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# Image Color Correction via Feature Matching and RANSAC

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***Abstract* — Color correction aims at modifying input image colors to match reference image colors. Various non-color changes between input image and reference image makes this problem difficult. In this paper, we present a method that first extracts invariant features and their descriptors on both images, finds matches between them, and applies RANSAC on the matched colors to yield a color transfer function robust to both the non-color changes and the matching outliers. Experimental results show that the proposed method yields better performance than those in the literature.**

## I. Introduction

In this paper, we consider a color correction problem where input image colors need to be modified to match reference image colors. There are both color changes and non-color changes between the two images, and we want to keep the non-color changes while correcting the color changes. Examples of non-color changes may include 2D geometric transformations, 3D view point changes, editing changes like letterbox, subtitles, and graphics overlays, and etc., while the color changes are assumed to undergo a global color transform.

Many color correction methods exist in the literature and some of them go by different names like color transfer and color balancing. Reinhard et al. [1] proposed a simple but effective global color transfer method based on image statistics, specifically, the mean and standard deviation of three individual color channels in Lab color space. Unfortunately this simple approach does not work well for the situations where those statistics are altered by non-color changes. Tai et al. [2] proposed a local color transfer approach that solves the color transfer between two natural images region-wise by probabilistic segmentation. They modified the expectation maximization (EM) algorithm to impose both spatial and color smoothness to obtain the soft region segmentations in both source image and target image. The Reinhard method [1] is applied to the matched local probabilistic segmentations to obtain a seamless color transfer. However, it is difficult to obtain exact segmentation matches between two images, and once there is an error in segment matching, the local color transfer method will significantly degrade the image quality in the final result.

In the field of automatic panoramic stitching, gain compensation is the technique applied to perform color correction if there is partial overlap between the images. Brown et al. [3] proposed their gain compensation method which obtains the overall gain between images through minimizing a cost function with a prior term to keep the gains close to unity. This method requires the overlap regions to be estimated, which is either difficult or error prone if overlapping part is altered by editting.

There are other methods in the literature that solve color correction problem that also assume an available spatial overlapping between images, including the principal regions method [4], Bayesian correction method [5], Tensor voting method [6]. Since in many cases we cannot assume known overlapping between the reference and input image, especially when there are editing changes, the application of these methods can be difficult.

In our proposed method, we find matching feature points instead of overlapping regions. A robust estimation method is then applied to estimate a color transfer function that is robust to the matching outliers. Experimental results show that our proposed methods have better performance in both PSNR and SSIM measurements.

## II. Approach

### A. Overview

Figure 1 shows an overview of our approach. First, robust features in both reference and input images are extracted. Descriptors are then calculated based on their local neighborhoods. Based on these descriptors, a one to one match of a subset of the feature points is computed. We use parametric models to model the color changes, and estimate model parameters based on colors of the matching pixels. The estimated color transfer function is then applied to the input image for a color corrected output.

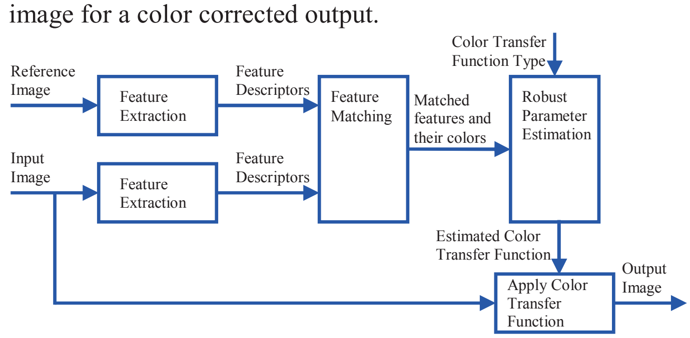


**Figure 1**. Overview of our color correction algorithm.

### B. Feature point detection and matching

Detecting invariant feature points within an image has been a common task in computer vision. Many different feature point detection methods are proposed in the literature. A comprehensive comparison of those detectors is described in [7]. Given the detected local feature points, many different descriptors have been proposed to characterize the local regions, i.e., to extract their distinctive signatures, including using SIFT [8], GLOH[9], and SURF[10], among others. If two sets of descriptors are obtained from two different images, matches can be computed based on the similarity of the descriptors. For the experiments in this paper, we use the method described in [8] to obtain the feature points, calculate



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their descriptors, and compute the matches.

### *C. Robust parameter estimation*

We assume the color change between reference and input image undergoes a global color transfer model. For simplicity and comparison purpose, we first applied the gain compensation method [3] on the matched feature points and yield a SIFT + GC method. On top of this method, two things are improved. The first is to apply a better color distortion model, and the second is to apply a robust parameter estimation method to take care of the outliers in the match.

For a better color transfer model, we assume the color distortion goes through both intra-channel mapping in each individual color channel, and an inter-channel transform. The intra-channel non-linear transform is approximated by a quadratic polynomial in our model (higher order approximation can also be used), while the inter-channel transform is assumed to be a linear transform within the color space. The intra-channel and inter-channel color changes are combined together and for simplification, we apply the parameter estimation separately for each color channel and use the following parametric model:

$$R_{out} = r_1 R_{in}^{\ 2} + r_2 R_{in} + r_3 G_{in}^{\ 2} + r_4 G_{in} + r_5 B_{in}^{\ 2} + r_6 B_{in} + r_7$$

$$G_{out} = g_1 R_{in}^{\ 2} + g_2 R_{in} + g_3 G_{in}^{\ 2} + g_4 G_{in} + g_5 B_{in}^{\ 2} + g_6 B_{in} + g_7$$

$$B_{out} = b_1 R_{in}^{\ 2} + b_2 R_{in} + b_3 G_{in}^{\ 2} + b_4 G_{in} + b_5 B_{in}^{\ 2} + b_6 B_{in} + b_7$$

Estimating of the parameters from the colors of the matched feature points is a typical linear regression problem. A robust regression method is needed here to handle the outliers in the matching results. Random Sample Consensus (RANSAC) [12] has been popular in regression problem with samples contaminated with a certain amount of outliers. Therefore, we use RANSAC to estimate the parameters and apply the color transfer function directly to each pixel of the input image to obtain an output image.

## III. EXPERIMENTAL RESULTS

We compiled a test set with 26 images as reference images. The reference images are first applied non-color changes like scaling, letterbox and graphics overlays to obtain ground truth images. After that, color changes are applied including changes of RGB offsets and gains, overall brightness and contrast, gamma, hue and saturation to obtain input images. Five different methods are applied and compared, including the GCT[1], LCT[2], GC[3], SIFT + GC, and SIFT + RANSAC. The output color corrected images are compared with the original images with PSNR and SSIM [12] metrics. Figure 2 shows the comparison of the PSNR results of the five different methods on those 26 different input images, plotted as means and standard deviations. Figure 3 shows the corresponding SSIM results. In both figures, our proposed methods yield better results than other methods, and the SIFT+RANSAC method performs the best.

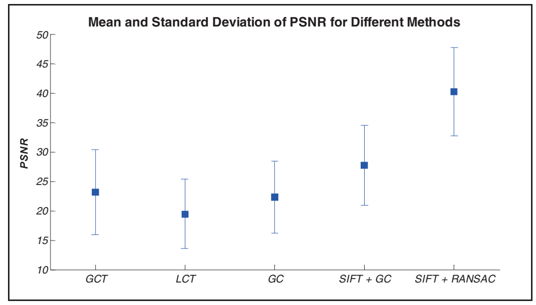


**Figure 2**. PSNR statistics comparison of different methods.

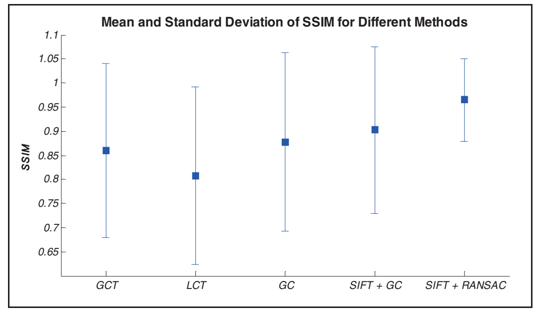


**Figure 3**. SSIM statistics comparison of different methods.

## IV. CONCLUSION

We present an effective method for color correction. The use of feature matching directly provides pixel to pixel color correspondences, while the use of RANSAC makes it robust to matching outliers. The method can be applied to many applications, including image stitching, multi-view color matching, as well as pre-filtering of video coding.

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