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Colorization of Gray Scale Images using Fully Automated Approach

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Abstract
In this paper, we are proposing a method for adding colors to grayscale images without human interference. In contrast to many previous computer-aided colorizing methods, which require intensive and perfect human interference, this method needs only the user to provide a target gray level image for the process of 'colorization', a colorful image of the similar content as the grayscale image is automatically retrieve from the database of images, as an input source image. Then, the best matching source pixel is determined using luminance and texture matching procedure, for each pixel of the target image into a perceptually de-correlated color space. Once a best matching source pixel is found, its chromaticity values are assigned to the target pixel while the original luminance value of the target pixel is retained.

Keywords
Image retrieval, Color Transfer, Luminance Matching, Texture matching.

I. Introduction

The colorization of grayscale images is a valuable tool for many applications such as "colorizing" black and white films or restoring old photographs. Color can be added to grayscale images in order to enhance the visual appeal of images such as old black and white photos, classic movies or scientific illustrations. The task of "colorizing" a grayscale image involves assigning three dimensional (RGB) pixel values to an image which varies along only one dimension (luminance or intensity). The simplest approach proposed by Gonzalez et. al.[11], is pseudocoloring of gray scale images. This method uses separate transformations for each color channel which results in coloring objects with the density of explosive in the bright orange and other object with a blue tone. Since dissimilar colors may have the same luminance value but vary in hue or saturation, the problem of colorizing grayscale images has no inherently "correct" solution. Due to these ambiguities, human interface usually plays a large role in the colorization process. Where the mapping of luminance values to color values is automatic, the choice of the color map is commonly determined by human decision. So amount of human interference needs for 'colorization' may decreased by transferring color from a source color image [5]. Our concept of transferring color from one image to another is motivated by work by Reinhardt et al. [2001] [4], in which color is transferred between two color images. In their work, colors from a source image are transferred to a second colored image using a simple but surprisingly successful procedure. The human intervention may further decrease by automatically selecting the source image from a database of images. The various image retrieval methods may be used to retrieve the best matching image [6]. We are using the luminance and gradient matching procedure to select the best match of the query (target) image from the database, this work is inspired by work by Carceroni L. Rodrigo et. al.[6] and Rathore et al. [1] in which a color image is chosen from an image database using content based image retrieval. In their work they retrieve the similar kind of color image from an image database for colorization of a target gray level image.
Here, In section 2 three algorithms are described, first for preparation of image database (A), second for image retrieval (B), and third for transfer color to gray scale image (C). The section-3 and section-4 covers the result analysis and conclusion respectively.

II. Method

A. Preparation of Image Database:

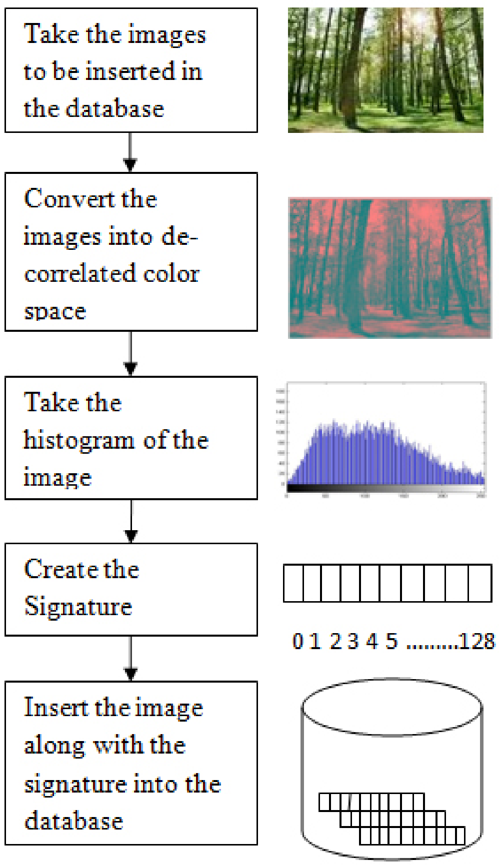

Fig. 1: Preparation of Image Database

Step 1
Convert the images into lαβ color space: The lαβ color space was proposed by Ruderman et al. [8], as a result of an analysis of the statistics of human photo sensor responses to natural images. More specifically, it was observed that while the responses on the bands of the three types of cones present in the human eye are strongly correlated, if these responses are converted to the lab space, the existing correlation disappears. In addition, the lab space has a property that is very useful in the case of image databases: because it is logarithmic, it is not affected by gamma correction [4],

Thus, we preprocess every database image by converting it to the lab space, where the l component is a measure of luminance, a measures variations in the green–red chromatic axis (with positive values meaning red and negative ones meaning green) and b measures variations in the blue–yellow axis (with positive values meaning yellow and negative meaning blue). More specifically, each image originally coded in the RGB space is initially converted to the LMS space, which corresponds to the bands of sensitivity of the human cones and was thus used by Ruderman et al. as the basis to define the lαβ space.

Step 2

Take the luminance and gradient histogram of each image: The use of similarity between intensity histograms as a relevant criterion to perform content-based image retrieval is a well-established idea [2] that has been used in a numerous of works. Thus, its choice as one of the methods to be evaluated for suitability to the novel application that we address in this paper is a natural one. Formally, the histogram of an m×n monochromatic digital image I is a discrete function that maps each value k in the image's intensity range to the fraction of pixels in image I that have intensity :

$$hI(k) = \frac{\lambda(k)}{m \times n}$$

where λI(k)={(x, y): I(x, y)=k}, and I(x, y) is the intensity of pixel (x, y) in image I. Here, we use this function to generate image signatures by applying it to the l channel obtained after the color-space conversion described in Section 1. The only precaution that we have to take is to perform a linear normalization of the channel before computing its histogram, to factor out fluctuations in the illumination conditions under which the various images were acquired and the effects of gamma correction [3]. One technique to generate these signatures uses what we call a luminance and gradient histogram. It starts by convolving the luminance image with a Sobel kernel, to estimate the image's spatial gradient. Then, it computes histograms both for the luminance image and for its gradient, but this time considering a coarser quantization of only 64 values on each image, so that signature size does not need to be increased. The final signature for each image is then obtained simply by a concatenation of the normalized pixel counts from the two histograms, in a predefined order.

Step 3

Create a signature: For each image in the database, a signature is created, that consists of the 128 values, first 64 values of its luminance histogram and other 64 values of gradient histogram.

Step 4

Store the signatures into the database: Now each signature is stored into an image database to make the matching procedure easy.

B. Image Retrieval Techniques:

The image similar to query image may be retrieved from the image by matching their signatures.

For this purpose Regardless of which of the technique described in the section (b) is used, the criterion used to compare the image signatures and thus to determine the best match is the same: the correlation between the query and database signature vectors, calculated using their internal product.

$$Match(Q) = argmaxi \frac{q.si}{||q||.||si||}$$

where Q and s are, respectively, the query image and its signature, and Si is the i-th signature in the database.

C. Transferring Color to Gray Scale Image:

The general problem of adding color to a grayscale image has no exact and objective solution, since one single grayscale value may correspond to a range of different colors. However, Welsh et al. [7] recently presented a technique to transfer color between a source, color image and a target, grayscale image. The method works as follows.

Step 1

Convert both the images into de correlated color space: Both the color (source) and grayscale (target) RGB images are converted into the de-correlated color space for subsequent analysis. This color space was developed to minimize the correlation between the three color coordinate axes. Choose say YCbCr as a de-correlated color space for subsequent analysis. This color space provides three de-correlated, principal channels corresponding to an achromatic luminance channel (Y) and two chromatic channels Cb and Cr , which roughly correspond to difference between the blue component with a reference value and difference between red component with a reference value, respectively. Thus, changes made in one color channel should minimally affect values in the other channels. The reason of choosing YCbCr color space for the current procedure is, because it allows us to selectively transfer the chromatic Cb and Cr channels from the color image to the grayscale image without introducing cross-channel artifacts., and also produces good results then the previously used lαβ as an intermediate color space [7][8].

Step 2

Divide the color image into small samples: A subset of pixels in the color (source) image is selected as samples. The samples should be (randomly) distributed over the entire area of the source image, to guarantee the availability of a characteristic sample for each of the details (materials) represented in the scene. For each of the sample pixels we compute the mean and standard deviation of the luminance (l) value over a small neighborhood of the pixel. We found that a neighborhood size of 7x7 pixels works well for most images. This agrees with the results of Welsh et al.[7]

Step 3

Apply luminance and texture matching: For each pixel in the grayscale (target) image in scan-line order the best matching sample in the color (source) image is selected, based on weighted of the luminance (50%) and the texture (50%) matching.

Step 4

Color transfer: Once the best matching pixel is found, its Cb and Cr chromaticity values are transferred (assigned) to the target pixel while the original luminance value of the target pixel is retained. We tried various ratios of the weighting coefficients but found no significant differences in the final results. This agrees with the results of Welsh et al.[7].

The algorithm works best when the luminance distributions of the target and source images are locally similar. Its performance will degrade when the pixel histograms of the target and source luminance images are substantially different. For example, a light source image will be of little use when processing a dark target image. As a preconditioning step we therefore compute a linear remapping of the luminance distribution of the source image. This remapping is such that the first and second order statistics of the luminance distribution of the source image become equal to those of the target image. This helps to create a better correspondence between the luminance ranges of the target and source images, but does not alter the luminance values of the target image. More concretely, if I(p) is the luminance of a pixel in the source image, then we remap it as follows:

$$I(p) = \frac{\sigma t}{\sigma s} (I(p) - \mu s) + \mu t$$

where μ represent the mean luminance, and σt and σs are the standard deviations of the luminance distributions, both taken with respect to the target and source luminance distributions respectively. This mapping yields better results than the standard approach of histogram matching [9], which yields non-smooth mapping with undesirable side effects [10]. Since most of the visually distinctive variation between pixel values arises from luminance differences, we can limit the number of samples we use as source color pixels and still obtain a significant range of color variation in the image. This decreases the number of comparisons made for each pixel in the grayscale target image and thereby decreases computation time. We found that approximately 100 samples taken on a regular grid is sufficient. This agrees with Welsh et al. [7] , who suggested to use about 200 samples on an irregular grid.

III. Result Analysis

Fig. 1 shows the result of applying above algorithms on given image, the first images in column (a) shows the result of colorization when using Lαβ as an intermediate color space, column (b) shows the result of colorization when using YCbCr as an intermediate color space and column (c) shows the result of colorization when using HSI as an intermediate color space. Here the top most images in all columns are target gray scale images to be colorized and the second images in columns shows the images retrieved from the image database (source image) and the last image in the column shows the final resultant images after color transfer.

Lαβ (b) YCbCr (c) HSI

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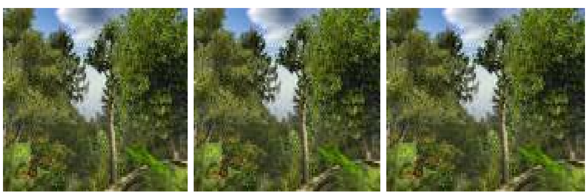

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Fig. 2 Result Analysis for Different Inter- -mediate Color Spaces

From Fig. 2 it is found that by using above described colorization algorithm for similar type of source image as of target image, and table 1.1 shows the effectiveness of colorization process for differenrent color spaces. From table 1 it may be easily observed that the accuracy of previously proposed methods [5,6,7] that uses Lαβ as an intermediate color space may be increases up to 2 - 5% by using YCbCr intermediate color space. Fig. 2 shows that on applying different intermediate color spaces on same image the accuracy increases from HSI to Lαβ and finally to YCbCr. For given Fig.s the accuracies are 89.5%, 90.5%, 79.5% for Lαβ, YCbCr and HSI intermediate color spaces respectively. The table 1.1 shows the comparisons between outputs getting from the colorization using different color spaces.

Inter-mediate color space	Images of column	Total Pixels	Unmatched Pixel with original RGB image	Accuracy
Lαβ color space	a	30000	3136	89.546
YCbCr color space	b	30000	2828	90.573
HSI color space	c	30000	6134	79.553

Table 1.1 Comparisons of the Output Images With the Original RGB Image.

IV. Conclusion

From Fig. 2 it may conclude that this algorithm is much better for different mages but the quality of the resultant images may be increase in future by using different image retrieval and color transfer techniques. While table 1.1 shows that by using YCbCr as an intermediate color space, accuracy of the colorization may be increased from previously proposed method by welsh [7].

V. Future Scope of Work

For image retrieval the result may be enhanced by using image retrieval by pattern matching or using neural network in pattern matching, we can also apply some fuzzy rules for retrieval of similar images from the database while color transfer algorithm may be applied for colorization of video in future.

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