Medical image colorization using learning

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Abstract

We propose a method for colorization of medical grayscale images using color learning. The colors are learned from a color image and predicted for a grayscale image. Earlier we introduced an efficient algorithm for image colorization which uses a dichromatic reflection model. The colorization algorithm is further developed in this study. First, we improve the algorithm performance by extending its capability to work with the grayscale images the contrast of which is lower than the contrast of the color images. Then, we propose a reliable technique to prevent negative contrast during colorization. In addition, we develop a simple approach for grayscale image colorization by a given RGB value. We give two medical applications of our algorithm: realistic color labeling of skin wounds and colorization of a dental cast models. In the former case we use grayscale images and labeling obtained after support vector classification as input data and for the latter application we use photometric stereo images.

Introduction

The demand for colorization is increasing, especially in the movie industry, medical imaging, computer graphics and scientific visualization. Colorization is still expensive, complicated and time-consuming and requires human participation.

The colorization methods can be divided into two groups: algorithms using pixel matching [14, 10, 7, 13, 4] and algorithms using PCA [1]. The pixel matching approach dominates. It considers two images: a color image (source) and a grayscale image (target). Color is transferred from the source to the target if pixels match in both images. Achromatic information - intensity, pixel neighborhood statistics, and texture features is used in matching. The pixel matching technique itself can be classified into two main groups: colorization of segmented regions [14] and color propagation methods [14, 10, 7, 8]. Many pixel matching algorithms are designed based on the method introduced in [14]. The drawback of the method is that color may be transferred to neighboring pixels from unrelated parts of image. Among color propagation algorithms the most impressive results are obtained in [10]. The purpose of their color propagation algorithm is to implement colorization and to reduce human intervention during colorization by using color scribbles [10]. Color scribbles are used for grayscale images to propagate color to the neighbor pixels via optimization. However, these algorithms may suffer from premature stop, i.e. algorithm does not reach the region boundaries, or color leaking when color propagates beyond the boundaries [11].

The PCA based algorithms work with segmented images [1, 2]. If the source and the target have approximately the same intensity range then colorization includes PCA decomposition, replacement of the first principal component by the scaled gray level image and reconstruction. The gray level image is scaled to be in the range of the first principal component. In general case, the two empirical formulas satisfying the particular conditions are proposed [1]. The conditions require that the gray level version of the color image and the gray level image have to be identical and the colorized image has the same color information as the source image. The formulas include the mean of the gray level image, the mean vector and the first eigenvector of the color image. Then combination of the mean and the mean vector are used for centering or shifting the gray level pixel values which are then multiplied by the first eigenvector and for computing the mean vector of a colorized image. The subjective evaluation of colorization results showed that the PCA based algorithms were superior to the pixel matching technique [1]. The optimization technique [10] performed slightly better than PCA based colorization. In all tests the PCA algorithms had much smaller computation time than pixel matching techniques [1]. However, the PCA colorization algorithms due to their linear character are not capable to correctly approximate the curve lying in the dichromatic plane when this curve is piecewise linear [9]. These methods particularly fail when color regions contain highlight.

Our method also requires image partitioning made in advance. The method based on Principal Component Regression (PCR) efficiently approximates the dichromatic curve and accurately reproduces highlight and color [2]. In general, good colorization approach could be a nonlinear technique, for example Locally Linear Embedding (LLE) [12]. Although LLE does not provide direct and especially inverse mapping between the input space and the subspace this problem can be easily solved by learning using regression. However, LLE works only with low resolution images. Our approach has not any such limitations. The dichromatic reflection model suggests that there are two nested subspaces in RGB color space: the dichromatic plane and the curve lying in this plane. The principal difference between our approach and LLE is that LLE learns the intrinsic dimension and computes the nonlinear embedded or principal component (PC) while the PCR algorithm learns the curve on the dichromatic plane. One may conclude that color is a result of learning. The PCR learning is efficient because it approximates the second principal component using the first one. The first PC in the PCR method is the same as the first PC of standard PCA, i.e. linear. But the nonlinear character of data is efficiently incorporated by the PCR algorithm due to nonlinear mapping between the first and second principal components. From the viewpoint of data compression LLE and PCR colorization are equivalent. They reduce color image to one principal component and the color parametric set. The color parametric set consists of vectors and values and does not include spatial information. However, to reproduce color a spatial component, i.e. an arbitrary image, is required. Three spatial components comprising color bands are derived from the color parametric set and the given spatial component.

We consider two medical applications of our algorithm: realistic color labeling of skin wounds and colorization of dental cast models. The medical images, like tissue and skin wound, are characterized by a low local contrast, i. e. contrast of image regions. Therefore we address to this problem. The teeth colors have small noticeable color differences. The colorization aspect in this case should also be analyzed to be proposed for dentistry.

Our colorization algorithm is further modified in this study. First, we improve the algorithm performance by extending its capability to work with the target images the contrast of which is lower than the contrast of the source images. Then, we propose a reliable technique to prevent negative contrast during colorization. In addition, we develop a simple approach for grayscale image colorization by a given RGB value.

Extended colorization method

Our design scheme for colorization includes a source, that is an RGB color image, and a target, that is a gray level image. The colors are learned from the source and predicted for the target. We assume that the region of the source image that is being considered must have a roughly constant hue. Earlier we introduced the simple, fast and accurate algorithm for grayscale image colorization [2] where the user manually defines the masks for both images. After selecting mask areas, PCA decomposition of the color image and learning, we compute the color parametric set. Then, the selected and scaled region of the gray level image replaces the first principal component of the color image. After reconstruction the colorized image is obtained.

The algorithm, however, works well with grayscale images the contrast of which is approximately similar to the contrast of color images. An additional problem is that the proposed early technique corrects negative contrast of many images but some images may still have negative contrast. Therefore, we extend the algorithm for colorizing the low contrast grayscale images and introduce a simple reliable method to prevent negative contrast. The colorized image may have negative contrast, i. e. the light image regions are reproduced as dark and vice versa, due to the first eigenvector which may reverse its direction. The pixels are centered before decomposition. Depending on eigenvector direction the mapped negative and positive pixels may turn over the origin. Replacing the first principal component by a gray level image without the knowledge of pixel location may produce the reconstructed image with negative contrast.

The flowchart diagram of the modified part of our colorization method is given in Fig. 1. Instead of images the segmented image regions can be used as well. The color image was converted to the grayscale intensity image retaining the luminance $I = 0.3R + 0.59G + 0.11B$. We assume that the pixel values of the grayscale image are inside the range of the intensity pixel values $max_g \leq max_i$ and $min_g \geq min_i$. The matrices representing grayscale, intensity and color image components are stacked by concatenating the pixels values along columns to arrange them as long vectors. Three color components are further used in PCA. Then, the grayscale maximum and minimum are used to find indices m of intensity pixels for which values v_m are $v_m \in [min_g, max_g]$. First, we use these indices for finding the index of the pixel with a minimum value. This index is used for correction to avoid negative contrast. The learning colorization algorithm uses this index to define the sign of the corresponding pixel of the first principal component computed using the color image. If the sign is positive the grayscale pixel values are multiplied by -1. Then, the found indices are also used for selecting the relevant pixels of the color image. Only those color pixels with evaluated indices are used for PCA decomposition. Thus, the developed algorithm provides the input data for colorization. The data includes the grayscale image, the grayscale minimum and maximum, the index used to correct negative contrast and the selected pixels of the color image.

The learning colorization part (Fig. 1) corresponds to our previous algorithm and includes PCA decomposition of the color image and learning. When the gray level image replaces the first principal component, the only requirement is that the gray level image should have the same dynamic range as the first principal component. Therefore, we scale the gray level image so that its minimum and maximum pixel values are equal to the minimum and maximum pixel values of the first principal component. Then we find the second principal component using the first principal component and polynomial regression. The degree of polynomial is 4. Finally, we reconstruct the image. As a result, we obtain the colorized image.

Thus, the proposed colorization algorithm scales the data twice. First scaling is done to provide the correspondence between intensities of the grayscale image and the color image undergone PCA decomposition. Then the grayscale pixels are scaled to be in the range of the first principal component which is replaced by the grayscale image. After reconstruction the colorized image has approximately the same intensity range as the grayscale image. This resembles luminance remapping [6, 14], where the purpose is to set the correspondence between the luminance ranges of color and grayscale images while not affecting the pixel values of the grayscale image. Luminance remapping is achieved by scaling and shifting the luminance histogram of the color image to be similar to the histogram of the grayscale image. Our algorithm may not work in the case of poor overlap between the intensity histograms of grayscale and color images.

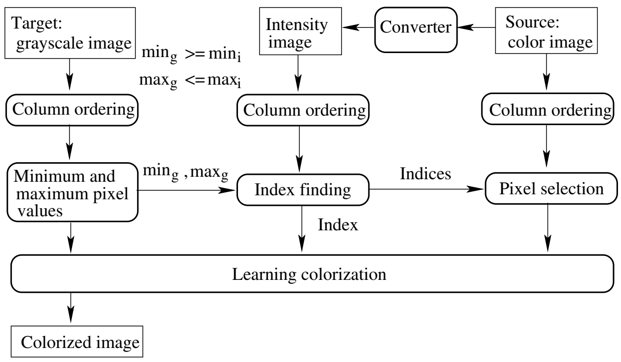

Figure 1. *The flowchart diagram of our colorization method [2]. The learning colorization part relates to our previous study. The developed part computes the input data for colorization including the grayscale image, the minimum and maximum of gray levels, the index used to correct negative contrast and the selected pixels of the color image.*

Applications

We consider two applications: realistic color labeling of segmented skin wound images and colorization of a 3D tooth cast models. We introduce a technique where we synthesize colors used for learning from a given RGB value.

Color labeling

For colorization we used images obtained with our visual-near-infrared imaging system where the support vector classifier was implemented for skin wound segmentation [3]. We used six classes: black/necrotic, yellow/fibrous, red/granulation tissue, pink/epithelial tissue, brown/healthy skin and unknown. The unknown class may include: background, shadows, cloth, objects, edges of camera extender etc. The traditional way of visualization of the segmentation results uses either grayscale or color indexed images when a gray level or flat color is assigned to the segmented region. The traditional way represents only the macro structure of the image while, in addition, the micro structure or texture is desirable to relate the wound area and skin surface. The reproduction of macro and micro structures may help clinicians to efficiently analyze the skin surface. Image colorization is a good solution in this case because it gives realistic color and texture reproduction.

Our task was to colorize the segmented skin wound images using synthetic colors. Initially, we defined several colors, one color per class. Then, each color was used to generate the color dataset for learning. According to the dichromatic reflection model for the given color we generated two connected line segments in RGB color space. One line segment connected the origin, i.e black, and the point of the given color and another one connected the point of the given color and the vertex diagonally opposite black, i.e. white. Visually, they are two gradients: black-color and color-white. The combined gradients produce the double gradient black-color-white (Table 1). It is desirable that the given color is saturated. The colorization algorithm colorized the grayscale skin wound image using colors learnt from the synthetic color image. For the double gradient we generated 200 pixels. Table 1 shows the given colors for classes.

Table 1: The given colors for classes.

Class	R	G	B	Double gradient
black	160	160	160	
yellow	255	255	0	
red	255	0	0	
pink	255	10	100	
brown	150	100	10	
gray	gray	gray	gray	

Colorization of 3D images

We colorize the 3D image of a dental cast model using spectral color measurements of a reference teeth model. This technique may be useful for reproducing the color of a synthetic crown used with a dental implant. Therefore we are interested in colorization of teeth and do not consider the gums and a dental cast background. In our preceding study we showed how the different sources can be used for colorizing the objects and textures [2]. However, in the current study our primary task is a grayscale image colorization using a given color which is accurately measured using a spectrophotometer.

The 3D model was based on the geometry measured by photometric stereo. Photometric stereo recovered surface orientation at each pixel of registered images taken under different lighting conditions. We used four LEDs and the digital camera Fujifilm IS-1 (Fig. 2). The distance between LEDs and the object was about 60 cm. To define the light source directions a chrome sphere was used. The color textured model was obtained by mapping the images onto the 3D geometric model. The color image for mapping was one of the images used for computing the 3D model. We converted this image into a grayscale image, segmented the regions related to teeth and used the approach similar to color labeling.

To use most realistic teeth colors we measured the colors of a reference teeth model (VITAPAN classical Shade Guide, DentExpo, Sucat, Paranaque City, Philippines). The reference model had 16 teeth with color levels from A1 to D4. Six of them shown in Table 2 were selected for colorization. The measurements were done by using the spectrophotometer (HR4000 High-Resolution Spectrometer, Ocean Optics, Dunedin, FL, USA). The device was connected to the light source with an optical fiber and to the computer with USB-connection. An integrating sphere (ISP-REF Integrating Sphere, Ocean Optics, Dunedin, FL, USA) was used as a light source. The measured reflectance spectra scaled to the wavelength range of 360-830 nm were converted to RGB values by the Colorlab Toolbox for Matlab [5].

Table 2:The measured colors for teeth.

Tooth	R	G	B	Double gradient
A3	255	255	220	
A3.5	248	200	133	
B3	255	220	149	
B4	255	236	155	
C4	220	176	122	
D3	250	217	166	

Experiments

For skin wound we conducted experiments with six RGB color images of size (width×height) 171×129, respectively. We note that, in general, our colorization algorithm works well with large scale images. The small image size used here is defined by the application. This image size provides 2 pixels per millimeter that is enough for measurement of wound area. In addition, the image classification algorithm has a small computation time.

For color texture mapping and 3D model we used RGB color image of size (width×height) 1433×1375, respectively. The four images used to build a 3D model were of equal size. One of them was selected for color texture mapping.

For the first experiment, we made colorization of skin wound images using the labels generated by an support vector classifier. We converted all color images into grayscale images. Then a color was assigned to each label and realistic color labeling was implemented for the segmented regions. The colors used were synthetically generated according to the proposed technique. The results are shown in Fig. 3. These results can be compared with pure color labeling. The difference is that realistic colorization highlight the segmented regions and reproduce the texture of the skin surface intact. We note that it is important to keep the class unknown shown by flat gray. This reduces the dependence of color perception of the particular region on color of neighbor regions. It can be clearly seen that all colorized regions have positive contrast. The synthetic colors (Table 1) have higher contrast than colorized regions which contrast is relatively low.

The second experiment was conducted with a dental cast model and a reference teeth model. The reference teeth model

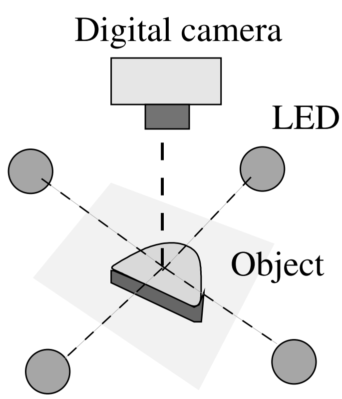

Figure 2. Photometric stereo. Four images are taken at different lighting.

Figure 3. Images of skin wounds (first column). Labeled images using colorization (second column). Color labeled images (third column). The class yellow/fibrous is not presented in our test images.

represents the group of shades that are found in natural teeth: A1-A4, B1-B4, C1-C4 and D2-D4 (Fig. 4). Photometric stereo and color texture mapping were used to reproduce shape and color. We measured color of six reference tooth models: A3, A3.5, B3, B4, C4 and D3. The double gradient was generated to prepare data for learning. Then one of those images used for the 3D model was selected and its color variant was used for texture mapping. We prepared the mask for teeth for selecting the teeth area. This segmented image was converted into a grayscale image and used for colorization. Fig. 5 shows the results of color textured mapping to 3D model. Color of teeth is close to white in Fig.5a) and slightly reddish in b). The colors of the rest teeth are varied.

Figure 4. A reference teeth model. The teeth color from left to right: A1-A4(reddish-brownish), B1-B4(reddish-yellowish), C1-C4(grayish shades) and D2-D4(reddish-gray).

During colorization the linear camera output was used in both applications. The generated data (Table 1) used for learning were also linear. The measured data were linearized by inverse gamma correction (Table 2). Thus, for colorization only linear signals were used. However, the final results are reproduced with gamma correction for sRGB. We used gamma correction for skin wound (Fig. 3, the first and second columns) and teeth reproduction (Fig. 5).

Conclusions

In this paper, we considered a learning technique for image colorization. We developed a method for the colorization using synthetic colors for 2D and 3D images. The proposed method is based on the physical approach. We extended the method to work with low contrast images. In addition, a reliable method for obtaining a proper image contrast was proposed. The developed algorithm requires only one adjustable parameter, i.e. the degree of polynomial. The used parameter is relevant for colorizing many images without validation. The learning algorithm performs well for synthetic colors.

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a

b

c

d

e

f

Figure 5. *Dental cast models. a) Color of tooth A3. b) A3.5. c) B3. d) B4. e) C4. f) D3. (Color of teeth are shown in Fig. 4)*