Literature Review on Palette-based Color Transfer

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Abstract

Palette-based Color Transfer is an area of image processing that has great artistic merit. Manipulating 2D images using color transfer has merit in both photorealistic and non-photorealistic areas of image manipulation. This literature review will cover a range of research covering Palette-based Color Transfer and related image processing tasks. I will also discuss the ways in which these papers contribute to the study of Color Transfer in Computer Visualization as a whole.

1 Introduction

For my final project, I have proposed a Palette-based Photo Recoloring project. This web interface will accept an image file as input. The palette will be automatically extracted at the click of a button, which the user can then change manually using a provided color picker. The user can then select to generate the image to match the new color palette. As will be discussed in the following sections, transferring colors between values requires more computation than simple subtraction of values in RGB color space. Below I will evaluate and discuss different methods of calculating these changes to be as smooth and appropriate to the source image as possible. For my implementation of a Palette-based Photo Recoloring application, I use JavaScript to recreate the algorithms learned in my research, as well as to create a user interface.

2 Palette-based Photo Recoloring

Chang et al. describe in their paper an interactive tool which extracts palettes from an image, provides a means to change palette colors, and reproduces the image in the new palette. This paper is the core study that my project is derived from. As such, the algorithms and methods are the most like those that I will be using in my final project. Chang et al. aim to create an interface that is efficient and easy to understand, even for non-experts in the field. The method of color transfer introduced is both fast and user friendly when compared to previous alternatives discussed in the paper.

For palette extraction from the source image, a modified K-Means Clustering algorithm is employed. The initial centroids are determined by calculating histograms in 16x16x16 space, with each dimension representing values of the RGB color channels. The mean color within the top k bins are used as centroids, plus an additional center around the color black. This k+1 is used to then calculate the k values in the palette, with the black cluster discarded.

As for the Color Transfer algorithm, Lab color space is used to calculate differences between old palette and new palette values. The L in Lab color space refers to the luminosity of the color. The values a and b represent a 2D vector in 3D space, with L representing the third dimension. The boundaries that are capable in RGB color space vary based on the L value in the color space. All computations occur in Lab color space. The difference between old and new colors are applied to every pixel in the image. If the resulting color is outside of the RGB bounds, the following formula is used to determine the resulting color. C represents the palette color, while x represents the pixel being acted upon. C' refers to the new palette color, C_b and x_b refer to the intersection with the boundary in Lab space. These values are used to compute x', the resulting color.

$$\frac{||x' - x||}{||C' - C||} = \min\left(1, \frac{||x_b - x||}{||C_b - C||}\right)$$

This computation is performed on every pixel, for every color palette change. These color changes are then weighted to determine the total overall color change. These weights are determined using a Radial Basis Function with a Gaussian kernel. The interface enforces a constraint known as Monotomic Luminance. The palette values are ordered by their luminance values, and user-selected changes are restricted between luminance values of the previous and next colors in the palette. This is enforced to maintain smooth color changes regarding brightness in the image.

The paper covers further possibilities, such as applying color transfer solely within a mask, performing the method based on user-painted strokes, and editing collections of images as opposed to a single image. The authors also expressed the possible extension of incorporating spatial information in the color transfer algorithm. My focus is on the primary method of Palette-based recoloring, which is effectively implemented with an interface that compliments both the technical model and user interaction. I found the paper to have expressed its goals and evaluation criteria very well. It thoroughly provided baselines to work with in a way that was easy to understand as a reader.

3 Color Harmonization

Color Harmonization is an image recoloring task in which a source image is automatically recolored to follow harmonic color schemes. Cohen-Or et al. introduce a method of enhancing the harmonization of an image through automatic image recoloring. This occurs by shifting hue values to fit pre-defined harmonic schemes, providing an aesthetically pleasing image with the least divergence from the original image as possible. This is done to best maintain the look and feel of the original image, while still enhancing its color harmony. They aim to provide a useful method of adjusting colors of an image using aspects of prominent features within the image as a baseline scheme.

Harmonic color schemes are defined over the hue channel of the HSV color wheel. The channels in this color space correspond with Hue, Saturation, and Value, respectively. There are eight harmonic types defined in this color space, with distributions of colors defining a template for each. Matching a color palette to its closest harmonic template is achieved by minimizing the distance between a palette and each possible template. Finding the best scheme uses the following function to minimize over every value of a template T. In the following formula, (m, a) represent a scheme, p represents a pixel value for all pixels in the image, and E represents the definition of a sector border within the template T.

$$F\big(X,\ (m,a)\big) = \sum_{p \in X} \left\| H(p) - E_{T_{m(a)}}(p) \right\| \cdot S(p)$$

The transfer between colors once a matching template is assigned occurs via Color Shifting. The template is defined in sectors and original colors are shifted to the closest sector within a template that it can reside. As such, colors that are within range of the template will experience no color change. This allows the image to forego small color changes for every pixel in the image, thus maximizing the colors remaining unchanged between images. The closest sector is obtained via a binary segmentation approach, which employs a graph cut optimization algorithm. This defines a label for each pixel to determine the sector is shifts toward, resulting in the ultimate color changes in an image.

Cohen-Or et al. manage to quantify harmonic schemes of an image in their paper, as well as a method to shift colors of a source image into a scheme while keeping as many attributes untouched. They also propose an interface which allows the user to tune the result by manipulating a provided color wheel, which would allow for more flexibility on the definitions of a sector for the matched harmonic palette. For future work, they express the possibility of user-defined colors which are exempt from color change, such as skin color, to preserve natural results. Notably, this study uses HSV color space rather than Lab color space for its calculations. It focuses heavily on the hue value of the color space to segment ranges of colors, rather than individual pixel values.

4 Color Decomposition Optimization

Following the topic of Palette-based Recoloring, Zhang et al. aim to edit the colors of an image by adjusting a limited color palette. While the intended goal is similar to what we have seen already, the paper describes a method of Color Decomposition, which decomposes colors into linear combinations of the base colors in the extracted palette. This a proposed improvement to the palette-based color transfer algorithm we have seen before, due to its update to the representations of each pixel computationally during color transfer.

The automatic extraction of the palette of an image is also expanded upon from previous methods described. While the core method is similar, Zhang et al. introduce the concept of silhouette filtering. A silhouette cluster is calculated as a measure of uniqueness between clusters in the K-Means Clustering algorithm. The initial center yielding the cluster with the smallest silhouette value is discarded, allowing for a palette with a larger difference than previous implementations of the clustering algorithm.

Color Decomposition, which the paper focuses on, bases itself on the assumption that every color can be represented as a linear combination of the colors in the image's palette. For a palette of size m, a pixel color would be represented as the following distribution, in which C_p represents the color vector in Lab color space, using only the a and b color values, w_p^i represents the weight of the palette color for the desired pixel:

$$C_p = \sum_{i=1}^{m} w_p^i \bar{C}_i$$

An energy minimization function is used to obtain the coefficients used during the color change, which is made up of terms determining color fidelity (validity), color non-negativity, smoothness, and regularization. The combinations of these terms describe the color change for each pixel in their representation given above. This occurs using Lab color space, though only using the a and b color channels, represented as a vector.

The color transfer method seen in this paper uses many of the same concepts as other palette-based recoloring algorithms. The use of Color Decomposition and the energy minimization function utilizes Lab color space as a means of performing linear algebraic functions, rather than operating on a per pixel basis. Though evaluation is inherently qualitative, there are noticeable improvements between the algorithms of Chang et al. against this method, as demonstrated in the paper itself. A limitation listed in the paper references the inability to reference scene semantics during color transfer and palette extraction, though this can be said of many palette-based recoloring methods. The paper provided a fascinating and detailed description of its approach to Palette-based Photo Recoloring, though its mathematical concepts can take multiple reads to understand completely, to the detriment of understanding the paper to its fullest.

5 Natural Image Colorization

In this paper focusing on natural color mapping of grayscale images, there are many of the same names seen in the paper regarding Color Harmonization. Luan et al. discuss the colorization of monochromatic images, as well as an interface through which a user can intuitively define colors and image segments to operate upon. The implementation of this method is very closely tied to the problem of Image Segmentation, which is used to map user-specified colors to regions of a grayscale image.

The method of Natural Colorization proposed is split into two stages, Color Labeling and Color Mapping. Color Labeling is the task of assigning regions of the image to a user-specified color value. To the user, this is achieved by painting strokes onto the image with the desired color value. Using these strokes as guidelines, the image is segmented into the user-specified regions. Texture features are taken into consideration by defining highly contrastive locations of the image. Additionally, smoothness and energy optimization are used to better reflect the detailed features of the specified region. This is all calculated during graph cut, which ultimately segments the image into the user-specified regions.

For Color Mapping, the user can select individual pixels and select a color which will populate that region of the image. Regions are colorized with the specified color, taking texture features into account, and soft blending is applied on the region borders to achieve a smooth transition.

Luan et al. presented an interactive colorization system, whose results showed highly textured regions with full colorization per user input. Most of the paper's focus revolved around the problem of Color Labeling, which goes into great mathematical detail. As evidenced qualitatively by the resulting image examples, these methods succeeded in producing high quality output in colorizing grayscale images. Though the paper goes into strong detail of the image segmentation problem, specific Color Mapping calculations are not elaborated on within the paper. Though this paper is related to Color Transfer, it ultimately does not discuss this issue with as much depth as the Color Labeling aspect of the application. Future work is described as the potential to incorporate more sophisticated texture cluster techniques, further highlighting their focus on Color Labeling in their implementation of grayscale image colorization. Nonetheless, the study presents impressive results regarding its final product.

6 Color Traits to Grayscale Image

Another method of image colorization of grayscale images is presented by Kekre and Thepade, though with a different means of input and computation. With their work, the user provides a reference image, from which colors are extracted and applied automatically to another user-provided grayscale image. The method attempts to minimize steps taken by the user in this process, which serves to further automate the already semi-automatic colorization process as seen before.

Computations for this method of colorization use the LUV color space, where u and v represent chromaticity as a vector. The L value represents luminance, as seen in Lab color space previously. The implementation of Color Transfer seen in this paper revolves around the concept of Color Traits. Color palette retrieval follows a similar method to what we have seen before. The target grayscale image is then divided into pixel windows, which are represented as an array of grayscale intensities. Due to the monochromaticity of grayscale pixels, this allows windows to be represented as scalar values, rather than in 3 channels as with color images. Values between color and grayscale are then matched in RGB color space.

In the explanation of the algorithm given in this study, there are not many explicit mathematical equations provided to help understand the method of color transfer as described. The proposed method of colorization is computationally light, requiring minimal interaction from the user. This results in a less sophisticated approached than the one seen in the work of Luan et al. approximately one year prior. Given the examples in the paper, this automated method seems imprecise in determining region boundaries and diversifying colorization based on the texture of an image. This is one of the weakest papers of those that I review in this study.

7 Correlated Color Space

In this paper from Xiao and Ma, I will be returning to the concept of Color Transfer between two color images. This method uses an input image which provides the color and a target image on which the color scheme will be applied. However, the proposed method modifies the color transfer algorithm to become a linear algebra problem in 3D color space. With their method, color transfer can be performed in any 3-dimensional color space, though they demonstrate primarily using RGB color space.

The paper proposes two methods of color transfer, Statistics-based and Swatch-based. Statistics-based Color Transfer is performed by calculating the mean pixel data across all RGB channels in both images. The covariance matrix is also performed across all three components in color space. An SVD algorithm is used to decompose the covariance matrices, and a combination of transformations is applied to the matrices to get a homogenous representation of the pixels in the color space. The transformation performed is as follows, which is applied to all points to calculate the new value:

$$I = T_{src} \cdot R_{src} \cdot S_{src} \cdot S_{tgt} \cdot R_{tgt} \cdot T_{tgt} \cdot I_{tgt}$$

The Swatch-based method is similar to what we have seen previously, though with less sophisticated methods of segmenting the image. In this method, the Statistics-based method is performed within color spaces as defined by the user. The user selects swatches to color regions of the image in the same color as one another. Regions with the same color designation will be calculated using the Statistics-based method. The color change is then blended between the regions, for smooth transitioning.

The benefits of this method of Color Transfer is the ability to perform the operation in any 3-dimensional color space, including RGB. The paper presents results as computed using RGB and other color spaces, which produce noticeably similar resulting images. The mathematical operations in the paper can be hard to follow at times, which can either be attributed to the need to elaborate or different avenues of explaining the material. Nonetheless, the paper presents a method of color transfer between images which allows limited user interaction in the form of swatches and can be performed in any 3-dimensional color space. A possible extension of the work would be to expand this color transfer method to a color palette of the user's choosing, rather than using a source image for color transfer.

8 Pigment-Based Recoloring

This paper by Mack et al. demonstrates a method of Pigment-Based Recoloring, specifically with regards to watercolor-style images. The tool implemented is intended to allow experimentation with different color palettes on existing watercolor images. This is proposed to aid in the artistic process or, more directly, all experimentation with alternate versions of an existing art piece.

That core concept of this Pigment-Based Recoloring model is the Kubelka-Munk Pigment Model. This model allows colors to be represented as reflectance of a homogeneous, isotropic pigment. The details of which are explained in much further detail in the paper. This method is used to calculate reflectance of a pigment layer. To mix these pigments, the Kubelka-Munk Model is used to calculate a set of weights to apply to the linear mixture of base pigments for the image. The best mixture is found by calculating the minimum distance between target color and the proposed mixture.

To find the palette of a painting, K-Means Clustering is used with an added spatial term that incorporates edge-awareness to the algorithm. This is intended to apply spatial smoothness to the color transfer algorithm. Once colors are decomposed and transferred to their resulting value, the decomposition coefficients are used once again to derive the pixel values from their mathematical representation.

The results of the model are qualitatively superior to other algorithms, including Chang et al. as we analyzed at the start of this review. The paper thoroughly lays out its artistic principles and parameters, with which it evaluates success and derives model design. A cited limitation is that reconstruction of output colors back into pixel values performs poorly when there is not a black color in the automatically generated palette. The authors expressed interest in future work implementing another model from Kubelka-Monk which is a Layer Composition model. This would increase the ability to handle watercolor glazing effects, as well as enable the user to modify color palette more effectively in a watercolor environment.

Though I found this paper interesting, I found its mathematical foundation to be hard to follow in their description. This Pigment-Based model is the farthest deviance from those seen previously in this review.

9 Conclusion

Color Transfer, with many projects employing Palette-based transfer, is a wide-reaching task in 2D image processing ranging between artistic styles, color representations, and other visualization techniques. As discussed, my implementation of a Palette-based Photo Recoloring project will most resemble the paper by Chang et al. This will feature the algorithms introduced regarding Palette Generation and Color Transfer, including a web interface for user interaction.

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