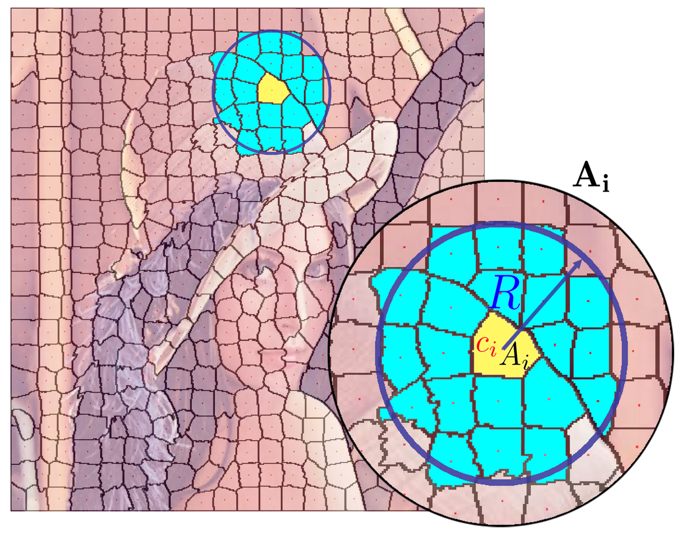
- **Definition:** $\mathbf{A_i}$ superpatch of a superpixel A_i

Superpixels with barycenter in a fixed radius search R,

$$\mathbf{A_i} = \{A_{i'}, \text{ s.t. } i' \in \mathcal{I}_i^A, \ \|c_i - c_{i'}\|_2 \leq R\}$$

c_i spatial barycenter of A_i

F_i feature of A_i (mean color, histogram, etc.)



- **Comparison of 2 superpatches:**

All superpixels of $\mathbf{A_i}$ are compared to all superpixels of a superpatch $\mathbf{B_j}$,

$$D(\mathbf{A_i}, \mathbf{B_j}) = \frac{\sum_{i' \in \mathcal{I}_i^A} \sum_{j' \in \mathcal{I}_j^B} w(A_{i'}, B_{j'}) d(F_{i'}^A, F_{j'}^B)}{\sum_{i' \in \mathcal{I}_i^A} \sum_{j' \in \mathcal{I}_j^B} w(A_{i'}, B_{j'})}$$

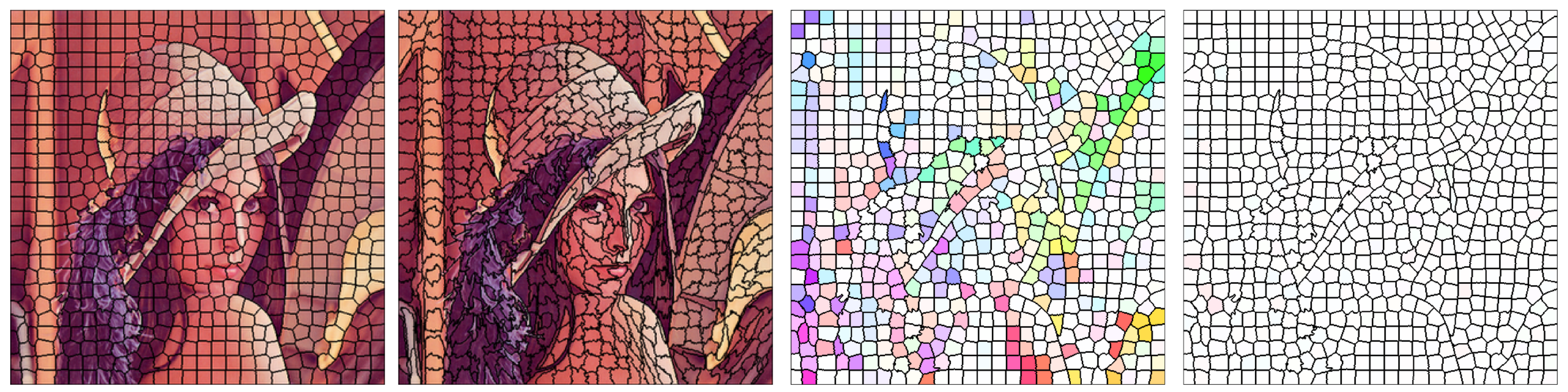
Weighting according to relative registered positions,

$$w(A_{i'}, B_{j'}) = \exp\left(-x_{i'j'}^T x_{i'j'}/\sigma_1^2\right) w_s(A_{i'}) w_s(B_{j'})$$

with $\quad x_{i',j'} = c_{j'} - c_{i'} + c_i - c_j \quad$ and $\quad w_s(A_{i'}) = \exp\left(-\|c_i - c_{i'}\|_2^2/\sigma_2^2\right)$

- **Robustness of superpatches:**

Matching displacement (optical flow display) between two decompositions:



Decomposition n°1 — Decomposition n°2 — Superpixel matching — Superpatch matching

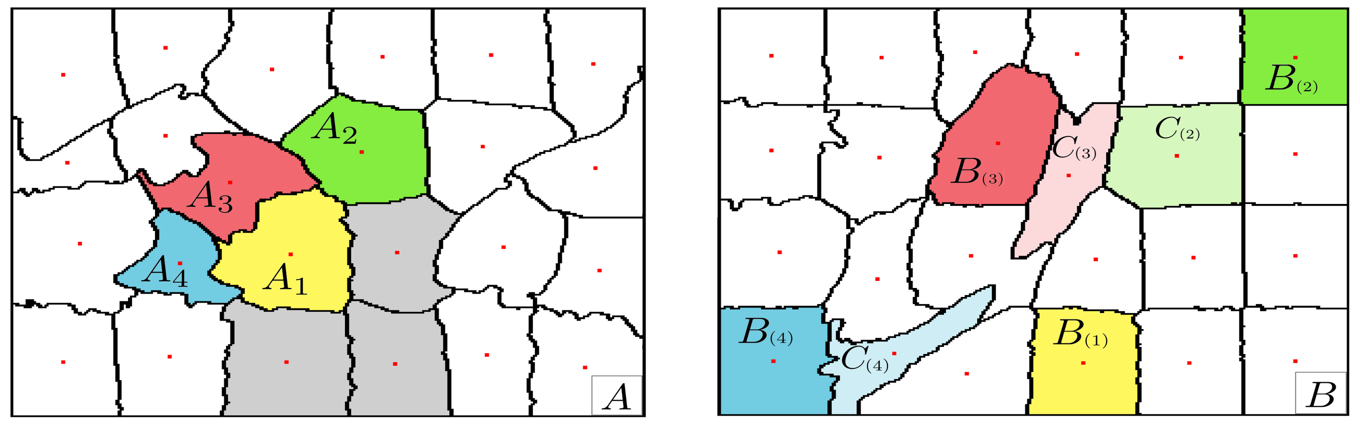
→ Accurate comparison of structures defined on irregular neighborhoods

SuperPatchMatch

- **PatchMatch:** Fast approximate nearest neighbor (ANN) matching of 2D patches between two images, based on cooperative and random strategy [1]
- **SuperPatchMatch:** Adaptation of PatchMatch to superpatch matching
  - **Initialization:** Each superpixel A_i is randomly associated to a superpixel $B_{(i)}$
  - **Propagation:** Test of shifted matches of adjacent superpixels A_j

  Irregular decompositions of A_i's neighborhood

  → selection of the candidate $C_{(j)}$ with the most similar orientation



  - **Random search:** Sampling of superpixels in B around the best match

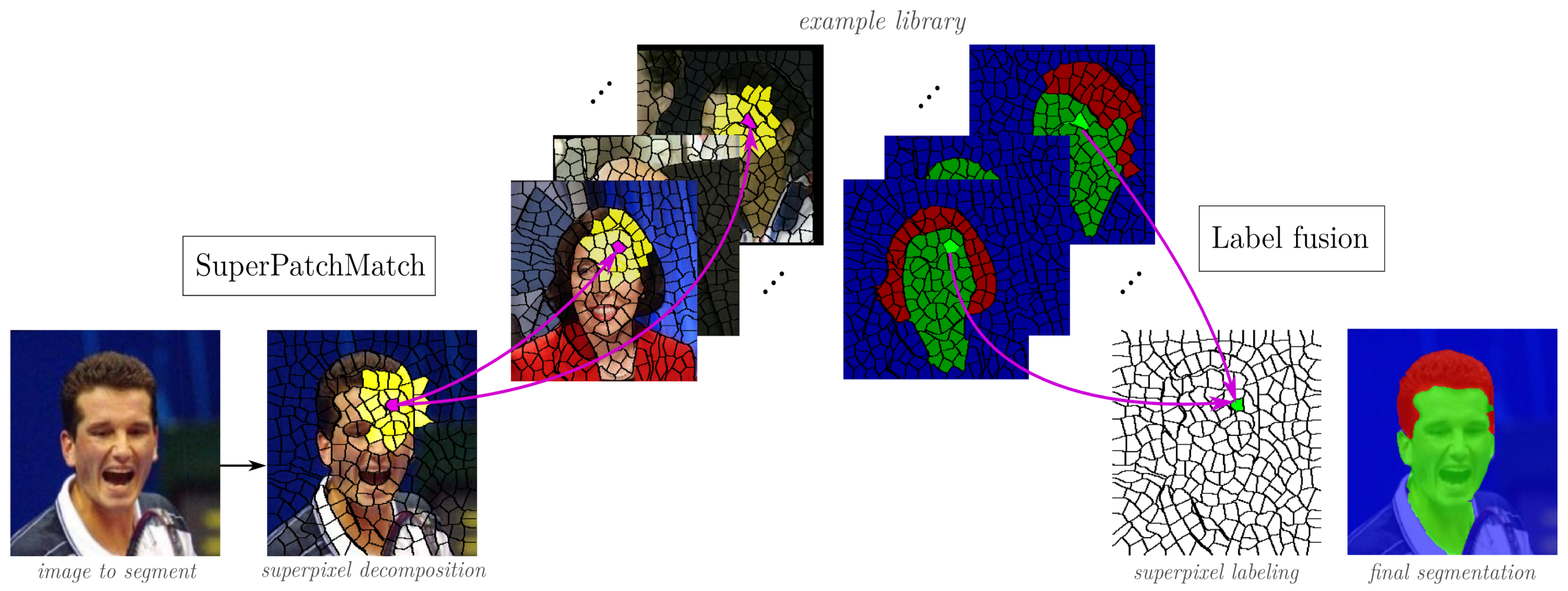
Iterative process to find better matches

Application to Segmentation and Labeling

- **Multiple SuperPatchMatch (SPM) in a library:**

SPM is adapted to find matches in a library of example images T

k independent SPM give k-ANN T_j in T, with labels $l(T_j) = m \in \{1, \ldots, M\}$



- **Label fusion from superpixel matches:**

Label map: $L_m(A_i) = \dfrac{\sum_{T_j \in \mathcal{K}_i^m} \omega(A_i, T_j) l(T_j)}{\sum_{m=1}^{M} \sum_{T_j \in \mathcal{K}_i^m} \omega(A_i, T_j)}$ with $\mathcal{K}_i^m = \{T_j\}$ s.t. $l(T_j) = m$

Map regularization and labeling (highest probability): $\mathcal{L}(A_i) = \underset{m \in \{1,\ldots,M\}}{\text{argmax}} \ L_m(A_i)$

Results

- **Dataset:** LFW [2] (927 test images, 1500 example images)
- **Labeling examples:** k=50 ANN

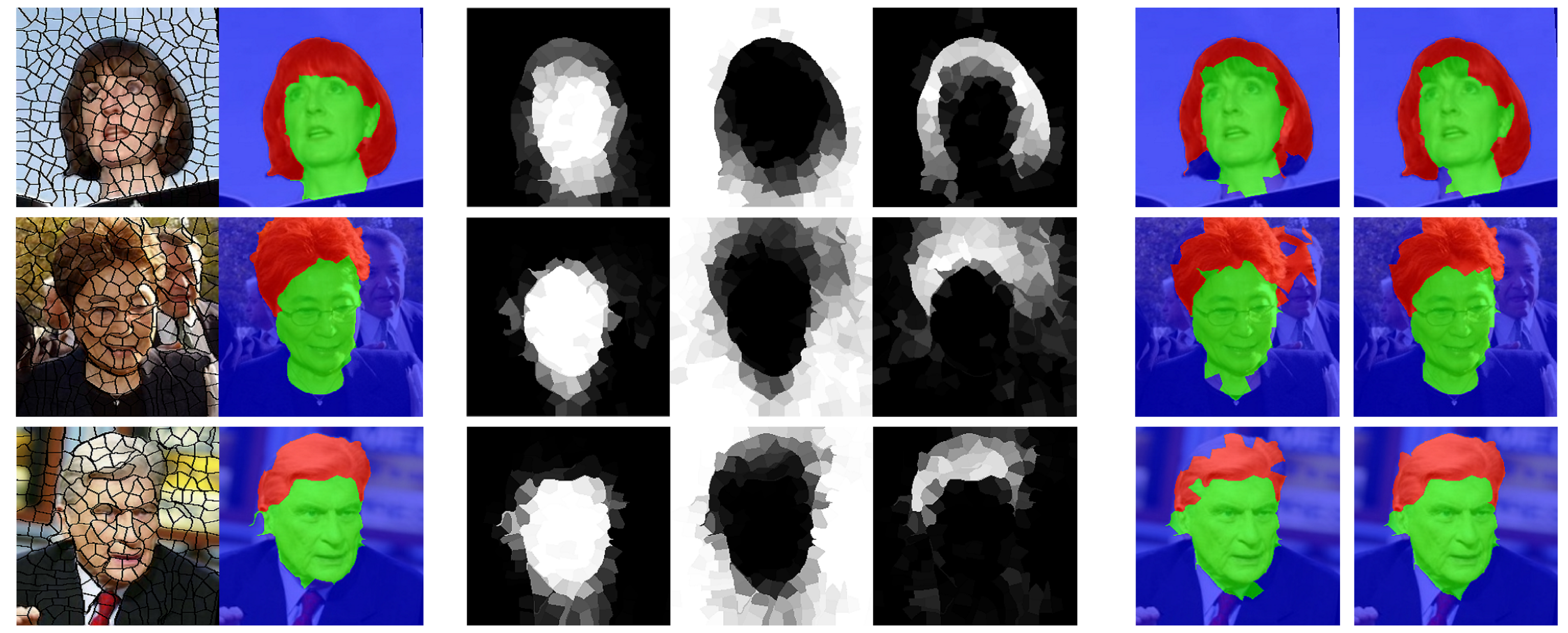


Image — Ground truth — Labeling probabilities (Face, Hair, Background) — Highest prob. — Regularization

- **Comparison to state-of-the-art:**

Method	Accuracy (superpixel)	Accuracy (pixel)	Computational time	Learning time
PatchMatch	87.73%	87.02%	3.940s	0
CRBM [3]	94.10%	x	x	*hours*
GLOC [3]	94.95%	x	0.323s	*hours*
DCNN [4]	x	95.24%	x	*hours*
SuperPatchMatch	**95.08%**	**95.45%**	**0.280s**	**0**

→ SuperPatchMatch outperforms recent CNN architectures
→ No necessary learning

Application to Color Transfer (ICIP 2017)

- **Superpixel-based color transfer (SCT) [5] between two images:**
  - Decomposition into superpixels
  - Matching with SuperPatchMatch (specific constraints)
  - Color transfer with respect to initial grain and exposure

Images — Superpixels — Matched colors — SCT color fusion result

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