Style Transfer for Headshot Portraits

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Professional portraits look better

Ordinary photo

Professional photo
The goal: make good portraits easy

- Make ordinary photo look like a professional photo
- Transfer the style from the example photo
- Automatic
We work on headshots

• What we match: retouching, texture, lighting

• What we do not match: pose, expression, clothing, focal length, aperture
Preview our result

Input

Example

Output
Hard problem: color transfer is not sufficient

- Humans are intolerant to artifacts on faces

Input  Example  Our method  [HaCohen et al. 2010] (lighting and details are missing)
Related work: global transfer

[Bae et al. 2006, Sunkavalli et al. 2010...]

- Work well on landscapes

- Do not work as well on portraits
Related work: global transfer

[Bae et al. 2006, Sunkavalli et al. 2010...]

• Work well on landscapes

Input  Model  Output by Bae et al. [2006]

• Do not work as well on portraits
Related work: local style transfer

- Time hallucination [Shih et al. 2013, Laffont et al. 2014]

Input: afternoon  
Example images  
Output: night

- Requires two images: before and after
Related work: face enhancement

[Joshi et al. 2010, Shih et al. 2013 ...]

• Image restoration: deblurring, denoising ...

Blurred input face  Examples  Output: deblurred face

• We focus on photographic stylization.
Problem statement

• **Input**: a casual frontal portrait and an example

• **Output**:
  - The input portrait rendered in the example style
  - Automatic
  - The style includes texture, tone, and color
Key idea #1: local transfer

- Local: eyes, nose, skin, etc. are treated differently
Key idea #1: local transfer

- Local: eyes, nose, skin, etc. are treated differently
Key idea #2: multi-scale transfer

- Textures at different scales are treated differently
Key idea #2: multi-scale transfer

• Textures at different scales are treated differently.
Overview of the algorithm

1. Dense matching between the input and example
2. Multiscale transfer of local statistics
3. Post processing on eyes and background
Step 1: dense matching

- Rigid warp + SIFT flow to align semantic features
  [Liu et al. 2008]
Step 2: multi-scale local transfer

Input

Example
Step 2: multi-scale local transfer

1. Construct Laplacian stacks for the input and the example
Step 2: multi-scale local transfer

1. Construct Laplacian stacks for the input and the example

2. Local match at each scale
Step 2: multiscale transfer of local statistics

1. Construct Laplacian stacks for the input and the example

2. Local match at each scale

3. Collapse the matched stacks to create the output of this step
Step 2: multi-scale local transfer

1. Construct Laplacian stacks for the input and the example

Input

Example

2. Local match at each scale

3. Collapse the matched stacks to create the output of this step

Output
Local energy $S$

\[ S = L^2 \otimes G_\ell \]

- $L$: Example Laplacian
- $S$: Local energy
- $G_\ell$: Gaussian kernel at this scale
At each scale: match local energy

Input energy

Example energy
At each scale: match local energy

Compute the gain map

Example Laplacian \rightarrow Local energy \( S[E] \)

Input Laplacian \rightarrow Local energy \( S[I] \)

Gain map = \( \sqrt{\frac{\text{warp}(S[E])}{S[I]}} } \)
At each scale: match local energy

Compute the gain map

Modulate the input Laplacian

Gain map = \sqrt{\frac{\text{warp}(S[E])}{S[I]}}
Robust transfer

• Clamp the gain map to avoid artifacts caused by moles or glasses on the example
Laplacian using a face mask

- Preserve the hair boundary using normalized convolution and a face mask
Step 3: post-processing

- Adding eye highlights
- Replacing the background
Algorithm recap

Input

Example

Step 1.
Dense alignment
Algorithm recap

Input

Example

Step 1.
Dense alignment

Step 2.
Local transfer
Algorithm recap

Input

Example

Step 1. Dense alignment

Step 2. Local transfer

Step 3. Eyes and background
Automatic example selection

- Retrieve the best examples based on the face similarity between the input
Automatic example selection

• The results are robust to the example choices
Results

Examples are shown in the insets
Close-up

Input

Example

Output
More results

Input

Style 1

Style 2

Style 3
Outdoor input
Extra results

Input

Style 1

Style 2

Style 3
Comparisons

Input  Example  Global transfer  Our result
[Bae et al. 2006]
Input Example Our method [Sunkavalli et al. 2010]

Histogram transfer [Reinhard et al. 2001] [Pitié et al. 2007] Photoshop Match Color
Different success levels: good results

• The inputs are well lit
Hard case

- Matting (face mask) failure
Limitations

• Require the input and the example to have similar facial attributes, e.g., skin color

• Cannot handle hard shadows on the input
Evaluation

• 94 headshot inputs from Flickr

• Available on our website
Extension to videos

Input sequence with extreme facial expressions

Our style transfer result using the example in the gray box
Conclusion

• We introduce a style transfer algorithm tailored for headshot portraits.
• Based on multiscale transfer of local image statistics.

Input  Example  Output
Code and data are available

• Matlab code
• Flickr evaluation dataset

people.csail.mit.edu/yichangshih/portrait_web/
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Conclusion

• We introduce a style transfer algorithm tailored for headshot portraits.

• Based on multiscale transfer of local image statistics