Split and Match: Example-based Adaptive Patch Sampling for Unsupervised Style Transfer

Contents

Abstract

- Objective is to transfer the style of an example image to a source image using unsupervised method.
- Example-based style transfer: transform an image to mimic the style of a given example
- Style as a combination of global color and local texture transfer
- Previous patch-based texture transfer methods assume regular grid

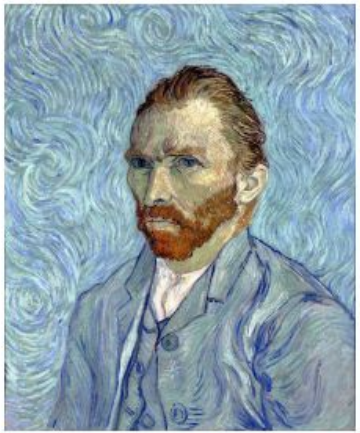
Model

- Let $u: \Omega_u \rightarrow IR^3$ be an input image and $v: \Omega_v \rightarrow IR^3$ an example style image.
- Search for correspondence map $\varphi: \Omega_u \rightarrow \Omega_v$ with texture transfer defined as $\hat{u}=v$
- We follow the steps below to achieve style transfer:

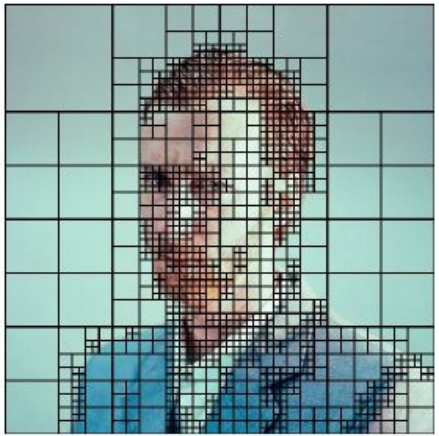
1. Split and match: compute an adaptive partition R of Ω_u
2. Optimization: Search for the optimal map φ
3. Bilinear blending b/w neighbor regions and reconstruction of $\hat{u}$
4. Globalcolor transfer and contrast matching.

Illustration of the proposed unsupervised style transfer

Original



Example



Adaptive partition

Stylization with our method

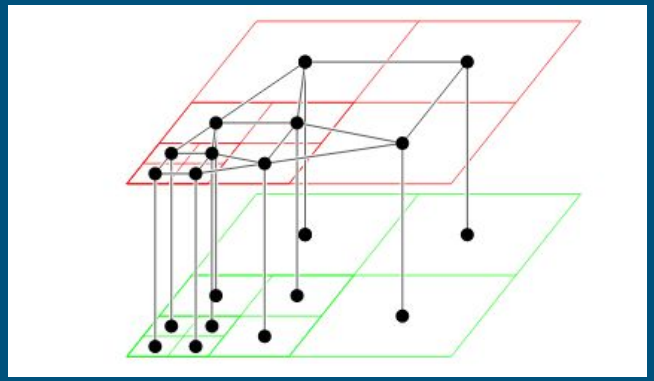
Adaptive patch partition

- Quadtree partition inspired by classic Split and Merge
- Region R_i is split in four regions only if
- $(\sigma_i + d[p^u_{xi}, p^v_{yi}] > \omega \text{ and } \tau_i > Y0)$ or $\tau_i > Y_1$
- Y_i is the best match of p^u_{xi} in v, σ_i is the standard deviation of p^u_{xi}
- Distance between patches p^u_{xi} and p^v_y of size τ^2_i given by

$$d[p^u_{xi}, p^v_{yi}] = (\| p^u_{xi} - p^v_y \|^2) / \tau^2_i$$

Optimal Candidate Selection

- Patch correspondences as a **labeling problem**
- Label assignments given by MAP inference from joint probability distribution on $L = \{L_i\}_{i=1}^{n}$
- MRF model over **non-regular grid**



Continues…

- For quadtree patch $p^u_{x_i}$, K candidates $L_i = \{l_{i_k}\}_{k=1}^{K}$ are computed by k-nearest neighbors
- Then we search for label assignments $\hat{L} = \{\hat{l}_i\}_{i=1}^{n}$ maximizing

$$P(L) = \frac{1}{Z}\prod_i \phi(l_i) \prod_{(i,j)\in\mathcal{N}} \psi(l_i, l_j),$$

  - where $\phi(l_i) = \exp(-d[p^u_{x_i}, p^v_{l_i}]\lambda_d)$
  - $\psi(l_i, l_j) = \exp(-d[\tilde{p}^v_{l_i}, \tilde{p}^v_{l_j}]\lambda_s + |l_i - l_j|^2\lambda_r)$
- Approximate inference by **loopy belief propagation** [4]

Blending

- Given a set of overlapping patches P of arbitrary sizes, seams can still be noted in the reconstructed image û across the quadtree patch boundaries. Blending method is useful to remove visible seams
- Blending as a weighted sum of all overlapping intensities:

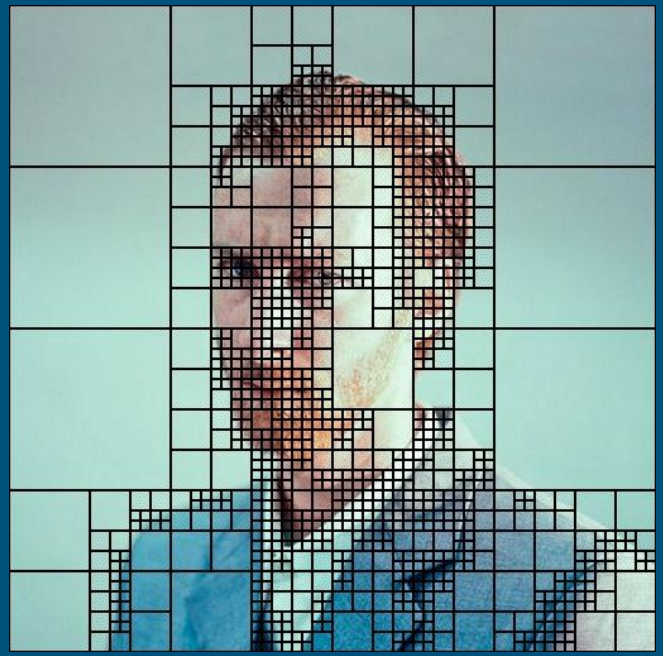
$$\tilde{u}(x) = \sum_{s=1}^{S} \alpha_s(x)\, \tilde{p}^{\hat{u}}_{x_s}(x), \text{ where } \alpha_s(x) = \frac{\delta(x, \partial\tilde{p}^{\hat{u}}_{x_s})}{\sum_{s=1}^{S} \delta(x, \partial\tilde{p}^{\hat{u}}_{x_s})} \text{ and } \delta(x, \partial\tilde{p}^{\hat{u}}_{x_s}) = \frac{|x - \partial\tilde{p}^{\hat{u}}_{x_s}|^2}{\tau_s^2}$$

$\alpha_s(x)$ is a weight and $\delta(x, \partial\tilde{p}^{\hat{u}}_{x_s})$ is the distance between pixel x and patch border $\partial\tilde{p}^{\hat{u}}_{x_s}$

Global color transfer and contrast matching

- Color and contrast are two features in style that may be consistently modeled as global transformations.
- Color transfer method used to match consistently the color palettes of the original and example images.
- This color transformation is combined with a global contrast transformation achieved by a parametric histogram specification.

3. Results
Adaptive Partition Results



Texture Transfer Output

Color transfer Results

Conclusion

Proposed a new style transfer method is able to synthesize textures independently of their scale.

This method is naturally not guaranteed to transfer textures that belong to the same semantic category in the input and example images.

Thank you