

Style Transfer for Headshot Portraits

YiChang Shih

MIT CSAIL

Sylvain Paris

Adobe

Connelly Barnes

University of Virginia

William T. Freeman

MIT CSAIL

Frédo Durand

MIT CSAIL



Professional portraits look better



Ordinary photo



Professional photo

The goal: make good portraits easy

- Make



Ordinary photo

look like



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



Input



Model



Output by Bae et al. [2006]

- Do not work as well on portraits

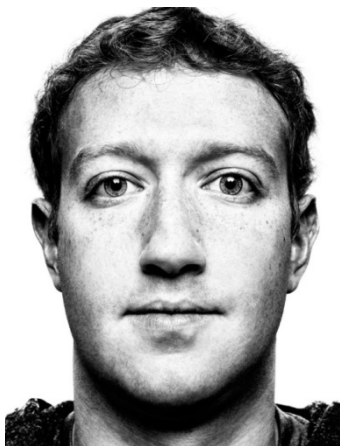
Related work: global transfer

[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



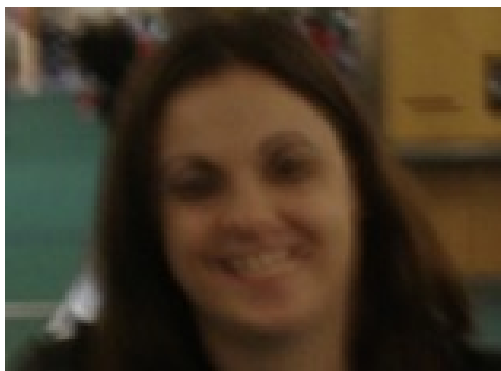
Output: night

- 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



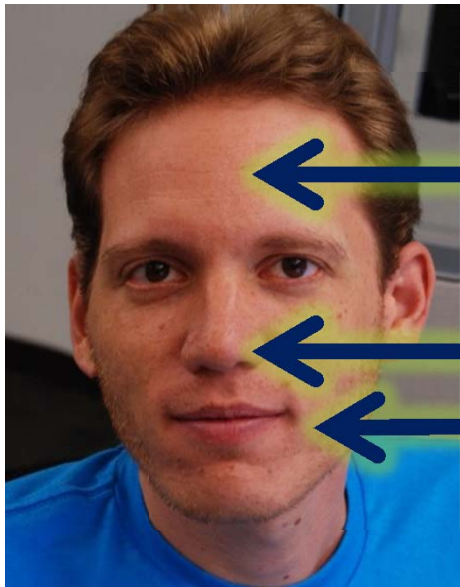
Input



Example

Key idea #1: local transfer

- Local: eyes, nose, skin, etc. are treated differently



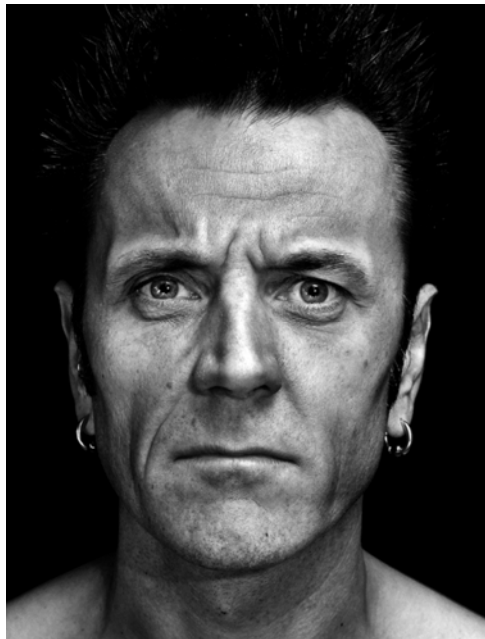
Input



Example

Key idea #2: multi-scale transfer

- Textures at different scales are treated differently



Portrait #1



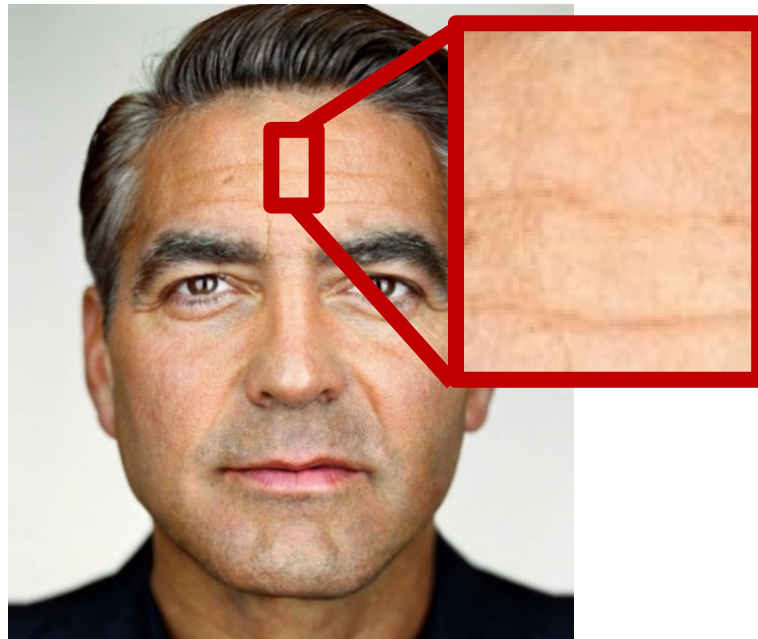
Portrait #2

Key idea #2: multi-scale transfer

- Textures at different scales are treated differently



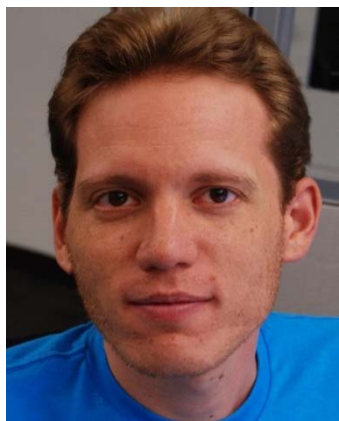
Portrait #1



Portrait #2

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



Input



Example



Step 1: matching



Step 2: transfer



Step 3: post processing

Step 1: dense matching

- Rigid warp + SIFT flow to align semantic features
[Liu et al. 2008]



Input

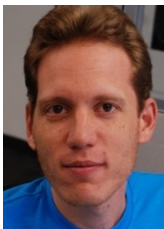


Example



Warped example

Step 2: multi-scale local transfer



Input



Example

Step 2: multi-scale local transfer

1. Construct Laplacian stacks for the input and the example



Input

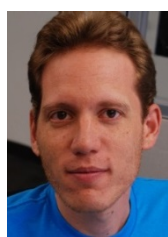


Example

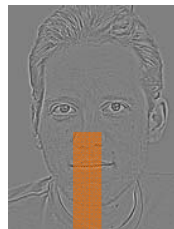


Step 2: multi-scale local transfer

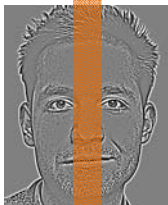
1. Construct Laplacian stacks for the input and the example



Input



Example



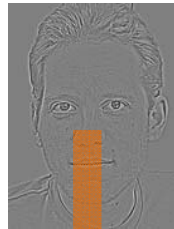
2. Local match at each scale

Step 2: multiscale transfer of local statistics

1. Construct Laplacian stacks for the input and the example



Input



Example



2. Local match at each scale

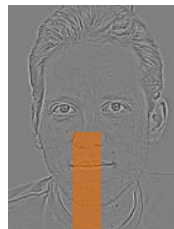
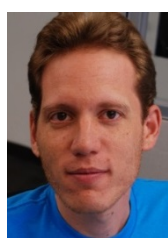


3. Collapse the matched stacks to create the output of this step

Output

Step 2: multi-scale local transfer

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

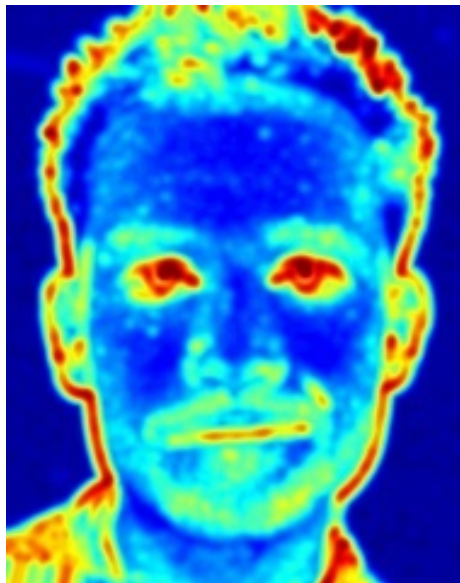


Local energy S



L

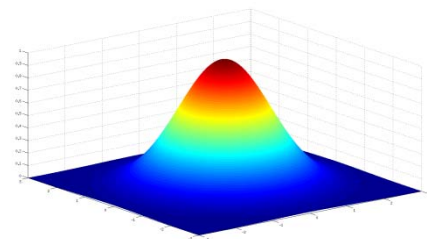
Example Laplacian



S

Local energy

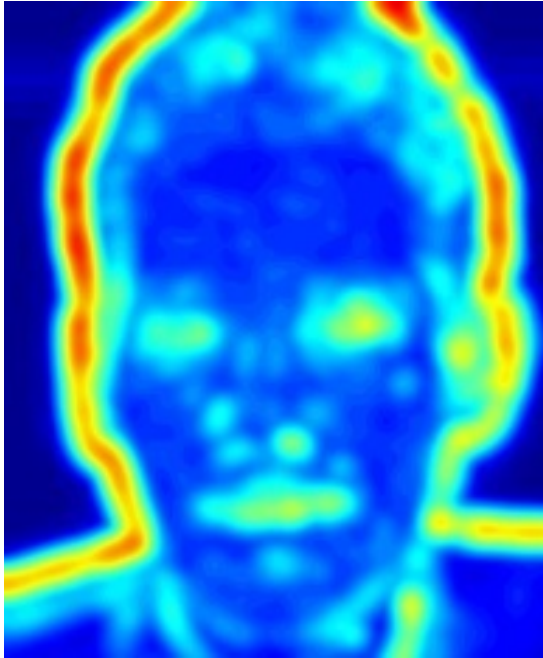
$$S = L^2 \otimes G_\ell$$



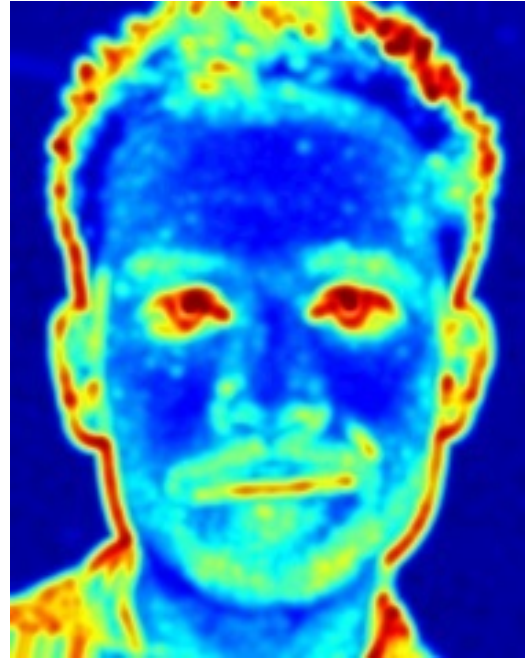
G_ℓ

Gaussian kernel at this scale

At each scale: match local energy



Input energy



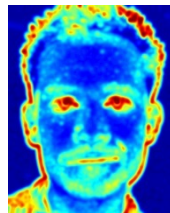
Example energy

At each scale: match local energy

Compute
the gain map



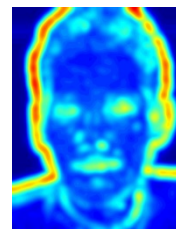
Example Laplacian



Local energy $S[E]$



Input Laplacian



Local energy $S[I]$



Gain map =

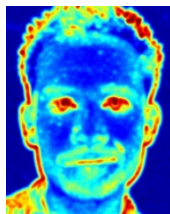
$$\sqrt{\frac{\text{warp}(S[E])}{S[I]}}$$

At each scale: match local energy

Compute
the gain map



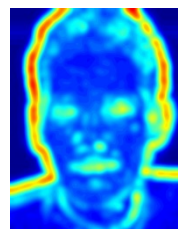
Example Laplacian



Local energy $S[E]$



Input Laplacian



Local energy $S[I]$



Gain map =

$$\sqrt{\frac{\text{warp}(S[E])}{S[I]}}$$

Modulate
the input Laplacian



Input Laplacian

×



Gain map

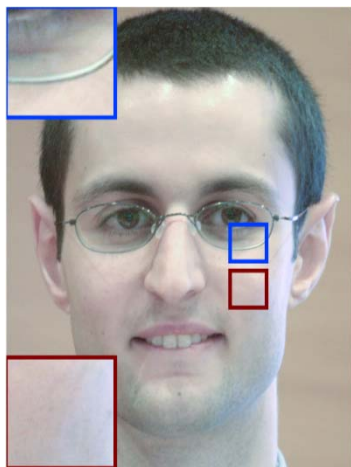
=



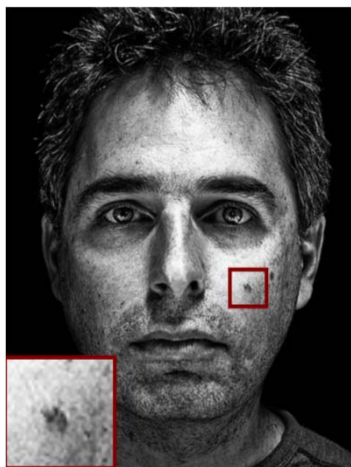
Output Laplacian

Robust transfer

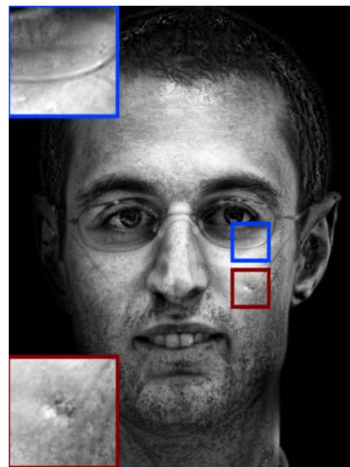
- Clamp the gain map to avoid artifacts caused by moles or glasses on the example



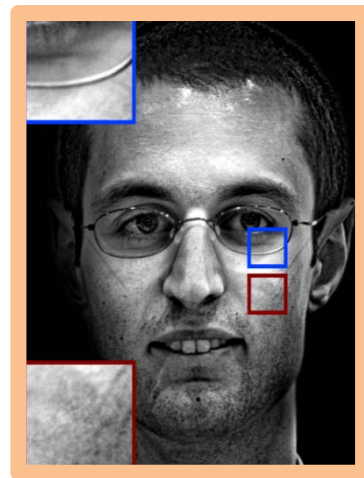
Input



Example



Without robust transfer



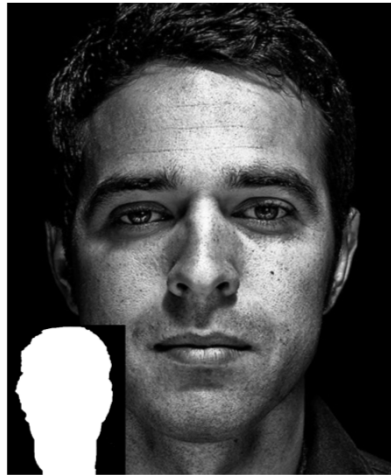
Our robust transfer

Laplacian using a face mask

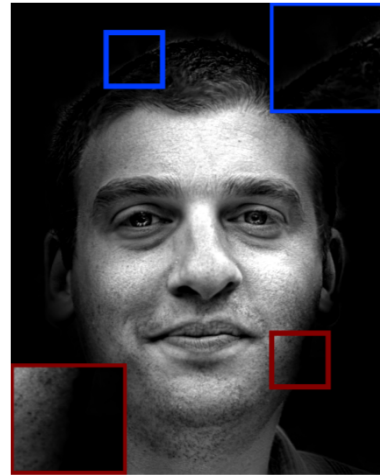
- Preserve the hair boundary using normalized convolution and a face mask



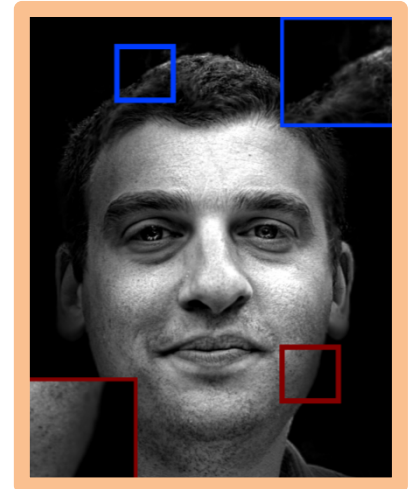
Input



Example



Without using the mask
(the edges disappear)



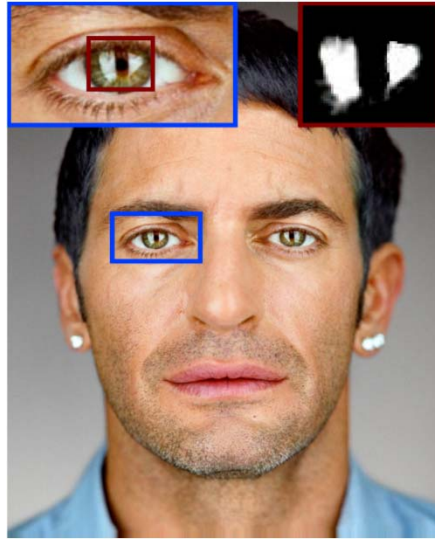
Our method
(the edges are preserved)

Step 3: post-processing

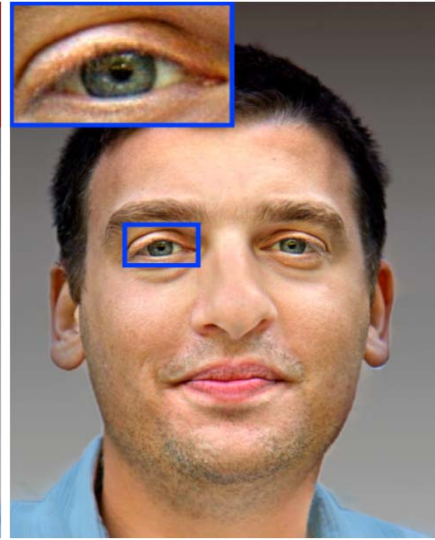
- Adding eye highlights
- Replacing the background



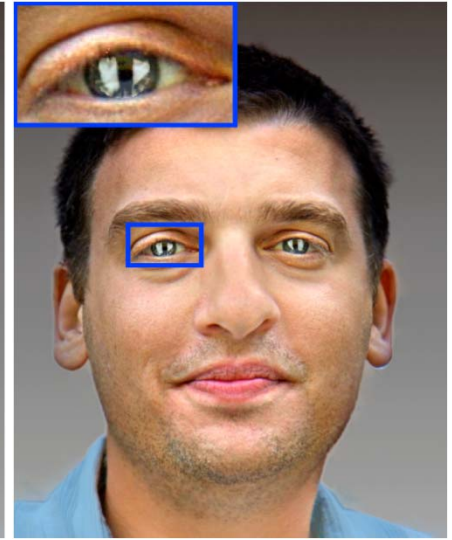
Input



Example

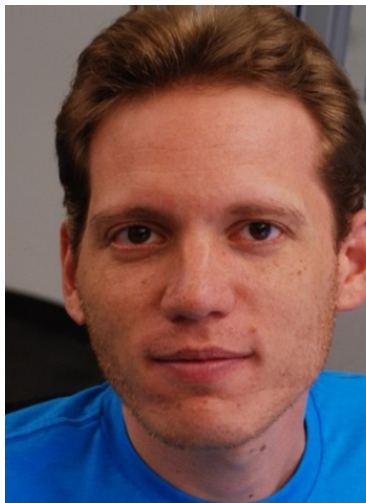


Without eye highlights



Adding eye highlights
(Our final result)

Algorithm recap



Input

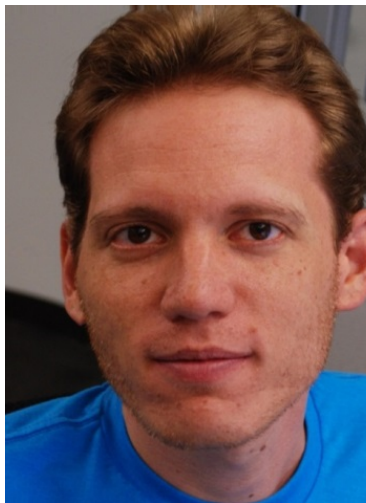


Example



Step 1.
Dense alignment

Algorithm recap



Input



Example

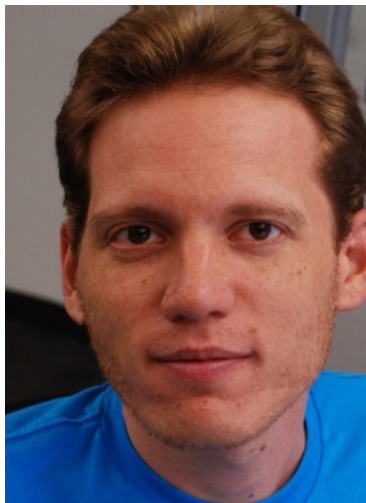


Step 1.
Dense alignment



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



Input



The top three retrieved results

Automatic example selection

- The results are robust to the example choices



Input



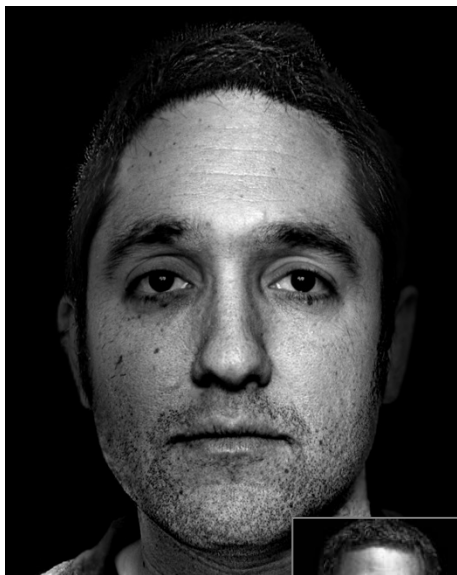
Style transferred results using the top three examples

Results

Examples are shown in the insets



Input



Style 1



Style 2



Style 3

Close-up



Input



Example



Output

Example



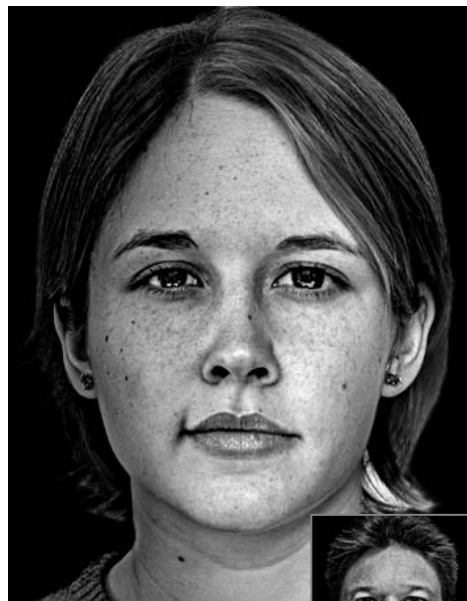
Output



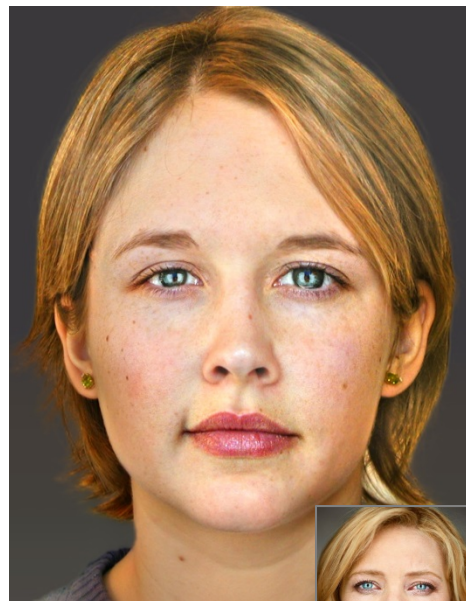
More results



Input



Style 1



Style 2



Style 3



Outdoor input



Input



Style 1



Style 2



Style 3



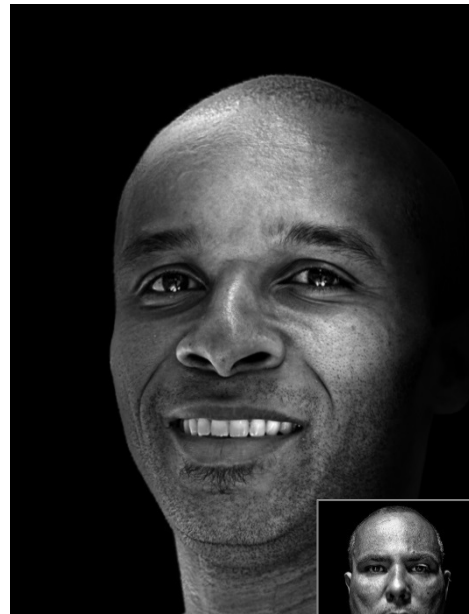
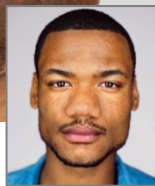
Extra results



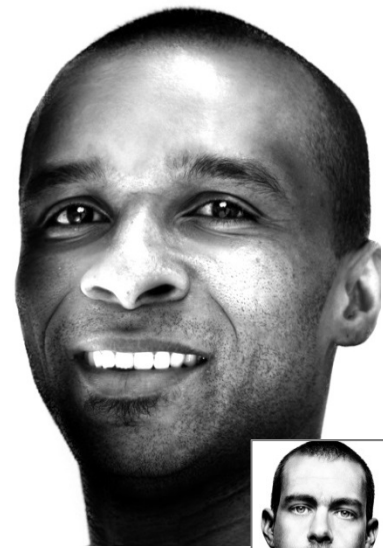
Input



Style 1



Style 2



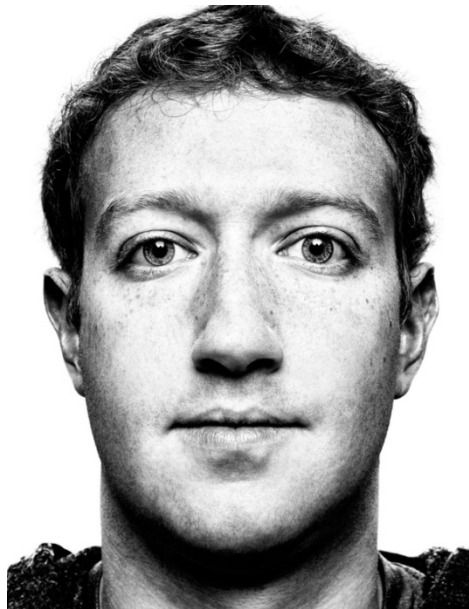
Style 3



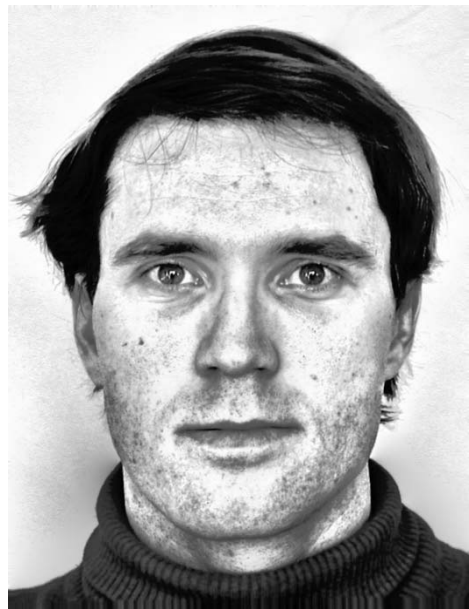
Comparisons



Input



Example



Global transfer
[Bae et al. 2006]



Our result



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



Input



Output

Hard case

- Matting (face mask) failure



Input



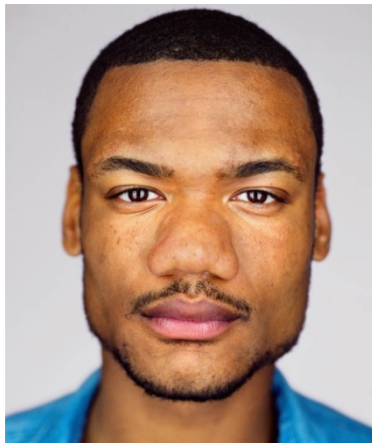
Output

Limitations

- Require the input and the example to have similar facial attributes, e.g., skin color
- Cannot handle hard shadows on the input



Input



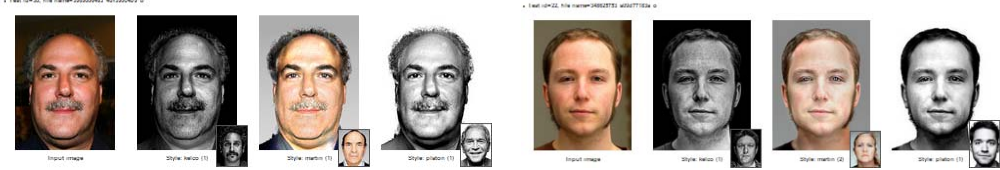
Example



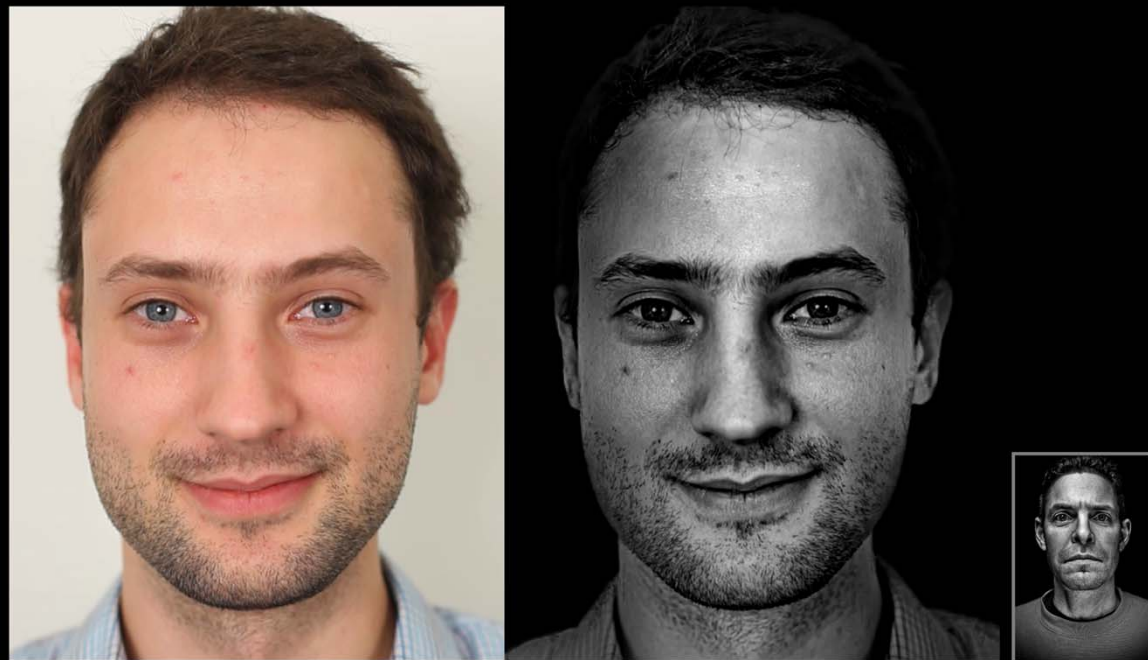
Failure output

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



Input



Example



Output