Superpixel-based Color Transfer

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Definition

Transfer of the colors of a source image to a target image.


Target image

+


Source image

=


Color transfer result

Applications:
- Graphics/artistic (photoshop).
- 3D reconstruction from multiple images.

Properties:
- Reduced computational time (HD, video).
- Transfer of the global source color palette.
- Respect of the target grain and exposure.

Related Works


Target image


Source image

- Parametric methods: statistics transfer.
  (Reinhard et al., 2001; Tai et al., 2005)

→ No guarantee to have a relevant color transfer.


Reinhard et al., 2001

- Optimal transport (OT): transfer of color histogram.
  (Pitié et al., 2007; Rabin et al., 2011, Frigo et al. 2014)

→ The exact transfer may lead to visual outliers.


Pitié et al., 2007

- Relaxed OT: adaptive transfer of the source colors using superpixels. (Rabin et al., 2014)

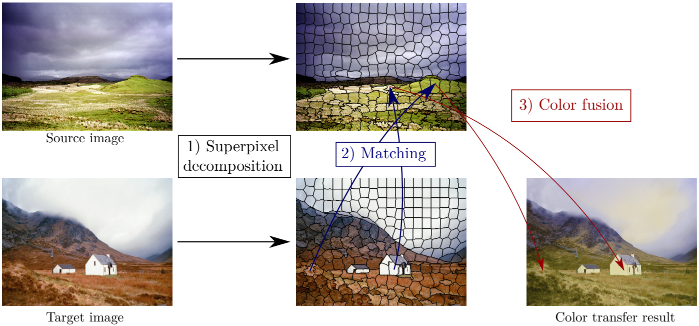
→ High computational cost with OT methods.


Rabin et al., 2014

The Proposed Method

Superpixel-based Color Transfer (SCT):

1) Decomposition into superpixels.
2) Fast superpixel matching, capturing the global source color palette.
3) Color fusion based on spatial and color similarities.



1) Superpixel decomposition

Superpixels: group pixels into homogeneous regions.

→ Provides a reduced set of color candidates.

Use of a regular superpixel decomposition approach (SCALP, Giraud et al. 2016).

→ Approximately the same number of pixels in each superpixel.
→ Capture of the visual color palette.

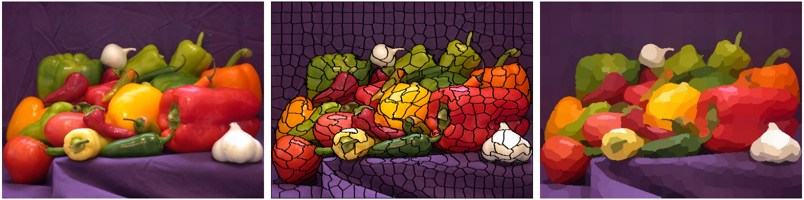


Image Superpixels Average colors

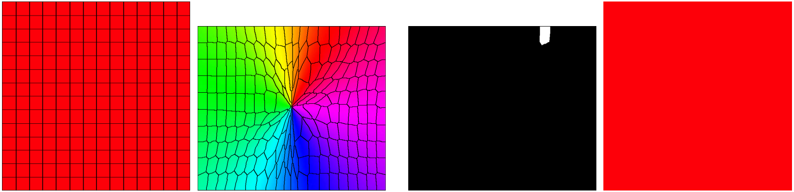
2) Superpixel matching - ANN method

SuperPatchMatch: Superpixel-based approximate nearest neighbor (ANN) method (Giraud et al. 2017) [1]:

- Random Initialization step.
- Iterative refinement process: Propagation and Random Search steps.

Problem:

No control on the number of selected superpixels in the source image B.



Target image A — Source image B — Selected superpixels — Avg. color transfer

$\rightarrow$ The source color palette must be globally captured.

[1] *Presentation at ICIP 2017 - Poster TQ.PE.7, Tuesday 16:30 - 18:00, Poster area E*

2) Superpixel matching - Constraint on match diversity

Proposed solution: A superpixel in B cannot be selected more than ϵ times.

What if a superpixel A_i finds a better match B_k taken by ϵ superpixels A_j?
Cost of switch move:

$$C(A_i, A_j) = \big(D(A_i, B_k) - D(A_i, B_{(i)})\big) + \big(D(A_j, B_{(i)}) - D(A_j, B_k)\big) \,.$$

$$\text{If } \exists A_j, C(A_i, A_j) < 0 \quad \begin{cases} \underset{A_j}{\text{argmin}}\ C(A_i, A_j) \rightarrow B_{(i)}, \\ A_i \rightarrow B_k. \end{cases}$$

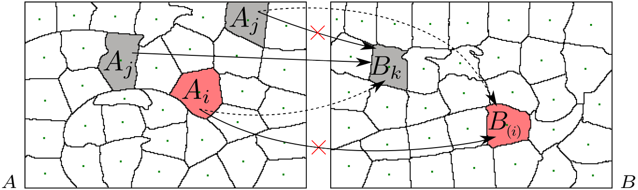
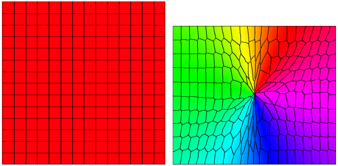


Illustration of the switch move ($\epsilon = 2$)

$\rightarrow$ Optimization of the global matching distance $\sum_i D(A_i, B_{(i)})$.

2) Superpixel matching - Constraint on match diversity

$\rightarrow$ With the ϵ constraint, global selection of the source color palette.

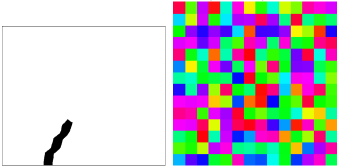


Target image Source image

Without constraint ($\epsilon = \infty$)

Selected superpixels Avg. color transfer

With constraint ($\epsilon = 1$)



Selected superpixels Avg. color transfer

3) Color fusion

- Fusion of matched colors with Non-Local Means (Buades et al., 2005):

  Superpixel $A_i = [X_i, C_i] = [(x_i, y_i), (r_i, g_i, b_i)]$.

  For all pixels $p \in A_i$, contribution of all superpixels A_j.

$$A_t(p) = \frac{\sum_j \omega(p, A_j)\bar{C}_{B_{(j)}}}{\sum_j \omega(p, A_j)}.$$

- Weighting based on spatial and color similarity:

  Distance using covariance information of A_i,

$$\omega(p, A_j) = \exp\Big(-(p - \bar{A}_j)^T Q_i^{-1} (p - \bar{A}_j)\Big).$$

→ Only transfer of the source colors with respect to the target structure.

Summary of SCT steps

Total computational time < 1s (480×360 pixels).

Target image

Source image

< 0.2s

Superpixels

< 0.1s

Avg. color transfer

< 0.3s

Color transfer result

Influence of match diversity

With the ϵ constraint, homogeneous selection of source superpixels.
$\rightarrow$ global transfer the source color palette.

Target image

SCT result $\epsilon = \infty$

Transfer result

SCT result $\epsilon = 3$

Transfer result

Source image

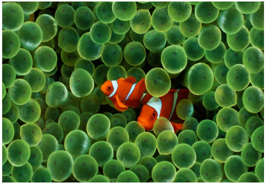
Selection map

Selection map

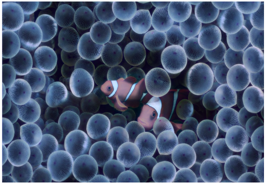
Comparison to state-of-the-art methods (1/3)

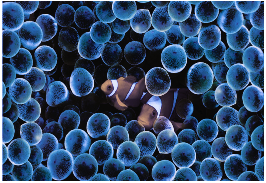
Comparison to:
- optimal transport (Pitié et al., 2007).
- variational histogram transfer (Papadakis et al., 2011).
- 3D color gamut mapping (Nguyen et al., 2014).

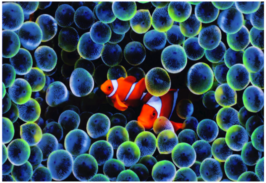
→ Visually competitive results. Respect of the target grain and exposure.

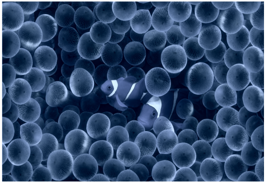

Target image


Source image


SCT


Pitié et al., 2007


Papadakis et al., 2011


Nguyen et al., 2014

Comparison to state-of-the-art methods (2/3)

Comparison to:
- optimal transport (Pitié et al., 2007).
- variational histogram transfer (Papadakis et al., 2011).
- 3D color gamut mapping (Nguyen et al., 2014).

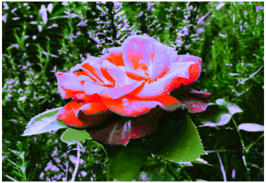
→ Visually competitive results. Respect of the target grain and exposure.


Target image


Source image


SCT


Pitié et al., 2007


Papadakis et al., 2011


Nguyen et al., 2014

Comparison to state-of-the-art methods (3/3)

Comparison to:

- optimal transport (Pitié et al., 2007).
- variational histogram transfer (Papadakis et al., 2011).
- 3D color gamut mapping (Nguyen et al., 2014).

→ Visually competitive results. Respect of the target grain and exposure.

Target image

Source image

SCT

Pitié et al., 2007

Papadakis et al., 2011

Nguyen et al., 2014

Conclusion

SCT method summary

- New color transfer method respecting the target grain and exposure.
- New method to constrain the correspondences of a matching algorithm.
- Competitive results in limited computational time (< 1s).

Work in progress

- Extension to image colorization.
- Extension to video processing with supervoxels.

Perspectives

- Adaptation of the matching constraints for fast style transfer.

Superpixel-based Color Transfer

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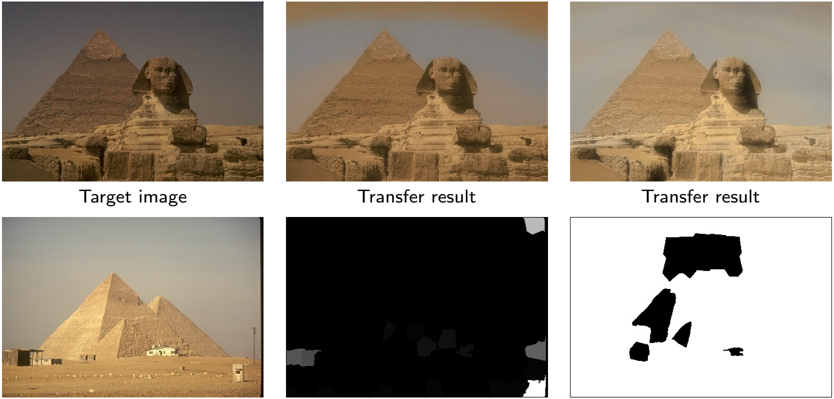
Influence of match diversity

With the ϵ constraint, homogeneous selection of source superpixels.
$\rightarrow$ global transfer the source color palette.

SCT result $\epsilon = \infty$ | SCT result $\epsilon = 1$



Target image | Transfer result | Transfer result

Source image | Selection map | Selection map

Comparison to state-of-the-art methods

Comparison to:
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→ Visually competitive results. Respect of the target grain and exposure.

Target image

Source image

SCT

Pitié et al., 2007

Papadakis et al., 2011

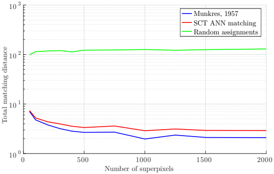
Nguyen et al., 2014

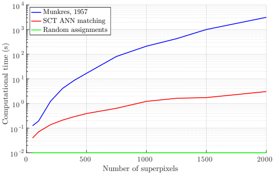
Superpixel matching - Optimal assignment problem

With $\epsilon = 1$, approximation of the optimal assignment problem:

"Given two sets $A = \{A_i\}_{i \in \{1,\dots,|A|\}}$ and $B = \{B_j\}_{j \in \{1,\dots,|B|\}}$ with $|A| \leq |B|$, association of each A_i to a unique $B_{(i)}$ that minimizes $\sum_i D(A_i, B_{(i)})$."

Problem addressed with costly optimal algorithms (Munkres, 1957).





Matched colors

Target image A

Munkres, 1957

Source image B

SCT ANN matching

$\rightarrow$ Close results to the optimal resolution in very reduced computational time.

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