OPTIMIZING COLOR CONSISTENCY IN PHOTO COLLECTIONS

GROUP 17

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AIM:

To ensure a consistent appearance of connected photos without user explicitly doing it on every single photo.

ABSTRACT:

With dozens or even hundreds of photos in today's digital photo albums, editing an entire album can be a difficult task. Existing automatic tools operate on individual photos without ensuring consistency of appearance between photographs that share content.

We used a method that operates by efficiently constructing a graph with edges linking photo pairs that share content and consistent appearance is achieved by globally optimizing a quadratic cost function over the entire graph.

Figure 1: *Editing a photo collection with our method. First row: input images exhibiting inconsistent appearance. Red arrows indicate pairs of images that were detected to share content. Second row: automatically induced consistent appearance. Third row: after propagating user adjustment of the leftmost photo (photos with similar content are affected more strongly). Fourth row: propagation of an adjustment done to the sixth photo. Previous adjustment remains as constraint. (Note: adjustments are deliberately exaggerated in this example.)*

INTRODUCTION:

Inconsistent appearance of photos in a personal album may result from

A] changes in lighting conditions

B] different camera settings

C] from different cameras altogether, where such inconsistencies become even more apparent.

CONSTRAINTS:

In the process of imposing color consistency, we attempt to balance between achieving color consistency and preserving the dynamic range and natural appearance of individual photos.

AVAILABLE WORKS:

Automatic enhancement tools exist, but they operate on each image independently, without attempting to ensure consistency of appearance between photographs depicting the same subject or scene.

Adobe Photoshop- There are many tools such as Auto Levels tool in Adobe Photoshop which are robust but these tools operate on each image independently.

Propagation Techniques: Many researchers have come up with several techniques to propagate appearance between images but they evolve around 3-D reconstruction. They are also confined to static and cannot be extended to wide variety of photo collections.

Our approach leverages recent developments in finding dense correspondences and transferring color between real-world photo pairs . To extend this approach to photo albums, we construct a match graph in which the photos are represented by nodes and shared content is represented by edges. Each edge is assigned a weight based on the size of the corresponding regions between the two photos and the quality of the correspondence. Consistency of appearance between connected photos is achieved by minimizing a quadratic cost function over the entire graph.

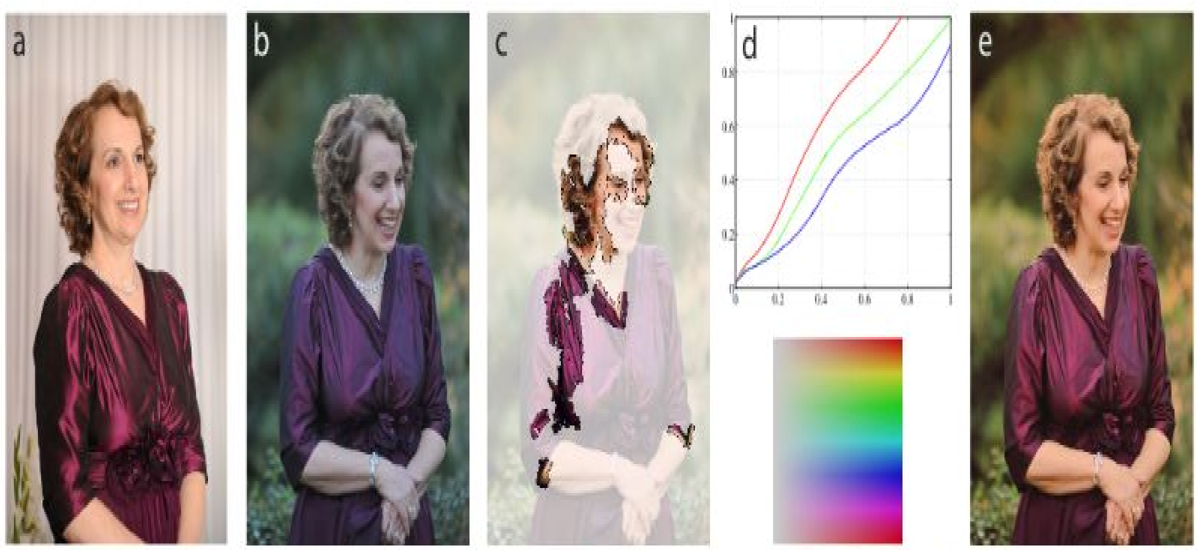
NON-RIGID DENSE CORRESPONDENCE:

WHAT IS NRDC AND HOW IS IT HELPFUL ?

- NRDC is a state-of-the-art method for finding corresponding regions and color transfer between two photos that share common content.

- This method can handle shared content under non-rigid deformations and color variations, and computes a parametric color transfer model between pairs of images.

- We utilize a new coarse-to-fine scheme in which nearest-neighbor field computations using Generalized PatchMatch are interleaved with fitting a global nonlinear parametric color model and aggregating consistent matching regions using locally adaptive constraints.



Color transfer using our method. The reference image (a) was taken indoors using a flash, while the source image (b) was taken outdoors, against a completely different background, and under natural illumination. Our correspondence algorithm detects parts of the woman's face and dress as shared content (c), and fits a parametric color transfer model (d). The appearance of the woman in the result (e) matches the reference (a).

OVERVIEW :

Optimizing over the entire match graph makes it possible to ensure consistent appearance even between pairs of photos that do not share any content directly. Thus, our framework supports indirect propagation, and edits made to a single image can, in principle, propagate to the entire collection.

Computing the full match graph is expensive, since each edge involves computing a dense correspondence between a pair of images. However, because we enable indirect propagation, it typically suffices to construct only a sparse subset of the full set of edges; namely, only edges connecting images with a substantial amount of shared content. To this end, we trained an SVM-based classifier for quickly predicting which pairs of images may have a significant correspondence, leading to a drastic reduction in the match graph construction time by reducing the number of accurate correspondence computations to be linear in the number of photos.

APPEARANCE CONSISTENCY OPTIMIZATION :

we attempt to strike a balance between three potentially contradictory goals:

- Ensuring that pixels depicting the same content have the same color across different images
- Avoiding unsightly visual artifacts, such as gradient reversals or severe loss of contrast
- Attempting to preserve as much as possible the original dynamic range of each photo

Let, I_j be the Img which we are Changing & f_j be the intensity transform for I_j.

The effect on other Images is represented by the f_is Which calculated by following optimization problem.

Our approach is to seek a set of dedicated color transformations fi (one for each image Ii), such that the resulting transformed images comply with our appearance consistency requirements. This is done by solving the following optimization problem:

$$\{\hat{f}_i\}_{i=1}^{n} = \underset{\{f_i\}_{i=1}^{n}}{\arg\min} \sum_{i \neq j} A(f_i, f_j) + \sum_{i=1}^{n} C_{soft}(f_i) \quad (1)$$
$$\text{subject to: } C_{hard}(f_i), \forall i \in \{1, \ldots, n\}$$

<u>COLOR TRANSFORMATION MODEL:</u>

- The color transformations f_i is based on an expressive global parametric model.
- Each f_i consists of three curves (one per each RGB channel). Each curve is a smooth piecewise-quadratic spline with 6 knots at (0, 0.2, 0.4, 0.6, 0.8, 1), which translates to 7 degrees of freedom per curve.
- This model is flexible enough to compensate for a variety of common appearance differences, such as gamma curves, S-curves, color temperature changes, and other common global operators.

- **$A(f_i, f_j)$** - Pairwise affinity term, penalizing color diff. between shared content
- **$C_{Soft}(f_i)$ & $C_{Hard}(f_i)$** - Term enforcing constraints on the color transformations

$C_{Soft}(f_i)$:

$$\begin{aligned} C_{soft}(f_i) &= \lambda_1 \textstyle\sum_{x\in\{0,1\}} |f_i(x)-x|^2 \\ &+ \lambda_2 \textstyle\sum_{x\in\{0.2j-0.1\}_{j=1}^{5}} |f_i(x)-x|^2 \\ &+ \lambda_3 \textstyle\sum_{x\in\{0.2j-0.1\}_{j=1}^{5}} |f_i''(x)|^2. \end{aligned} \quad (2)$$

- $\lambda 1$ and $\lambda 2$ control how much to pull the curve towards identity (no change) at the end points of the range (0 and 1) and at five midpoints between the knots (middle of each spline segment).
- $\lambda 3$ controls the smoothness of the curve by penalizing for large second derivatives.
- $\lambda 1$ controls preservation of dynamic range and $\lambda 2$ control preservation of original appearance

$C_{Hard}(f_i)$:

$$C_{hard}(f_i):\ \begin{aligned} &\text{i.} && 0.2 \le f_i'(x) \le 5, \quad \forall x \in \{0.2j-0.1\}_{j=1}^{5} \\ &\text{ii.} && f_i(0) \le 0 \end{aligned} \quad (3)$$

- The curve is forced to be strictly monotonic (at spline segments midpoints).
- The curve is forced to be strictly monotonic (at the spline segment midpoint

Affinity term:

The pairwise affinity term $A(f_i,f_j)$ is defined using the weighted SSD (sum of squared differences) between color-mapped pairs of matching pixels.

$$A(f_i, f_j) = \sum_{\mathbf{p}} w_{i,j}(\mathbf{p}) \left| f_i(I_i(\mathbf{p})) - f_j(I_j(M_{i,j}(\mathbf{p}))) \right|^2 \qquad (4)$$

- $M_{i,j}: N^2 \rightarrow R^2$ is partial pixel-wise mapping that maps pixels in I_i to I_j
- $w_{i,j} : N^2 \rightarrow [0, 1]$ is the confidence map associated with this mapping.

TECHNOLOGIES :

- Basic Implementation
- NRDC
- Splines Generation Tools : (ppmak, ppval to be specific)
- CVx Solver (for solving optimizations problems)

WORKFLOW:

➔Apply NRDC on all images with the reference image.

➔Find the link mapping between images to propagate changes .

➔Apply appearance consistency optimization and obtain best transformations for all images.

➔Transform all the images to obtain the color consistency among all images.

RESULTS:

We observed the following results :

- Images with high intensity coherency had a dense correspondence.

- Images with dense correspondence were observed to have more transform as compared to the ones with sparse or zero correspondence.

- The time for making the dense graphs and its further propagation is time consuming, hence, we need an even better mechanism to predict the links and propagate.

(Original Images)

(Output with Image-1 Edited)

ACCELERATING MATCH GRAPH CONSTRUCTION :

FUTURE WORK AND SCOPE

- Link prediction scheme eschews the full dense correspondence calculation on the majority of image pairs, thereby greatly accelerating match graph construction.

- Given a pair of photos Ii and Ij the link predictor can quickly estimate the likelihood that applying NRDC between these two images would result in a significant connection in the graph.

- The approach consists of training a support vector machine (SVM) to classify pairs of images into one of two categories: pairs that are likely to have a significant correspondence between them, and pairs that are unlikely to have such a correspondence.

- For every pair of images Ii and Ij we can apply a set of kernels on different types of feature vectors. The result is a continuous classification measure of the "matchability" between the two images (rather than a discrete classification), obtained by the dot product of the SVM weights and the vector of the kernels K(Ii; Ij).

LIMITATIONS:

- Our method currently accounts for global color appearance variations only.

- Our color transfer model is based on RGB curves and does not model saturation changes well.

- Our method works best when the collection contains a substantial amount of shared content, as typically occurs in personal and professional collections.