Exemplar-Based Face Colorization Using Image Morphing

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Joint work with :

Gabriele Steidl and Johannes Persch (Technische Universität Kaiserslautern).

General problem of colorization.

Input.

Output.

The YUV color space.

Definition of the gray-scale channel from RGB :

$$Y = 0.299R + 0.587G + 0.114B.$$

Chrominance channel :

- U and V, enable to recover the RGB image ;
- invertible linear map between YUV and RGB.

Challenge.

Recovering an RGB image from the luminance channel alone is an ill-posed problem and requires additional chrominance information.

The manual colorization.

Two approaches :

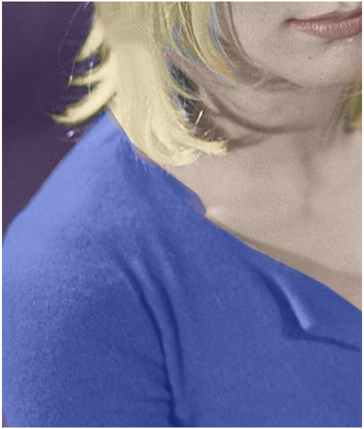
- fully manual (polygonal masks) ;
- automatic diffusion.

Input

Levin et al. SIGGRAPH 2004.

Colorization with masks

The manual colorization.



The challenging problem of exemplar-based face colorization.


Source


Target


Welsh et al. SIGGRAPH 2002.


Gupta et al. ACM int. conf. on Multimedia 2012.


Pierre et al. SIAM journ. of Imaging Sciences 2015.

"Most sophisticated" state-of-the-art approaches (CNN).

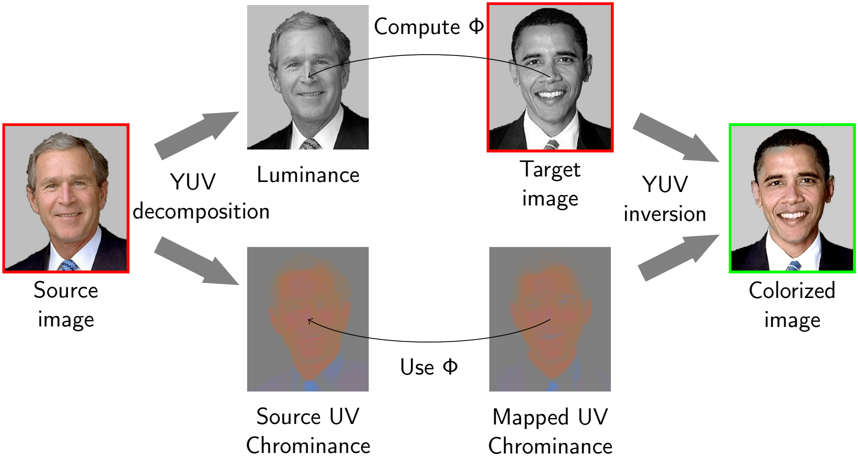
Wide use of deep learning for image colorization in 2016.

Zhang et al. ECCV 2016, **ImageNet** (1.3 millions images)

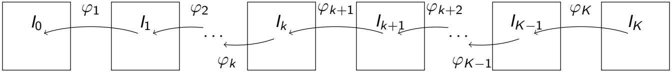
Larsson et al. ECCV 2016, **ImageNet**

Iizuka et al. SIGGRAPH, 2016, **Places** (2.5 millions images)

Our approach : global work-flow.



Map computation : the model.



Assumptions :

- $I_{\text{tar}} : \Omega \to \mathbb{R}$ continuously differentiable and compactly supported.
- $I_0 := I_{\text{temp}}, \quad I_K := I_{\text{tar}}.$

Maps regularization with linearized elastical potential.

Introduced and analyzed by Berkels et al. SIAM Journal on Imaging Sciences 2015.

Definition of the (Cauchy) strain tensor.

- $\varphi_k(\mathbf{x}) = \mathbf{x} - v_k(\mathbf{x}) = \begin{pmatrix} x - v_{k,1}(\mathbf{x}) \\ y - v_{k,2}(\mathbf{x}) \end{pmatrix}, \quad \mathbf{x} = (x,y)^T \in \Omega,$
- Cauchy strain tensor of $v = (v_1, v_2)^T$:

$$\varepsilon(v) := \frac{1}{2}(\nabla v + \nabla v^T) = \begin{pmatrix} \partial_x v_1 & \frac{1}{2}(\partial_y v_1 + \partial_x v_2) \\ \frac{1}{2}(\partial_y v_1 + \partial_x v_2) & \partial_y v_2 \end{pmatrix},$$

where ∇v denotes the Jacobian of v.

Maps regularization with linearized elastical potential Berkels et al. 2015.

Linearized elastical potential :

$$\mathcal{S}(v) := \int_\Omega \mu \,\mathrm{trace}\left(\varepsilon^T(v)\varepsilon(v)\right) + \frac{\lambda}{2}\,\mathrm{trace}\,(\varepsilon(v))^2 \; dx,$$

where $\mu, \lambda > 0$.

Maps functional :

$$\mathcal{J}(\mathbf{I}, \mathbf{v}) := \sum_{k=1}^{K} \int_\Omega |I_k - I_{k-1} \circ \varphi_k|^2 \, dx + \mathcal{S}(v_k)$$

$$\text{subject to} \quad I_0 = I_{\text{temp}}, \; I_K = I_{\text{tar}}.$$

Map computation : algorithm.

Alternate minimization.

1. Fixing $\mathbf{I}$ and minimizing over $\mathbf{v}$ (registration problems) :

$$\text{argmin}_{v_k} \mathcal{J}_{\mathbf{I}}(v_k) := \int_\Omega |I_k - I_{k-1} \circ \varphi_k|^2 + \mathcal{S}(v_k)\, dx, \; k = 1, \dots, K$$

   where φ_k is related to v_k.

2. Fixing $\mathbf{v}$ and minimizing over $\mathbf{I}$:

$$\text{argmin}_{\mathbf{I}} \mathcal{J}_{\varphi}(\mathbf{I}) := \sum_{k=1}^{K} \int_\Omega |I_k - I_{k-1} \circ \varphi_k|^2 \, dx.$$

   (Euler-Lagrange equation leads to a linear system of equations).

Color transformations.

Needed transformations :

- luminance remapping before maps computation :

$$I_{\text{temp}} := \sqrt{\frac{\text{var}(I_{\text{tar}})}{\text{var}(I_Y)}}\,(I_Y - \text{mean}(I_Y)) + \text{mean}(I_{\text{tar}});$$

- Global map between source and target : $\Phi = \varphi_1 \circ \varphi_2 \circ \ldots \circ \varphi_K$.

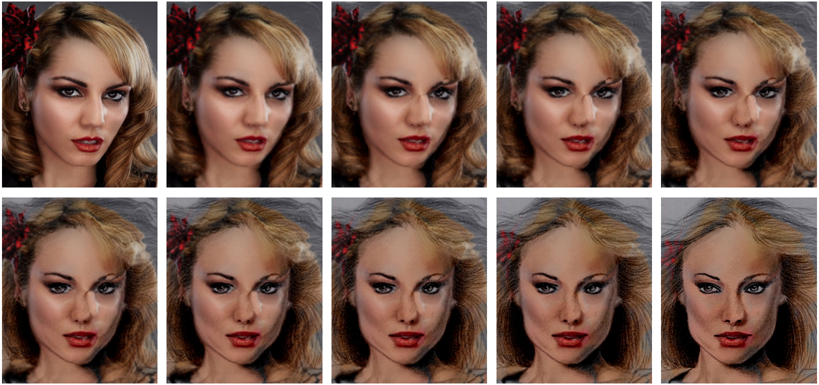
Chrominance of the result :

computed with

$$\big(U_{\text{tar}}(x), V_{\text{tar}}(x)\big) := \big(U(\Phi(x)), V(\Phi(x))\big).$$

Use of bilinear interpolation.

First numerical results.



Color transport along the image path.

Post-processing : constraint and projection.

Inspired of Pierre et al. 2015 SIAM journal of Imaging Sciences.

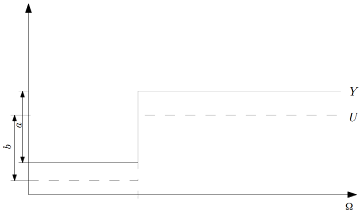
Color regularization.

$$\hat{u} = (\hat{U}, \hat{V}) = \operatorname{argmin}_{(U,V)} \mathrm{TV}_{Y_{\mathrm{tar}}}(U, V) + \alpha \int_\Omega |U(x) - U_{\mathrm{tar}}(x)|^2 + |V(x) - V_{\mathrm{tar}}(x)|^2 dx + \chi_{\mathcal{R}}(u),$$

with

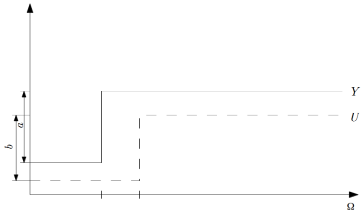
$$\mathrm{TV}_{Y_{\mathrm{tar}}}(U, V) := \int_\Omega \sqrt{\gamma |\nabla Y_{\mathrm{tar}}|^2 + |\nabla U|^2 + |\nabla V|^2}\, dx.$$

1D interpretation.



$$TV_{Y_{\mathrm{tar}}} = \sqrt{\gamma a^2 + b^2}$$

$$\leq$$



$$TV_{Y_{\mathrm{tar}}} = \sqrt{\gamma a^2} + \sqrt{b^2}$$

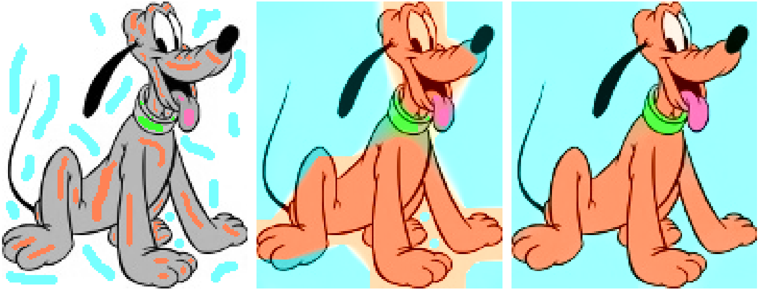
Chrominance inpainting.

$$\hat{u} = (\hat{U}, \hat{V}) = \text{argmin}_{(U,V)} \text{TV}_{Y_{\text{tar}}}(U, V) + \alpha \int_\Omega M \left(|U(x) - U_{\text{tar}}(x)|^2 + |V(x) - V_{\text{tar}}(x)|^2 \right) dx,$$

with

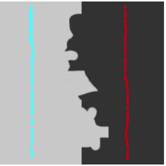
$$\text{TV}_{Y_{\text{tar}}}(U, V) := \int_\Omega \sqrt{\gamma |\nabla Y_{\text{tar}}|^2 + |\nabla U|^2 + |\nabla V|^2}\, dx.$$

M a mask, and $(U_{\text{tar}}, V_{\text{tar}})$ some color scribbles given by the user.

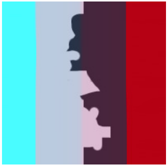


Scribbles — No coupling. — With coupling.

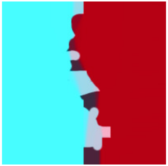
Intuition about coupling.



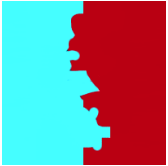
Scribbles.



$\gamma = 0.$



$\gamma = 1.$

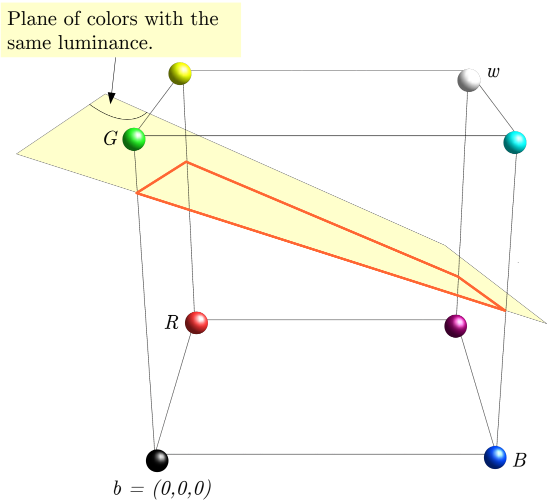


$\gamma = 10.$

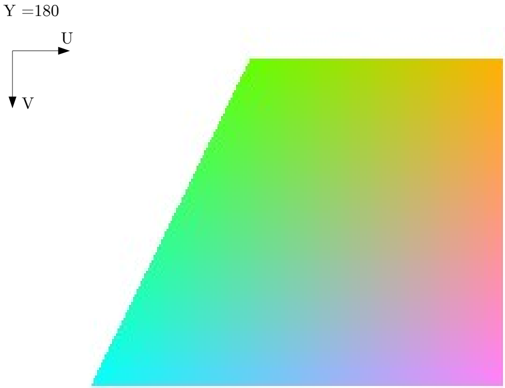
Parameter influence.

γ small : chrominance contours have low perimeters.

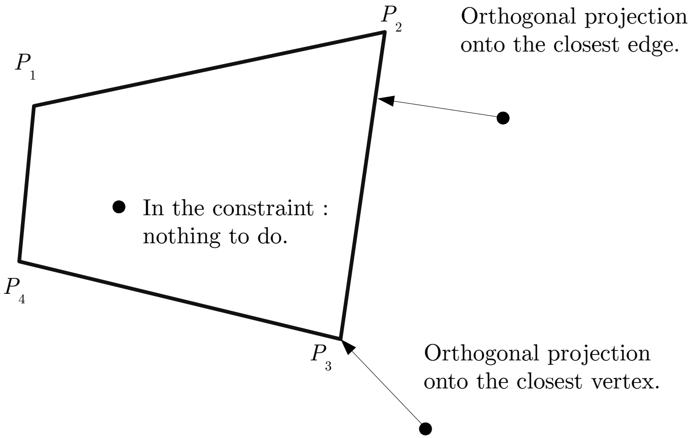
Geometric interpretation



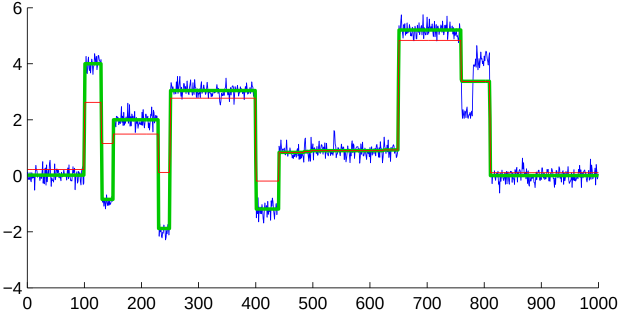
Geometric interpretation



Computation of the orthogonal projection



1D TV bias.



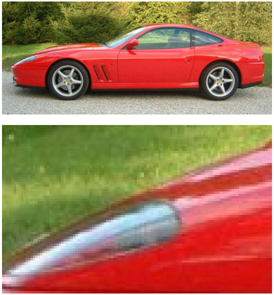
2D TV bias.

Initial image.

With bias.

Without bias.

Chrominance TV bias.



Initial image.

Noisy.

Biased regularization.

Model of Deledalle *et al.* 2017.

$$\hat{x}(y) \in \text{argmin}_{x \in \mathbb{R}^p} F(x, y) + G(x), \tag{1}$$

Bias reduction model :

$$\mathcal{R}_{\hat{x}}(y) \in \text{argmin}_{h \in \mathcal{H}} \|h(y) - y\|_2^2 \tag{2}$$

where $\mathcal{H}$ set of mapping $h : \mathbb{R}^n \to \mathbb{R}^p$ such that, $\forall y \in \mathbb{R}^n$:

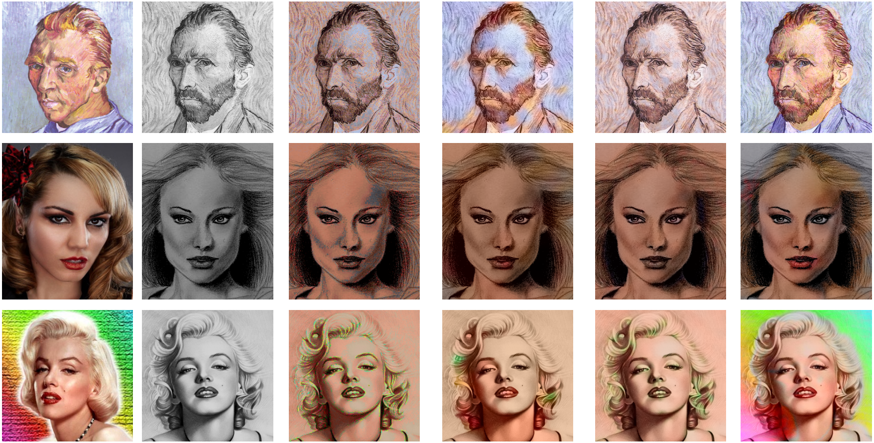
- $h(y) = Ay + b$ with $A \in \mathbb{R}^{p \times n}, b \in \mathbb{R}^p$;
- $J_h(y) = \rho J_{\hat{x}}(y)$ with $\rho \in \mathbb{R}$.
- $h(\hat{x}(y)) = \hat{x}(y)$.

$$\text{where } J_{\hat{x}}(y)d = \lim_{\varepsilon \to 0, \varepsilon > 0} \frac{\hat{x}(y + \varepsilon d) - \hat{x}(y)}{\varepsilon}. \tag{3}$$

Numerical results.

Source. Target. Welsh et al. Gupta et al. Pierre et al. Our.

Numerical results.



Source. Target. Welsh et al. Gupta et al. Pierre et al. Our.

Conclusion and future works :

Conclusion :

- system dedicated to face colorization from image morphing ;
- post-processing ensures the result quality.

Further improvement :

- experiments on cars, animals, etc.
- include constraints from face detectors ;
- theoretical guarantees for convergence (bi-convex problem).

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Many thanks for your attention.