Data-Driven Image Color Theme Enhancement

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Abstract

Proposed method

- Data-driven method
  - Enhancing a desired color theme
- Formulating unified optimization
  - Simultaneously considering a desired color theme, texture-color relationship, automatic, user specified color constraints
- Quantifying difference between an image and a color theme
- Use of prior knowledge
Introduction

◆ Aim of paper
  – Color theme enhancement of an image
    • Seeking global transformation of the colors in original image
      – Maintaining the realism of natural image
      – Perceptually close to a desired color theme
    • Problem of color theme editing
      – Commercial software (Photoshop)
        » Not explicitly support color theme editing
      – Time consuming
        » Operating a large number of trials
– Proposed method

• Learning relationships between texture classes and color histograms
  – Suppression of over-aggressive coloring

• Balancing among colors of a desired theme, colors of natural materials, and user-defined color constraints

• Quantification of difference between an image and a color theme
  – Large number of pixels in image
  – Small template of colors in color theme

• Use of color mood space

Fig. 1. An example of image color theme enhancement using our method. Left: Original image; middle: recolored result with the “nostalgic” color theme; and right: recolored result with the “lively” color theme.
Background and related work

Related work

- Color editing and transfer
  - Manual method
    - Reinhard et al.
      » Performing statistical analysis to impose the color characteristics of one image onto another
      » Use of mean and standard deviation ($l\alpha\beta$)
    - Welsh et al.
      » Similar Reinhard method (modified $\alpha\beta$)
      » Use of swatches
– Automatic method

• Chang et al.
  – Stylizing image
    » Use of image category

• Piti et al.
  – Extending Reinhard method
  – Linear mapping to minimize the displacement cost
    » Based on Monge-Kantorovitch (MK) theory

• Bae et al. and Lischinski et al.
  – Focusing effective tone adjustment
    » Manipulating luminance channel only

• Cohen-Or et al.
  – Performing color adjustment according to harmonization rules

• Shapira et al.
  – Editing image appearances interactively
    » Using Gaussian mixture models (GMM)
– **Edit propagation**
  
  • Stork-based method
    – Supplying edits by drawing scribbles in different regions
      » Editing automatically propagate to the rest of image by exploiting the constraint
    – An and Pellacini
      » Developing general and robust framework by efficiently approximating the all-pairs affinity matrix
  
  • Proposed method
    – Use of soft image segmentation
  
  • Xu et al.
    – Using adaptive clustering
      » Based on K-d trees

◆ **Color and mood**
  
  – Using result of psychological experiments
Overview

◆ Framework of our system
  – Consist of an offline phase(lower row) and a runtime phase(upper row)
  – Representation of color theme
    • 3 or 5 color
Fig. 3. The overall pipeline of our framework. Each sub-image in (b) is an influence map of a soft segment. Each soft segment finds the most relevant texture class in (f) and adopt the corresponding color histogram in (g). The histograms in (g) are further converted into continuous probability density distributions using Gaussian Mixture Model (GMM). The user needs to select a desired color theme from (d), then our optimization solver takes the prior knowledge (color probabilities), the desired color theme and the image segments into consideration to generate final recolored images in (h).
Data-driven prior knowledge extraction

- Color theme based image labeling
  - Theme database
    - Consist of representative color themes from existing literature and online communities

**Fig. 2.** A list of popular color themes from Adobe Kuler. Left: the color templates. Right: the associated verbal descriptions.
– Image database
  • Randomly choosing a subset of tens of thousands of color image downloaded from Flickr
– Using theme database to label each image from image database
– Proposed method
  • Setting discrete histogram bins by quantizing color from image in CIELAB color space
    – K-means algorithm
  • Using template of 3 or 5 colors
Texture-color relationship

- Highly correlated with certain color combinations
- Use of a universal texture library
  - Extracting classes of textures from images across all adopted color themes
    - Procedure
      » Dividing each image into small patches
      » Calculating mean and standard deviation of pixel-wise Gabor filter
      » Clustering texture descriptors using K-means algorithms
    - Use of only chrominance channels
Fig. 4. Color histograms for textures “sky” and “grass” among all images labeled with the same color theme. Their top five color bins are visualized by setting L=60 (as luminance is excluded during indexing).
Continuous probability density estimation

- Expression of color histograms with discrete bins
  - Helpful to convert continuous probability density functions

- Expressing probability density in texture class

\[
H'_{T_i}(c) = \sum_{j=1}^{U} H_{T_i}(h_j) \frac{1}{2\pi\sigma_j} \exp \left( -\frac{(a_t^* - a_j^*)^2 - (b_t^* - b_j^*)^2}{2\sigma_j^2} \right)
\]

where \( \sigma_j \) is estimated as the average distance between \((a_j^*, b_j^*)\) and the base colors of its three nearest color bins.

- Example of continuous models

![Continuous probability density functions for sky(Left) and grass(Right) textures respectively. Converted from discrete histograms.](image-url)
Color optimization

◆ Image color theme enhancement
  – Optimization problem
    • Supposing K soft segments in a given image
    • Energy function

\[ E = \alpha E_1 + \beta E_2 + \gamma E_3 \] (2)

where
\[ E_1 = \sum_{i=1}^{K} \Psi (\vec{c}_i), \quad E_2 = -\sum_{i=1}^{K} \log (H_{T_i} (\vec{c}_i)), \]

\[ E_3 = \frac{1}{N} \sum_{t=1}^{N} \sum_{k=1}^{m} F (\vec{c}_t) - \frac{1}{m} \sum_{k=1}^{m} F (\vec{c}_k) \]

\[ \Psi (\vec{c}_i) = \begin{cases} \| \vec{c}_i - \vec{c}_i' \|^2, & \text{a scribble over segment } s_i \\ \| \vec{c}_i - \vec{c}_i'' \|^2, & \text{otherwise} \end{cases} \]

and
\[ \vec{c}_i = c_{i_{\text{max}}}, \quad i_{\text{max}} = \arg \max_i \, P_{ii} \]
• E1: how well soft color constraints are satisfied

\[ \bar{c}_i \] denotes the new color of segment \( s_i \) that needs to be optimized. It has three channel. \( \bar{c}_i \) denotes the average color of a representative patch of \( s_i \) in the original image while \( c_i \) denotes the color of a scribble.

• E2: incorporates color preferences encoded in the underlying probability density function to ensure naturalness and realism

• E3: least-squares energy term, which steers the color composition of the image towards the desired color theme
  – Adapting three dimensional color mood space (activity, weight, and heat)
  – First part of E3 maps the edited image to the color mood space
  – Second part of E3 maps the chosen color theme to the color mood space
• Importance of the optimization

![Images showing the importance of optimization](image1)

**Fig. 6.** Left: an input image and a color theme. Middle: image generated by the greedy initial assignment in section 5.1, without further optimization. Right: final image with further optimization.

• Importance of the energy term $E_3$

![Images showing the importance of energy term](image2)

**Fig. 7.** Left: an input image and a target color theme. Middle: result image without $E_3$. Right: result image with $E_3$. 

• Importance of prior knowledge (E2) in enhancing the realism of the result for a texture image.

**Fig. 8.** Left: an input image and a color theme. Middle: result image without $E_2$. Right: result image with $E_2$. 
Automatic theme driven scribbles
  – Effectively steering image towards a given color theme
    • Automatically generating color scribbles
      – Associating every color from the template of target color theme
    • Supposing K segments ( K > m)
      \[
      \arg \max_j \omega_j c_{li} \rightarrow c_j
      \]
      where \( c_j \) is the average color of segment \( s_i \) in the original image.
Soft segmentation

– Suppose of soft segmentation

• Scalar numbers in the K edits \( \{v_1, v_2, \ldots, v_K\} \) \((0 \leq v_j \leq 1)\)

• Influence values at pixel \( t \) \( f_t \) \((0 \leq f_t \leq 1)\)

\[
P'_{ti} = \frac{\exp\left(\frac{(f_t - v_i)^2}{\alpha^2}\right)}{\sum_{j=1}^{K} \exp\left(\frac{(f_t - v_j)^2}{\alpha^2}\right)}, \quad i = 1, \ldots, K
\]

(4)

where \( \alpha \) is used to control the "softness" of the segmentation.

– \( \alpha \) approaches zero ("hard" segmentation)
  » Largest channel approaches 1
  » All other channels approach 0

– \( \alpha \) approaches infinity
  » All channels approach \( 1/K \)

– Appropriate \( \alpha \)
  » Keeping one of the channels dominant

– Typically set \( \alpha \) between 0.2 and 0.5
Automatic generation of seed areas

- Providing option to generate seed areas automatically

- Every function for texture labeling

\[
E' = \sum_{i \in V} E_4(l_i) + \sum_{(i,j) \in \varepsilon} E_5(l_i, l_j)
\]

\[
E_4(l_i) = \left\| \overrightarrow{T_i}^p - \overrightarrow{T_i} \right\|^2
\]

\[
E_5(l_i, l_j) = \exp \left( -\frac{\left\| \overrightarrow{u_i} - \overrightarrow{u_j} \right\|^2}{\eta^2} \right) \left\| \overrightarrow{H_{li}} - \overrightarrow{H_{lj}} \right\|^2
\]

where \( l_i \) is the texture label for patch \( i \), \( \overrightarrow{T_i}^p \) represents the texture descriptor of patch \( i \), and \( \overrightarrow{T_{li}} \) represents the descriptor of texture class \( l_i \), \( \overrightarrow{u_i} \) represents the average color of patch \( i \), and \( \overrightarrow{H_{li}} \) represents the color histogram corresponding to texture class \( l_i \).

- \( \delta \) : controls the relative importance of the two energy terms
- \( \eta \) : controls the smoothness of the labeling result in local regions
• First term in (5)
  – More likely for a patch to be labeled with a texture class
    » Similar to the texture descriptors of two

• Second term
  – Smaller the difference between average colors of two neighboring patches
Loopy belief propagation

– In our experiments, $\delta = 100$ and $\eta = 50$

– Final step in our algorithm
  
  – Merging any pair of resulting regions
    
    – Small difference between their average colors

![Figure 10](image-url)

**Fig. 10.** Left: Patches serve as graph nodes for texture labeling. Middle: Labeling result with color-coded regions. Right: Seed patches after the final merging step are indicated in white.
Results and analysis

◆ Performance
  – Experiment condition
    • Image size 1024 x 1024
    • 10 soft segments

Fig. 1. An example of image color theme enhancement using our method. Left: Original image; middle: recolored result with the “nostalgic” color theme; and right: recolored result with the “lively” color theme.
Fig. 12. A variety of images and their recolored ones with different color theme enhancement. The first column shows the original images.
◆ Comparison with color transfer
  – Previous and proposed method

Fig. 11. Comparisons with histogram matching and color transfer. The source image is shown in Figure 7 Left. (a) a reference image and its corresponding color theme, (b) result image generated by histogram matching, (c) result image generated by MK-based color transfer [Piti and Kokaram 2007], (d) theme enhancement result by our method.

◆ Comparison with simple filtering
  – Existing filtering based approaches
    • Performing with or without region segmentation
  – Our system
    • Initializing and optimizing color automatically according to the chosen color theme and texture information
User study

– Experiment condition
  • 25 participants (14 females and 11 males) with normal vision
    – Ages ranging from 18 to 45
    – 5 of professional designer
  • Choosing 20 test images

– T-test

\[ H_0 : u_a \geq u_b \]
\[ H_1 : u_a < u_b \]

where \( u_a \) represents the mean confidence value of the original image, while \( u_b \) represents the mean confidence value of the recolored image.

• Hypothesis
  – \( H_0 \) : fail to enhance and express the themes (good original)
– Result of experiment

- Accepting $H_1$

**Table 1. Paired T-test Results ($\alpha = 0.05$)**

<table>
<thead>
<tr>
<th>No.</th>
<th>Theme</th>
<th>T</th>
<th>P(two-tail)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td></td>
<td>-2.716</td>
<td>.000865</td>
</tr>
<tr>
<td>2</td>
<td></td>
<td>-9.309</td>
<td>.000000</td>
</tr>
<tr>
<td>3</td>
<td></td>
<td>-2.916</td>
<td>.005843</td>
</tr>
<tr>
<td>4</td>
<td></td>
<td>-8.753</td>
<td>.000000</td>
</tr>
<tr>
<td>5</td>
<td></td>
<td>-3.135</td>
<td>.003255</td>
</tr>
<tr>
<td>6</td>
<td></td>
<td>-11.703</td>
<td>.000000</td>
</tr>
<tr>
<td>7</td>
<td></td>
<td>-9.326</td>
<td>.000000</td>
</tr>
</tbody>
</table>
Conclusions and discussion

◆ Proposed method
  – Example-based method
    • Steering color composition of an image toward a desired color theme impression
  – Formulating unified optimization
    • Simultaneously considering desired color theme, texture-color relationships, and color constraints
Limitations

– Out-of-focus image

Fig. 13. A failure case for out-of-focus regions. Left: an input image. Right: the recolored result.
TABLE I. The 10 colour emotions in this study can be roughly categorized into three groups according to their literal meanings.

<table>
<thead>
<tr>
<th>Three primary factors identified by Osgood et al.</th>
<th>Colour emotions used in this study</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Clean–dirty</td>
</tr>
<tr>
<td></td>
<td>Fresh–stale</td>
</tr>
<tr>
<td></td>
<td>Like–dislike</td>
</tr>
<tr>
<td></td>
<td>Heavy–light</td>
</tr>
<tr>
<td></td>
<td>Hard–soft</td>
</tr>
<tr>
<td></td>
<td>Masculine–feminine</td>
</tr>
<tr>
<td></td>
<td>Warm–cool</td>
</tr>
<tr>
<td></td>
<td>Modern–classical</td>
</tr>
<tr>
<td></td>
<td>Active–passive</td>
</tr>
<tr>
<td></td>
<td>Tense–relaxed</td>
</tr>
</tbody>
</table>

FIG. 4. The 20 colour samples ranked along the three colour-emotion factors: colour activity, colour weight, and colour heat.
[16]
First, we subtract the mean from the data points:

\[ t' = t - \langle t \rangle \]
\[ \alpha' = \alpha - \langle \alpha \rangle \]
\[ \beta' = \beta - \langle \beta \rangle \]  \hspace{1cm} (10)

Then, we scale the data points comprising the synthetic image by factors determined by the respective standard deviations:

\[ t^* = \frac{\sigma_t}{\sigma_t^*} t' \]
\[ \alpha^* = \frac{\sigma_\alpha}{\sigma_\alpha^*} \alpha' \]
\[ \beta^* = \frac{\sigma_\beta}{\sigma_\beta^*} \beta' \]  \hspace{1cm} (11)
EMD between color signatures.

rotation invariance.

[20]

[23]
[25]