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A Survey on Color Transfer Methods

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***Abstract*-Color mapping or color transfer methods aim to recolor a given image or video by deriving a mapping between that image and another image serving as a reference. This class of methods has received considerable attention in recent years, both in academic literature and in industrial applications. Methods for recoloring images have often appeared under the labels of color correction, color transfer or color balancing, to name a few, but their goal is always the same: mapping the colors of one image to another. In this report, we present a comprehensive overview of these methods and offer a classification of current solutions.**

***Keywords*- Colortransfer, edgepreserving smoothing, image manipulation.**

I.INTRODUCTION

Color is an integral part of our visual world and one of the main features of images used in art, photography and visualization for relaying information, or conveying a specific mood. By modifying the colors in an image, it is possible to alter the overall emotion of a scene, to simulate different illumination conditions or to achieve different stylistic effects.

In many cases, color manipulation may also be necessary to reduce differences between images for further processing. When stitching a panorama for instance, consecutive images may have slight color variations, hindering the stitching process. Similarly, differences between individual camera sensors may lead to small changes across a stereo pair that could affect viewer comfort. In another scenario, when processing video content, color edits applied to one frame often need to be replicated to subsequent frames of a sequence.

Both in creative and in more practical scenarios such as these, editing the color content of images requires skilled and extensive user input, while the tools available to nonexpert users tend to not offer adequate control.

Color mapping or color transfer is a class of techniques that aims to provide a simple way of achieving complex color changes in images by allowing the color palette and possibly other properties of an image to be altered using a second image as a reference, as shown in Figure1.

The user can select a reference image whose colors are preferred and modify the original image such that it acquires the palette of that reference.

Color mapping has received a lot of attention within the computer graphics, computer vision and image processing communities in recent years, both because of its conceptual simplicity and the wide variety of solutions that it can employ. Applications of color mapping vary from making the appearance of renderings more realistic, to tone mapping and panorama stitching, with examples even within security and medical imaging. Yet, it is not clear which methods are best suited for which purposes or even what can really be achieved with this class of solutions.

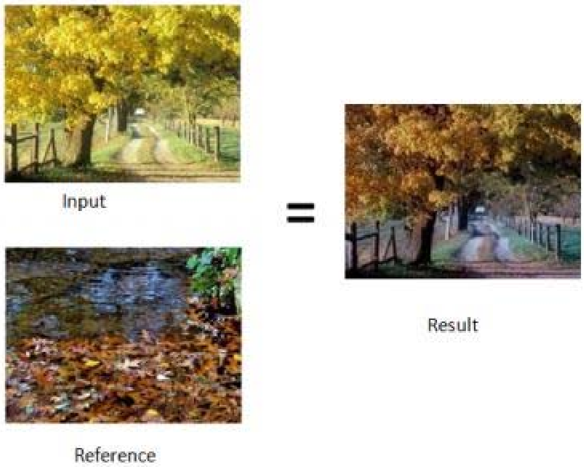

Fig1:Color Transfer

Despite the large number of available methods, there are still open and interesting research questions and challenges in this area that could help color mapping or color transfer solutions reach their full potential.

If the two images contain similar scenes, or even the same scene captured under different conditions, a desired mapping is conceptually easy to define: matching objects and regions between images should obtain the same colors. For example, multiple-view camera grids might have color differences due to a lack of color calibration or due to the use of automatic camera settings . These can be corrected by transferring the colors of one image to the other(s). Similarly, images intended for panorama stitching may be captured with varying camera settings, leading to exposure or color differences .

Although in these examples the differences between image pairs are likely to be small, it is the quantity of data that necessitates the use of color mapping rather than manual adjustments here.

The objectives of this report is to categorize existing color mapping techniques according to their algorithmic formulation.

II.GOALS AND CHALLENGES

At a high level, the goal of color transfer solutions is always the same, namely to change the colors of a given input image to match those of a reference. Yet, very different solutions have emerged depending on the type of input expected or the specific requirements of each application.

If a more general mapping is our goal, such as for instance transferring the color palette of a particular painting of a given artist to another image, an almost infinite space of solutions is available, many of which could be considered successful. Unlike the first case, where the goal is to achieve color consistency between similar views, the objective here is to transfer the overall color palette from one image to another. For instance, the style of a particular film may be transferred to other content or a photograph may be used to improve the appearance of rendered content .

Color correspondences between images typically only determine how a subset of the image colors should be transformed. The second challenge in color mapping is how to model the complete transformation from the input to the reference palette. Simpler changes, such as remapping of the illumination or overall intensity changes can be achieved through simpler, linear models whereas more complex changes are likely to require non-linear models

Most color transfer algorithms take as input two images, one exemplar and one image to be modified according to the exemplar. Sometimes it may be possible to find an image that is already transformed in a desirable manner. It is then possible to apply machine learning techniques to encode the transform, and subsequently apply the same transform to other images. Although this is a generally applicable technique, suitable not only for color but also for other image modalities such as texture, in most applications discussed in this paper exemplars are easy to find, but transform pairs are more difficult to come by.

III.COLOR MAPPING METHODS

A.Histogram Matching

Histogram Matching is able to specify the shape of the referred histogram that we expect the target image to have.However,histogram matching can only process the color components are separated.Researchers have conducted numerous studies on histogram matching :here we will review four of them.

Pichon use a mesh deformation approach to achieve histogram equalization—that is, a transform that sets an equal frequency for all colors. As long as the equalization transform for any histogram is invertible. we can match two arbitrary histograms

by treating the equalized histogram as the intermediate histogram. Using a 2D color space as an example, they apply a mesh deformation as follows: First, they start from a uniform mesh, where each cell's area is a constant, and the number of cells represents the number of histogram bins. They then iteratively deform the uniform mesh, so that each cell contains the same number of points (or pixels in the image space). The iteration adjusts the mesh vertice positions by moving them toward or away from their corresponding cells centroids to shrink (or enlarge) the area so that it contains less (or more) points.

They use the final deformed mesh to define a piecewise linear deformation function of the color space. By mapping the original and deformed meshes, they establish the color mapping and thus achieve histogram equalization.

Morovic proposed a histogram matching algorithm for grayscale images using a fast, noniterative Exact Histogram Matching algorithm, rather than the traditional iterative Earth Mover's Distance (EMD) algorithm.Essentially, they lay their source and target histograms end-to-end in ascending order and build a look-up table accordingly to transform the source pixel value into the target one.

Neumann and colleagues10 perform histogram matching in the hue, saturation, and value color space, and propose using three sequential 1D histogram matchings to achieve a 3D histogram matching. They also apply histogram smoothing and suppression to mitigate the artifacts incurred by the histogram matching process.

Almost all of the histogram matching approaches focus on building a perfect mapping from the input image's color space to that of the reference image, without accounting

for a transformed pixel's spatial properties—including its color and its relationship with neighboring pixels.color mapping deemed perfect in thecolor space can cause differences between two spatially adjacent pixels, thus leading to more visible artifacts.

The another approach variational model for intermediatecolor histogram equalization of two or more color images.

Given a set of images, we transform them by minimizing an energy functional which is composed by three different terms. on one side we have a histogram matching term that tends to approach the cumulative histograms of the original images; on the other side we have two conservative terms.that tend to maintain unaltered color and image geometry. The balance between these two opposite actions is important for our purposes: the original images evolve in order to approach a common intermediate histogram that does not need to be specified in advance.

This approach is devoted to a variational formulation of color grading, that is the color matching of two or more images.They show that, by minimizing a suitable energy functional,images are transformed so that they achieve an intermediate common histogram.

B.Means and Variance

Reinhard and colleagues pioneering work on transferring a color image's tone or mood to another image is the foundation for our work and that of others, including Welsh and colleagues' grayscale image colorization.

Reinhard and colleagues' algorithm consists of the following steps: First, it converts an input image from its original RGB color space into an Lαβ color space to eliminate RGB color representation's normally high correlation. (Here, high correlation refers to the fact that, when a pixel has a large value associated with its red channel, the blue or green channel values are often large as well.)

Second, the source and reference images might have different lightness distributions; they should therefore be “aligned”before conversion occurs. The alignment process starts by finding the means and standard deviations of the Lαβ color values for both the input and reference images. The output image is obtained by translating and scaling the input image so its mean and standard deviation match that of the reference image

Xiao proposed a similar approach, but their method differs from that of Reinhard and colleagues in at least two respects.

First, instead of Lαβ, they apply the popular RGB color system and demonstrate that this decision doesn’t affect their approach’s effectiveness.Second, instead of aligning the input image with the reference image only in terms of mean and standard deviation they also align bothimages’ principle axes. Such an alignment might sometimes be necessary, particularly when two different color distributions have the same mean and standard deviation.

In such cases, they can achieve alignment by performing principle component analysis—that is, in addition to translations and scalings, they can use rotations to seek a more matched color distribution.

Greenfield focus their color conversion work on oil painting images. Adopting the Lαβ color system, they first perform color segmentation, and then merge regions with similar colors. They then reduce the segments’ averaged colors into a more restricted set of representative colors to eventually derive the color palettes for both the input and reference images. They use a naive color-palette correspondence rule to transfer only the α and β values from the reference image’s palette color to that of the target image. To speed up computations,they use an image pyramid structure.

Finding a proper reference image is a key issue for Reinhard and colleagues, as well as for those who adopt their approach. This includes Greenfield and colleagues and Chang and colleagues for colored image-style conversion, as well as Welsh and colleagues for colorizing grayscale images. Viera and colleagues6 address the issue by proposing several metrics for identifying the most suitable reference image via comparisons of the luminance channels between input and candidate reference images.

Their proposed metrics include histogram, average brightness, gradients, hybrid of histogram and gradients, hybrid of average brightness and gradients, and direct comparison on pixel-wise differences. Their system can then choose, as the reference image, the image that most closely matches the input image. Viera and colleagues also built an image database after experimenting with the proposed metrics. However, their metrics are not directly applicable for selecting a reference image for a colored input image.

C.Color Category Based Approach

To prevent from the grain effect,chang proposed a color category based approach that categorized each pixel as one of the basic categories .Then a convex hull was generated in Lαβ color space for each category of the pixel set,and the color transformation was applied with each pair of convex hull of the same category.

Chang perform color conversion using 11 basic colors and assume that the reference images are paintings. They convert both the input and reference images into the Lαβ color space, which is partitioned into 11 regions. They build 11 convex hulls for both images and the correspondence of pixel colors—represented as points in their individual color spaces—according to their relative positions to the centroids and corresponding convex hull boundaries. In situations where some of the 11 colors are missing, users can select multiple reference images.

D.Modified EM Algorithm

For the color distortion, Tai et al.proposed a modified EM algorithm to segment probabilistically the input images and construct Gaussian Mixture Models (GMMs) for them, and the relationship was constructed by each Gaussian component pairs between the target and the reference under Reinhards approach .In this address the problem of regional color transfer between two natural images by probabilistic segmentation.

It use a new Expectation-Maximization (EM) scheme to impose both spatial and color smoothness to infer natural connectivity among pixels. Unlike previous work,this method takes local color information into consideration, and segment image with soft region boundaries for seamless color transfer and compositing.

This modified EM method has two advantages in color manipulation: First, subject to different levels of color smoothness in image space, our algorithm produces an optimal number of regions upon convergence, where the color statistics in each region can be adequately characterized by a component of a Gaussian Mixture Model (GMM).

Second, we allow a pixel to fall in several regions according to our estimated probability distribution in the EM step, re-sulting in a transparency-like ratio for compositing different regions seamlessly. Hence, natural color transition across regions can be achieved, where the necessary intra region and inter-region smoothness are enforced without losing original details. We demonstrate results on a variety of applications including image deblurring, enhanced color transfer, and colorizing gray scale images.

E.Dominant Color Idea

Dong et al. proposed a dominant color idea for color transfer. When the amount of dominant colors of the target was consistent with that of the reference, the color of the reference would be transferred to obtain a satisfactory result.

F.Distribution-aware

Wu et al. improved Dongs approach and further proposed a distribution-aware conception to consider the spatial color distribution in the reference image.

G.Learning-based Color Transfer

Wang et al.developed the learning-based color transfer methods to train out the proper color mapping relationship.

H.Edge-preserving Smoothing

The grain effect can be treated as a special type of noises and it would be removed by linear smoothing. Although the linear smoothing can remove the grains, the over-blurring would destroy the original image details and lower the sharpness of edges.

I.Edge-preserving smoothing (EPS) Filters

Edge-preserving smoothing (EPS) Filters are proposed to overcome this problem. They can prevent the edge blurring by linear Filtering according to their intensityor gradient-aware properties.

J.Joint bilateral Filter (JBF)

Joint bilateral Filter (JBF)is the First guided edge preserving smoothing approach. The JBF exploits the pixel intensity of the reference which is correlated to the target to improve the Filtering effect.

K. Two Multiscale Schemes

Fattal et al. proposed an elaborate scheme for details, but their adoptive bilateral decomposition has defects as aforementioned. Farbman et al. proposed two multiscale schemes which are simpler than Fattals, because the WLS based decomposition overcomes the defects of bilateral decomposition. Farbman et al.introduced the diffusion maps as a distance measurement to replace the Euclidean distance in their weighted least square filter.et al. introduced the diffusion maps as a distance measurement to replace the Euclidean distance in their weighted least square Filter.

M.Interactive Local Color Transfer Between Images

Altering image's color is one of the most common tasks in image processing. However, most of existing methods are aimed to perform global color transfer. This usually means that the whole image is affected. But in many cases colors of only a part of an image needs changing,so it is important that the rest of the image remains unmodified. In this article they offer a fast and simple interactive algorithm based on local color statistics that allows altering color of only a part of an image, preserving image's details and natural look.

In this paper they consider the task of partial image recoloring for the case, when user loosely specifies an object or region of interest at the target image. The goal of their algorithm is to save user from the trouble of complicated manual work of object matting.

Selecting the object is supposed in terms of object's color range. It is enough for the user to select a rectangular region, including main colors of the object of interest,to achieve natural-looking recoloring result.

The data of the selected region is used to calculate its color statistics. use them to estimate pixels of the target image belong, or rather are close enough, to the selected color range. Then color transformation is applied to the image, according to this estimation.Their method is developed to correct an object on a target image, selected by user.

It is important, that user doesn't have to select the object by shape, for it is di_cult to do precisely.The object is selected in terms of its color range and calculating its color statistics.The source color can be de_ned as a single color or a region of another image, that we will call the source image. In this case source color statistics are calculated. After the information of the target color range is gathered, we prepare the target image's Color Influence Map (CIM).

It is a mask that speci_es what parts of the target image will be a_ected according to the selected color range.

The next step is recoloring itself, that is applied to the target image according to the prepared CIM. To recolor the target image we use a modified version of the Color Transfer algorithm. The basic algorithm uses transformation method, based on source and target color statistics in Lαβ lcolor space.The limitations of this method are

1) only an image can be used as a source for recoloring

2) only the whole image can be recolored. These limitations are removed in this algorithm.

At first user has to select an object to correct at the target image. This can be done by loosely selecting a rectangular region of the object, that needs correction. There's no need to select the region precisely close to the edges of the area, that user wants to correct, because we will use its color range without spatial characteristics. The only limitation is that the whole region must be inside this object.

CIM contains weights for color transformation for each pixel of the target image. Each pixel's weight is determined from its proximity to the color range, selected by user and stored in color statistics information. That is Mahalanobis distance between the pixel and the center of the color distribution, defined by the stored color statistics. Since Lαβ is a color space with decorrelated axes.

In this article they proposed a simple and fast algorithm for partial image recoloring that allows user to correct an object of interest at an image saving one from the trouble of selecting it precisely. The proposed method allows the user to recolor a part of the image in a simple and intuitive way, preserving other color intact and achieving natural look of the result for wide variety of input images.

IV.CONCLUSIONS

Some images have a more interesting look and feel to it than other images. Photographs may have more natural color distributions than some rendered content. This was the inspiration that led to the development of early color transfer algorithms.The idea was that an example-based post-process could make a mundane image appear more interesting by taking some color characteristics from an existing image.

Whenever color transfer is applied between images that show overlap, including in stereo and image stitching applications,color transfer based on finding feature correspondences are applicable. When images come from entirely different domains, then statistical techniques may be more appropriate.In all cases, one of the main open problems is that there is often no good ground truth available. Especially in statistical transfers where the two input images are unrelated,it is difficult to assess whether a result is good or not.

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