Optimizing Color Consistency in Photo Collections

By team thankyoudoctor

AIM

To ensure a consistent appearance of connected photos without user explicitly making changes to every single photo.

AIM

Source

Source

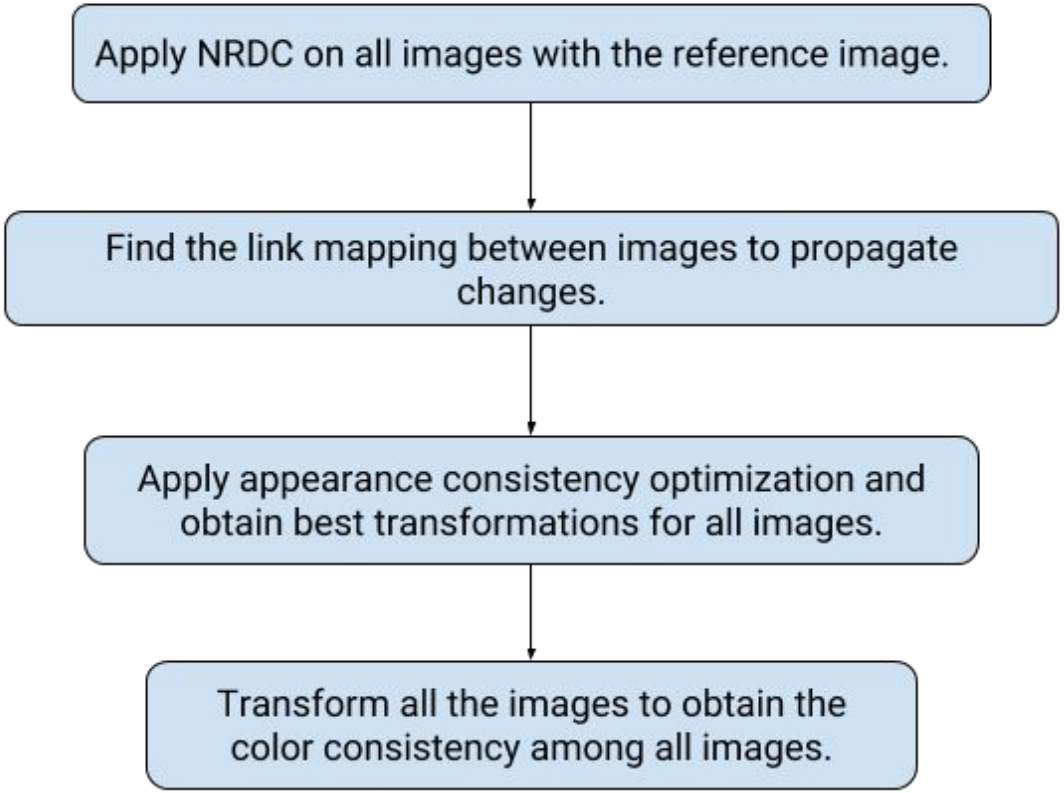
Constraints

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.

Causes for inconsistencies

- Changes in Lighting Conditions.
- Changes in Camera Settings.
- Changes due to different Cameras altogether.

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.

APPROACH:

Histogram Matching in different colour spaces

Histogram Matching

Top Left: *Source*

Top Right: *Reference*

Bottom Left: *Image obtained after histogram matching of source image with that of reference in RGB colour space*

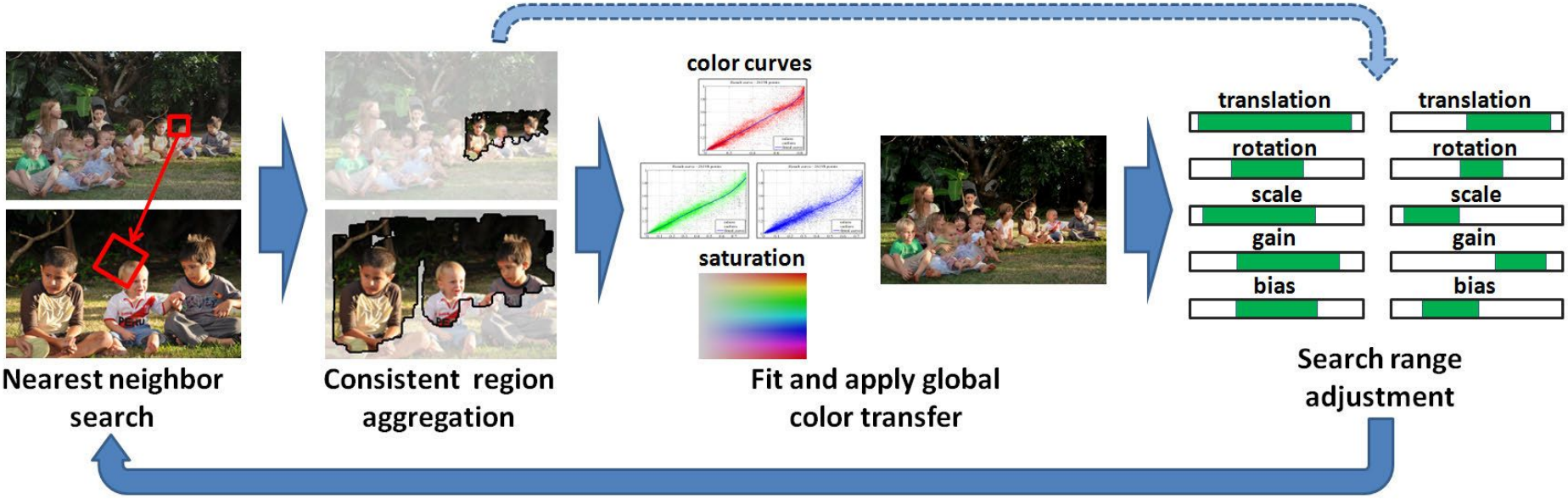
Bottom Right: *Image obtained after histogram matching of source image with that of reference in HSI colour space*

Histogram Matching

First: *Source* ***Second:*** *Reference* ***Third:*** *Image obtained after histogram matching of source image with that of reference in RGB colour space* ***Fourth:*** *Image obtained after histogram matching of source image with that of reference in HSI colour space*

APPROACH:
Finding correspondences using NRDC

Non-Rigid Dense Correspondence (NRDC)



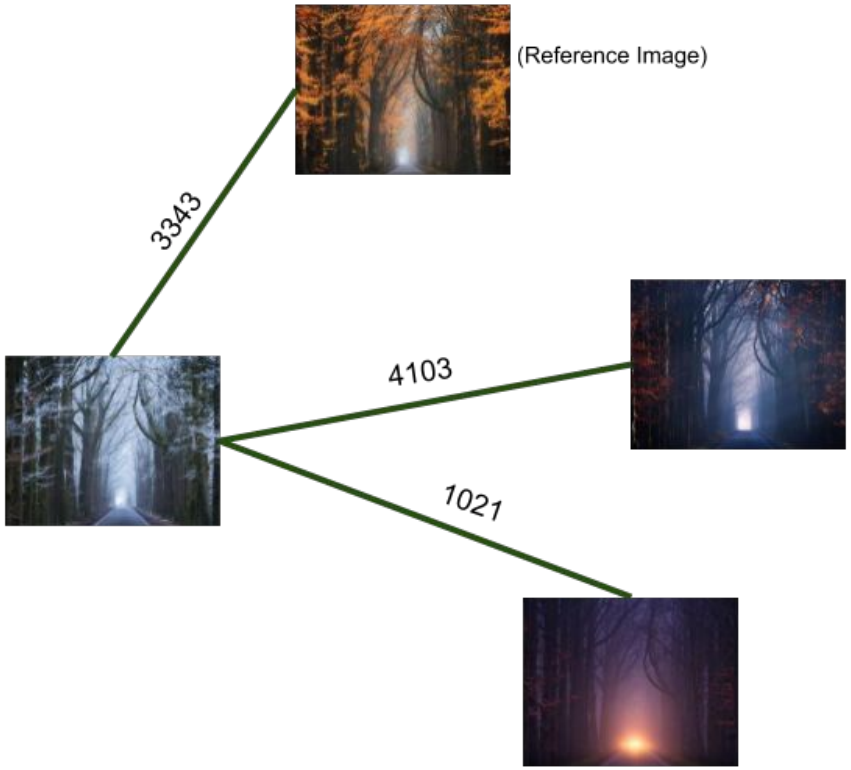
Colour consistency using SIFT

SIFT feature are very sparse and contain error while creating the consistent regions

*Source and Reference (**First Column**), Consistent Regions in Source and Reference and using SIFT (**Second Column**) and Consistent Regions in Source and Reference and using NRDC (**Third Column**)*

Colour consistency using SIFT

***Left**: Source image **Middle**: Reference image **Right**: Image obtained after applying the previous steps*



Match Graph

- Vertices are images
- Edges contain information regarding the correspondences between photo pairs

Appearance Consistency Optimization

Appearance Consistency Optimization

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

Color Transform Model

an expressive global parametric model for transformation of each image

- The model fits three monotonic curves, one per channel of the RGB color space
- Each curve is a smooth piecewise-quadratic spline with 7 knots at (0, 0.2, 0.4, 0.6, 0.8, 1)

Color Transform Model

$$\{\hat{f}_i\}_{i=1}^{n} = \underset{\{f_i\}_{i=1}^{n}}{\arg\min} \sum_{i \neq j} A(f_i, f_j) + \sum_{i=1}^{n} C_{soft}(f_i)$$

$$\text{subject to: } C_{hard}(f_i), \forall i \in \{1, \ldots, n\}$$

For every pair of images vi ,vj ∈ G(V) we would like to find a transformations fi , fj such that we can minimize A(fi , f j) for the entire graph.

Affinity Term A(fi ,fj):

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

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.

Regularization

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

The shape of each curve is regularized via unary soft constraint term

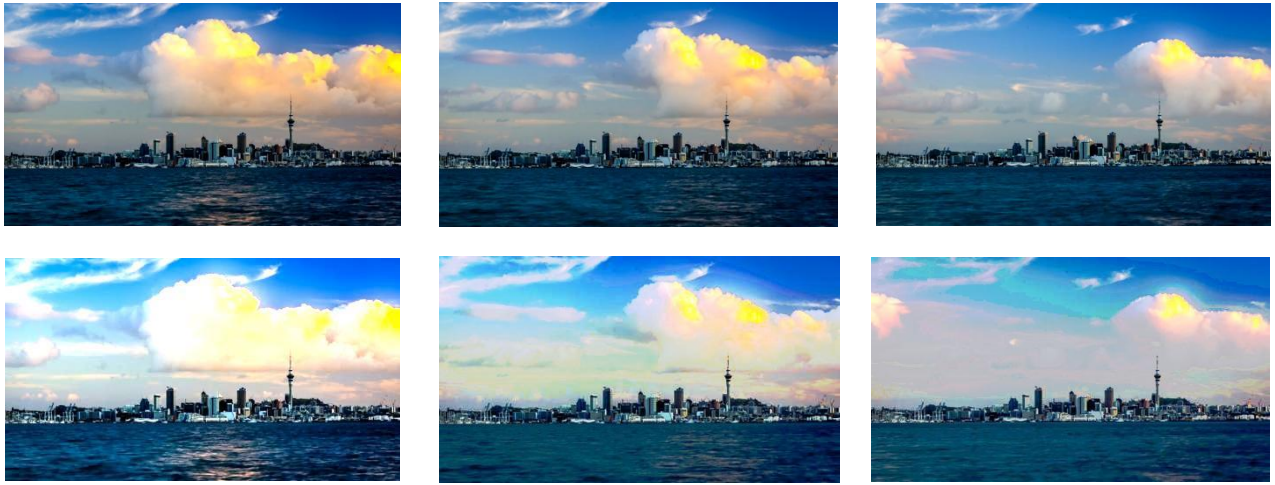
1. λ1 and λ2 together try to pull the curve towards identity mapping
2. λ3 controls the smoothness of the curve by penalizing large deviations in the second derivative
3. λ1 preserves the dynamic range and λ2 to control preservation of original appearance

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

The curve is forced to be strictly monotonic and to cross the x axis right of the origin

Propagating changes in a photo album

When the user does make changes to selected photos in an album, these changes automatically propagate to other images, while still maintaining as much consistency as possible



RESULTS

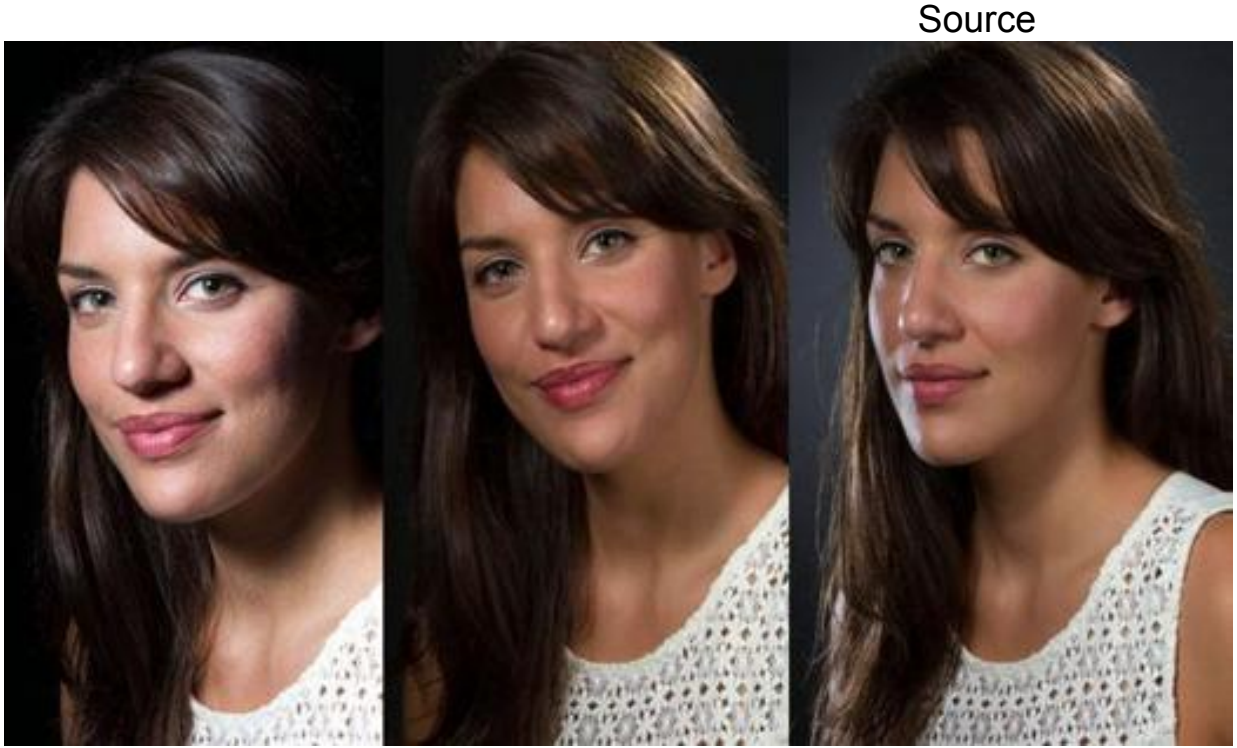
Input

Source

Output

Source

Input



Output

Source

Input

Source

Output

Source

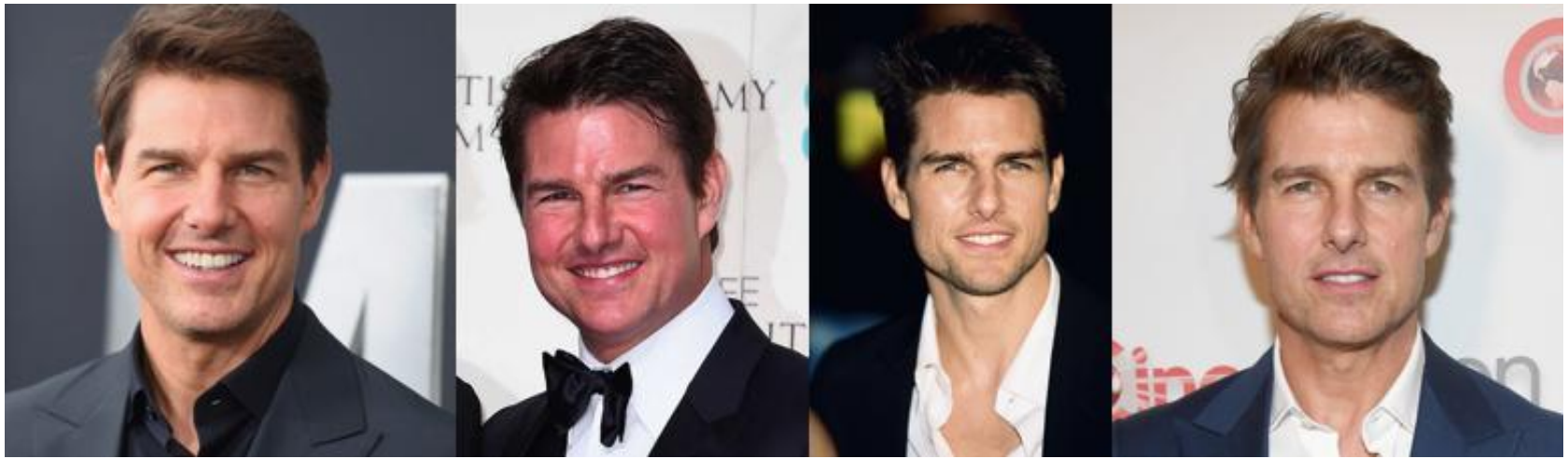
Input

Source

Output

Source

Input



Source

Output

Source

Application in Panorama Stitching

Panoramic Stitching without colour correction

Application in Panorama Stitching

Panoramic Stitching after colour correction

Application in Panorama Stitching

Panoramic Stitching without colour correction

Application in Panorama Stitching

Panoramic Stitching after colour correction

Propagating user edits in a video

Increasing constrast of first frame

Failure Cases (Input)

Source

Failure Cases (Input)

Source

Discussion and analysis

1. NRDC is a state of the art method the find correspondences for non rigidly objects but NRDC has difficulty in finding reliable correspondences in very large smooth regions, such as clear sky in the above case.
2. The global parametric color model is robust to errors in correspondence and is easier to regularize. Hence this model is used over a localized model.
3. 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

Future Work

1. Accelerating Match Graph Construction

   NRDC is very computationally expensive, instead we could only use NRDC when there's a higher likelihood of correspondence edge being present between 2 images. To calculate the likelihood of edge being present we can train an SVM classifier where the kernel matrix would be defined by using the sift features.

2. Link Prediction Strategy

   As most of the images would have correspondence with some images we will obtain a sparse weight matrix.

Conclusion

A consistent appearance of connected photos
without user explicitly doing it on every single photo

Propagate changes made by user from an image to the collection of images.

Thank you

Any questions?