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CS780 Computational Colorimetry

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Color alteration in photographs COLORIZATION Acknowledgements: some of slides are courtesy of Anat Levin, Prof. Dani Lischinski (Hebrew Univ.), Prof. Gabriel Brostow, and Prof. Tim Weyrich (UCL)

Scope

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- Colorization using Optimization
 Levin, Lischinski, Weiss, SIGGRAPH2004
- Color Transfer Between Images
- Reinhard, Ashikhmin, Gooch, Shirley, CG&A 2001
- N-Dimensional Probability Density Function Transfer and its Application to Color Transfer
 - Pitie, Kokaram, Dahyot, ICCV 2005

Colorization

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Colorization: a computer-assisted process of adding color to a monochrome image or movie. (Invented by Wilson Markle, 1970)

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Motivation

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· Colorizing black and white movies and TV shows





Earl Glick (Chairman, Hal Roach Studios), 1984: "You couldn't make Wyatt Earp today for \$1 million an episode. But for \$50,000 a segment, you can turn it into color and have a brand new series with no residuals to pay"

Hugh O'Brien as Wyatt Earp, 1957

Motivation

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· Colorizing black and white movies and TV shows

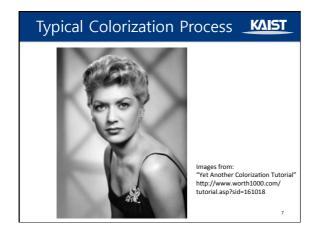


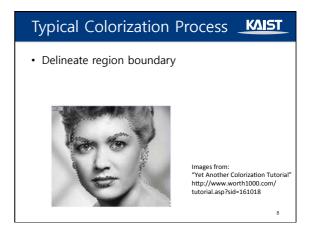
• Recoloring color images for special effects

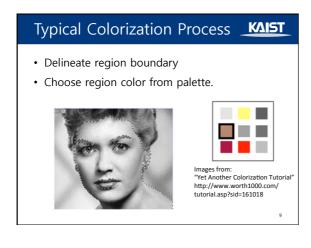


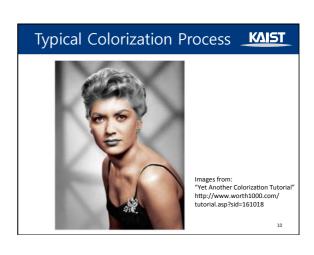


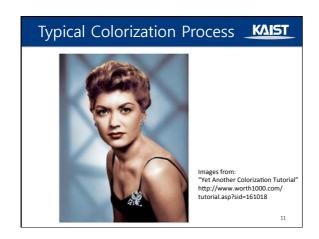
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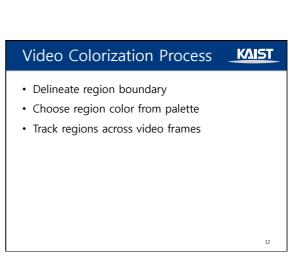




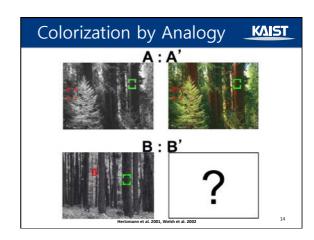


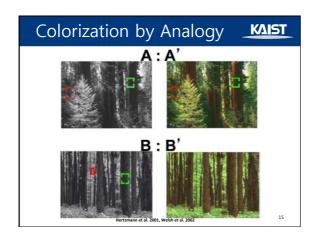


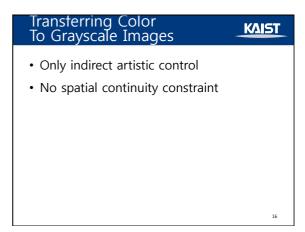




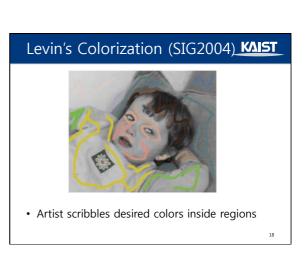












Levin's Colorization (SIG2004) KAIST



- Colors are propagated to all pixels
- · "Nearby pixels with similar intensities should have the same color"

Propagation using Optimization KAIST

 $Y \Rightarrow U,V$

- Work in YUV color space
- Input: Y, Output: U,V
- · "Neighboring pixels with similar intensities should have similar colors"

Propagation using Optimization KAIST

Luminance uv chromaticity channel
$$J(U) = \sum_{r} \left(U(\mathbf{r}) - \sum_{s \in N(\mathbf{r})} w_{\mathbf{r}s} U(\mathbf{s}) \right)^2$$

 \mathbf{r} , \mathbf{s} denote (x, y, t)

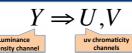
- $Y(\mathbf{r})$ is the intensity of a particular pixel.
- Minimize difference J(U), J(V) between color at a pixel and an affinity-weighted average of the neighbors

Propagation using Optimization KAIST

$$J(U) = \sum_{r} \left(U(\mathbf{r}) - \sum_{s \in N(\mathbf{r})} w_{rs} U(\mathbf{s}) \right)^{2}$$

• The notation $\mathbf{r} \in \mathcal{N}(\mathbf{s})$ denotes the fact that \mathbf{r} and **s** are neighboring pixels.

Propagation using Optimization KAIST



• Key idea: "Neighboring pixels with similar intensities should have similar colors"



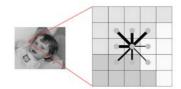


Affinity Functions

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$$w_{\rm rs} \propto e^{-(Y({\bf r})-(Y({\bf s}))^2/\sigma_{\rm r}^2}$$

 $\sigma_{\mathbf{r}}~$ is proportional to local variance W_{rs} is large when $Y(\mathbf{r})$ is similar to $Y(\mathbf{s})$

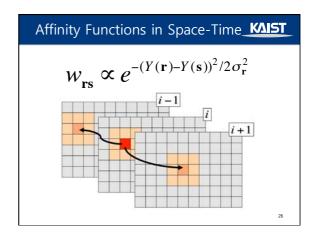


Affinity Functions

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- The correlation affinity can also be derived from assuming a local linear relation between color and intensity [Zomet and Peleg 2002; Torralba and Freeman 2003].
- Formally, it assumes that the color at a pixel $U(\mathbf{r})$ is a linear function of the intensity $Y(\mathbf{r})$: $U(\mathbf{r}) = a_i Y(\mathbf{r}) + b_i$ and the linear coefficients a_i , b_i are the same for all pixels in a small neighborhood around \mathbf{r} .

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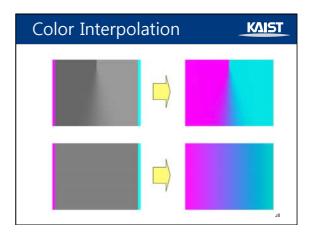


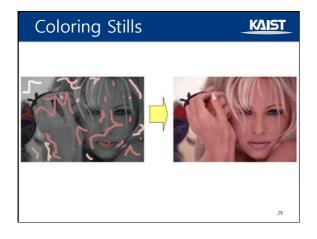
Minimizing cost function K

• Minimize:

$$J(U) = \sum_{r} \left(U(\mathbf{r}) - \sum_{s \in N(\mathbf{r})} w_{rs} U(\mathbf{s}) \right)^{2}$$

- Subject to *labeling constraints*
- Since cost is quadratic, minimum can be found by solving sparse system of linear equations.
- Using Matlab's least-squares solver for sparse linear systems (see their code for detail):
- http://www.cs.huji.ac.il/~yweiss/Colorization/ 27



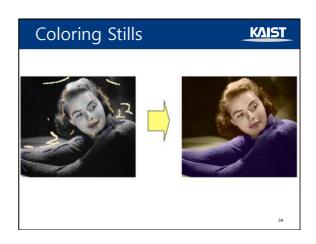


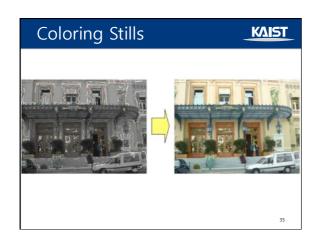




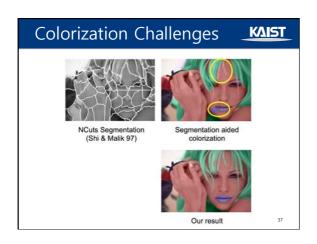


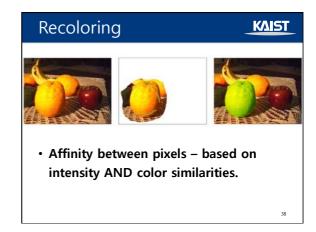


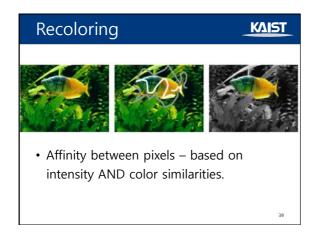


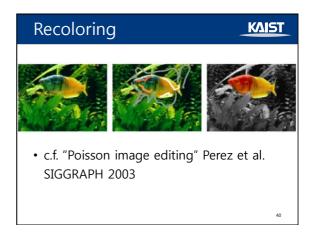








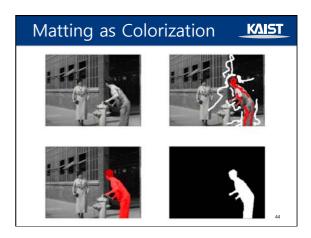












Still Needed:

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- Import image segmentation developments:
 - affinity functions, optimization techniques.
- Alternative color spaces, propagating hue and saturation differently

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Other Approaches?

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- Color space was YUV
- Small amount of user effort needed
- For film/color *grading*, can this be automated?

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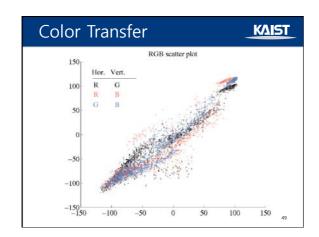
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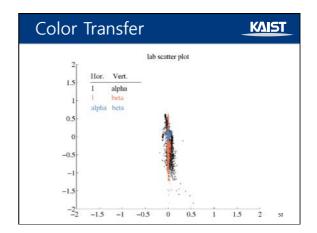
Color Transfer

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- (R, G, B) is ambiguous: all channels are correlated
- (L*, a*, b*) is good
- Algorithm (per channel):
 - Align mean
 - Rescale standard deviation

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Color Transfer	KAIST
 Subtract the mean from the data points Scale the data points comprising the synthetic image by factors determined by the respective standard deviations: 	$l^* = l - \langle l \rangle$ $\alpha^* = \alpha - \langle \alpha \rangle$ $\beta^* = \beta - \langle \beta \rangle$ $l' = \frac{\sigma_t^l}{\sigma_s^l} l^*$ $\alpha' = \frac{\sigma_t^\alpha}{\sigma_s^\alpha} \alpha^*$ $\beta' = \frac{\sigma_t^\beta}{\sigma_\beta^\beta} \beta^*$ 51







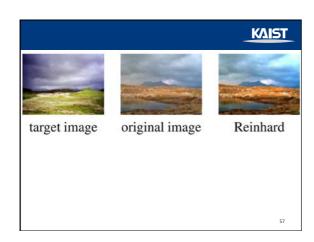


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Iterate 1D Solution at Different Rotations

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• 1D solution uses cumulative probability density function (PDF):

 $t(x) = C_Y^{-1}(C_X(x))$

- where t(x) is a mapping function; Cx and Cy are the cumulative pdfs of X and Y images.
- · N-D solution:
 - Pick a rotation matrix R, apply to both 3D distribs.
 - Project both distribs. onto each axis in turn Apply 1D solution
 - Unproject, unrotate
 - <repeat> until convergence on all marginals for every possible rotation

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Algorithm 1 pdf transfer algorithm 1. Initialisation of the data set source x and target y. For example in colour transfer, $x_j = (r_j, g_j, b_j)$ where r_j, g_j, b_j are the red, green and blue components of pixel number j. 2. repeat 3. take a rotation matrix R and rotate the samples: $x_r \leftarrow Rx^{(k)}$ and $y_r \leftarrow Ry$ 4. project the samples on all axis is to get the marginals f_i and g_i 5. for each axis f_i , find the D transformation f_i that matches the marginals f_i into g_i 6. remap the samples x_r according to the 1D transformations. For example, a sample (x_1, \dots, x_N) is remapped into $(t_1x_1, \dots, t_N(x_N))$, where N is the dimension of the samples. 7. rotate back the samples: $x_i^{(k+1)} \leftarrow R^{-1}x_i$ 8. $k \leftarrow k + 1$ 9. until convergence on all marginals for every possible rotation 10. The final one-to-one mapping t is given by: $\forall j, x_j \mapsto t(x_j) = x_j^{(\infty)}$

• Example of 2D pdf transfer. Note the decrease of the measure of the Kullback-Leibler distance (see the paper for proof) • Example of 2D pdf transfer. Note the decrease of the measure of the Kullback-Leibler distance (see the paper for proof)

