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Automatic Color Transfer of Images

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Abstract: Color transfer of images means transferring color characteristics from one image to another, so that the target image and source image have similar colors. This study proposed a method of automatic color transfer of sampling images. The main steps are as follows. First, based on the unsupervised clustering, divide the target images and source images into a number of subsets with similar color and extract sample points with higher density from each subset to form sample sets. Then according to the definition of similarity measure, the correspondence between the sample sets is established. Third, use the best matching algorithm to find the best matching samples of the target sample set in the source sample set and pass the color information to the target sample points. At last, take color transfer of the non-sampled part in the target image with the sampled set which has been taken color transfer. Experimental results show that, although there is no interactive sampling operation, this method can approximate the results of the color transfer with interactive operation.

Key words: Clustering, color transfer, sample set, interactive operation, sampling

INTRODUCTION

In the field of digital image, one of the most common methods dealing with images is changing the colors of images. Color transfer is such a method, passing the color characteristics of one image to another to make the target image similar to the source image in color.

Color transfer of images includes transfer between color images as well as that between grayscale images and color images. Color transfer of images can be applied not only in two images, but also in videos which is completed by transferring the color of each frame, respectively. Adding colors to grayscale images can improve the visual effects. This has been applied to old black and white film, scientific charts and the pseudo-color gray-scale images from the test of airport X-ray baggage inspection system (Gonzalez and Wintz, 1987). Besides, it is also an image enhancement technology (Pratt, 1991). It has been shown that information in some scientific images can be significantly enhanced by using different colors and luminance processing techniques. In medicine, making the gray images resultant from MRI, X-ray and CT tests, etc. color can enhance the description effect. Therefore, the color transfer of images has great potential availability in many different areas.

Color transfer algorithms dealing with color images are first proposed by Reinhard *et al*. (2001) based on the lαβ color space proposed by Ruderman *et al*. (1998). This algorithm is simple, feasible and has good transferring results within a certain range. The transferring process relates to the values of three channels of lαβ space. In the circumstances that the target image and the source image are very similar, global transferring algorithms can be applied. While there are some differences between the source image and the target image, sample blocks can be chosen by human intersection. Then the color transfer of the total image can be completed based on the transferred results of the sample blocks. Welsh *et al*. (2002) promoted the color transfer to the colorizing of grayscale images. Since, there is only one value of luminance information, the color transfer in this algorithm only involves l channel in lαβ space to find the best matching point. Similarly, user interaction is also needful to select sample blocks in the algorithm when there are certain differences in the target image and source image. Hogervorst and Toet (2010) proposed a method to make night image be colorful, Li *et al*. (2010) gave a new method for image segmentation based on different color space, Zhou and Peng (2011) proposed a method to perform color transfer based on constraint.

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These existing algorithms on color transfer of images have achieved the global color transfer. Besides, color transfer can also be accomplished by the way of user intersection with sample blocks. Although, the algorithms are simple and direct, there still exist some problems: (1) To transfer color well, users need to choose the sample blocks from the source image and the target image, respectively and build the correspondence relationship between them. (2) Intersection operation improves the accuracy rate of color transfer to some extent, but leads to low implementation efficiency, particularly in the case of batch processing of multiple images which is often difficult to complete. This study has proposed an automatic color transfer algorithm based on clustering. After users input the target image and source image for color transfer, the number of clusters can be automatically set to be optimal. Then take out the sample set based on the clustering results. Third, build the map between the sampling sets of the target image and source image with the luminance values of sample set and the neighborhood statistics. In this way, the color transfer between sample sets is accomplished. When the clustering result is good, color transfer of non-sampled pixels can be realized only by finding the best matching pixel in the corresponding class of sample set, thereby reducing the matching number of each pixel.

FAST FUZZY C-MEANS CLUSTERING (FFCM)

Fast Fuzzy C-means clustering is a kind of improved Fuzzy C-means clustering method proposed by Lin *et al*. (2004). FFCM is based on iterative optimization, so it involves a mount of calculations when the size of the sample is large. FFCM algorithm uses hierarchical clustering subtraction to divide the entire sample set S into n_p sub-set S_k (k = 1,2,..., n_p) according to certain similarity criteria, then fuzzily cluster on these subsets and thus greatly increase the clustering speed.

The steps of Fast Fuzzy C-means clustering algorithm (FFCM) are as follows:

(1) Using second subtraction clustering to cluster the image data, obtaining n_p sub-set

In the first layer, divide the data set into t subsets with size b (n = bt) denoted as C^l_x, l = 1,2,..., t. The density function of one data point x_i is defined as the number of data points in its neighborhood, where the neighborhood is the super-sphere centered with x_i and has an appropriate radius r. First define the function:

$$u(x)=\begin{cases}1 & x\geq 0\\ 0 & x<0\end{cases}$$

and then the density of data points in the neighborhood of x^l_i is as follows:

$$D^l_i(x^l_i)=\sum_{j=1}^{b}u(r-\|x^l_i-x^l_j\|) \tag{1}$$

If the data point $x^l_{c1} \in C^l_x$ has the maximum distribution density that is, $D^l_{c1}=\max_i D^l_i$ then the first cluster center of subset C^l_x is:

$$c^l_{c1}=\frac{\sum_{x_j\in C^l_{c1}} x^l_j\cdot D^l_j(x^l_j)}{\sum_{x_j\in C^l_{c1}} D^l_j(x^l_j)} \tag{2}$$

where, C^l_x is the data set of the neighborhood of x^l_{c1}. After finding the first cluster center, look for the data points x^l_{c2}, which has the maximum value of density function in the set $\{C^l_x - C^l_{c1}\}$ and take the centroid of the data points in its neighborhood as the second cluster center x^l_{c2}. Repeat the same process, until $C^l_x-\sum_k C^l_{ck}=\varnothing$, where k is the number of achieved centers.

Let l = 1,2,..., t and repeat the above process, the first layer subtraction clustering center set and the corresponding distribution density are obtained. Recombine the center of these clusters into a new data set and take the second layer subtraction clustering of the data sets. Then the density function is transformed from Eq. 1-3:

$$D_i=\sum_{j=1}^{n_c}u(r-\|x_x-x_j\|)\cdot D^{(1)}(x_j) \tag{3}$$

where, n_c and $D^{(1)}$ are the number of centers and the density of the centers, respectively obtained in the first layer. In this way, cluster centers c_{cj}, j = 1,2,..., n_p are obtained, where n_p is the number of centers obtained in the second layer

(2) Arrange the center set C^c_x in descending order and let c = 2
(3) Fuzzily cluster the center set V initialized from the first c elements in C^c_x:

(I) Initialize the cluster center V = $\{v_1, v_2, \ldots v_c\}$
(II) Compute the membership degree matrix:

$$u_{ik}=\left[\sum_{j=1}^{c}\left(\frac{d_{ik}(x_k,v_i)}{d_{jk}(x_k,v_j)}\right)^{\frac{2}{m-1}}\right]^{-1},\ k=1,2,\cdots,n_p \tag{4}$$

where, the distance from $\forall x_l \in S_k$ to the center v_i is denoted by the distance from the center x^c_k of S_k to v_i, that is:

$$d_{il}^2(x_l, v_i) \approx d_{ik}^2(x_k^c, v_i) = \left\| x_k^c - v_i \right\|_A^2 \tag{5}$$

(III) Update the cluster center:

$$v_i = \frac{\sum_{k=1}^{n_p} (u_{ik})^m x_k^c D^c(x_k^c)}{\sum_{k=1}^{n_p} (u_{ik})^m D^c(x_k^c)}, \quad i = 1, 2, \cdots, c \tag{6}$$

(IV) Repeat the steps I, II, III until expression (7) converges:

$$J_m(U, V) = \sum_{k=1}^{n_p} \sum_{i=1}^{c} (u_{ik})^m d_{ik}^2(x_k^c, v_i) D^c(x_k^c) \tag{7}$$

(4) With the results in step 3, calculate:

$$F_{XB}(U, V, c) = \frac{J_m(U, V)}{n(\min \left\| v_i - v_j \right\|)}, \quad i, j = 1, 2, \cdots, c \tag{8}$$

where, F_{XB} (U,V,c) is the Xie and Beni (1991), used for cluster validity analysis

(5) Let C = c+1, if $c>c_{max}$, go to the next step; Otherwise, go to step 3
(6) Determine V corresponding to the minimum value of F_{XB} (U, V, c)
(7) Use V to recalculate the fuzzy membership degree matrix $U = \{u_{ik}\}$

AUTOMATIC COLOR TRANSFER OF IMAGES BASED ON CLUSTERING

Select the sample set: Transform the target images and source images from RGB space to lαβ space. The channels of β space, in which l is the luminance value, α and β are yellow-blue color values and red-green color values, respectively, are almost completely independent, thus changing the value of one channel has little impact on the other two values. The conversion process from RGB space to lαβ space is in work (Reinhard *et al*., 2001). Take unsupervised learning clustering of the target image and source image and the cluster numbers of the target image and source image are expressed by c1 and c2, respectively. If c1 ≠ c2 and c1>c2, for example, merge the target images in one class. Calculate the average luminance value of each class in the target image and merge the two classes which have the minimum difference in average luminance value. And then let c1 = c1-1. If c1>c2, continue the above merging process until c1 = c2.

Calculate the density of each datum point (Tao, 2002) and take out 200 sample points which have larger density in each class to form the sample set. Repeated experiments show that taking out 200 sample points in each class can have relatively good performance. If the number of class pixels is less than 200, it is necessary to adjust the number of sample points to the total number of class pixels.

Establish the mapping relationship between the sample set: In the interactive color transfer, the mapping between the sample blocks is specified by the user. Although, the user-specified mapping is relatively flexible and a variety of effects can be got, mapping relationship can also be established between sample sets with their feature attributes by analyzing the needs of general users.

This study, has proposed the use of luminance values of the sample set and neighborhood statistics to establish the mapping relationship. Using the luminance values to establish the mapping between the sample sets can be applied to transfer colors both between color images and between one color image and another grayscale image. The steps are as follows:

First, take the luminance mapping between two images (Hertzmann *et al*., 2001) and map the luminance histogram of the source image to that of the target image linearly.

Then, calculate the average luminance of each sample set and the average standard deviation of neighborhood luminance. Repeated experiments show that the size of 5×5 of the neighborhood can adapt to most images. Eigenvalues of the sample set is assumed to be the weighted sum of the average luminance value and the average standard deviation of the neighborhood luminance, where the weight of the former is 80% and the latter 20%.

After evaluating the eigenvalues of each sample set in the target images and the source images, map the range of the eigenvalues of the sample set of the source image to that of the eigenvalue of the sample set of the target images. Y(p) is the eigenvalues of the sample set of source images:

$$Y(p) \leftarrow \frac{\sigma_T}{\sigma_S}(Y(p) - \mu_S) + \mu_T \tag{9}$$

where, μ_S and μ_T are the mean values of the eigenvalues of the sample set of source images and target images, respectively, σ_S and σ_T are the standard deviation values of the eigenvalues of the sample set of source images and target images, respectively.

Successively, find the blocks in the sample set of the source image that match the sample set of the target images best that is, the blocks whose eigenvalues are closest and then establish the correspondence.

Color transfer: After establishing the correspondence between the sample sets, transfer the color in the corresponding sample set. That is accomplished mainly by comparing the luminance value of each pixel and the standard deviation of the luminance value of the neighborhood to find the best matching pixel. In the sample set of the source image, first find the points that match the points in the target image best and then pass the color values that is, the values of α and β channel, to the target pixels. Because the luminance range of the source image and the target images are different, it is necessary to scale the luminance range of the source image to that of the target image linearly to improve the accuracy. Neighborhood luminance standard deviation is the current standard deviation of the pixel luminance in the pixel neighborhood; and it is proposed to take the neighborhood size of 5×5 for fitting most images (Welsh *et al*., 2002). In the process of finding the best matching point, the weighted values of the luminance value and the standard deviation of neighborhood luminance can be used to make the comparison, where the two weights are both 50%. The point that has the value closest to the weighted value is the best matching point.

After the color transfer between the sample sets of the source image and target image has been made, the sample set in the target image, whose color has been transferred, can be used to make the color transferring of the non-sampled pixels. The minimum error distance E which is similar to L_2 distance (Efros and Freeman, 2001), is used to complete color matching:

$$E(N_g, N_s) = \sum_{p \in N} [I(p) - S(p)]^2 \tag{10}$$

where, N_g is the neighborhood of the target pixel, N_S is the neighborhood of the sample set, I(p) is the luminance value of the neighborhood of the target pixel and S(p) is the luminance value of the neighborhood of the sample set.

Then it is necessary to deal with pixels that are not sampled in the target image in the order of scan line. To improve the matching efficiency in the process, the previous clustering results can be used to find the best matching point only in the sample set of the corresponding class. First determine the class that the current pixel belongs to. Then find the sample set of the corresponding class. Third compute the minimum error distance E from the current pixel to each pixel of the sample set. At last transfer the color value of the sample point that has minimum E to the current pixel and keep the luminance value.

In summary, automatic image color transfer is as follows:

- Cluster the target image and source image, respectively
- Transform the target image and source image from RGB space to $l\alpha\beta$ Space
- Based on clustering results, take out 200 sample points with higher density to form the sample set of each class
- Map the luminance space of the source image to that of the target image linearly
- Establish the correspondence between the sample set of the target image and that of the source image according to luminance value and the standard deviation of the neighborhood luminance value of the sample set
- Take the color transfer between the sample sets of the target image and that of the source image. Use the weighted value of the luminance value and the standard deviation of the neighborhood luminance value to look for the best matching point. And pass the color channel values of the pixel to the target pixel, keeping the luminance value of the target pixel
- Look for the point that non-sampled pixels in the target image best matches in the sample set of the corresponding class in the target image according to Eq. 10 and pass the color value of the pixel to the target pixel

EXPERIMENTAL ANALYSIS

Different clustering algorithms can be selected according to users' needs to implement the cluster of the target image and the source image. When the class structure of the image is more distinct, simple and fast unsupervised learning clustering can be chosen; otherwise clustering algorithms with better clustering results should be chosen. Fast fuzzy C-means clustering is selected in this paper. In hierarchical subtraction clustering, each line of the image is taken as a subset of the sample. The distance between pixels is calculated according to RGB color space. Each r value in Eq. 1 and 3 is taken as r_{min} and $r_{min}/2$, where r_{min} is the minimum value of the standard deviation of each component in the data points. LUV color space is adopted to calculate the distance in Fuzzy C-means clustering. Other parameters are set as follows: m = 2, the maximum iteration times T = 100, the convergence error of J_m is $\varepsilon = 0.0001$ and the distance between pixels is Euclidean distance.

An example in Welsh *et al.* (2002) is adopted as the test image to compare the result of the interactive

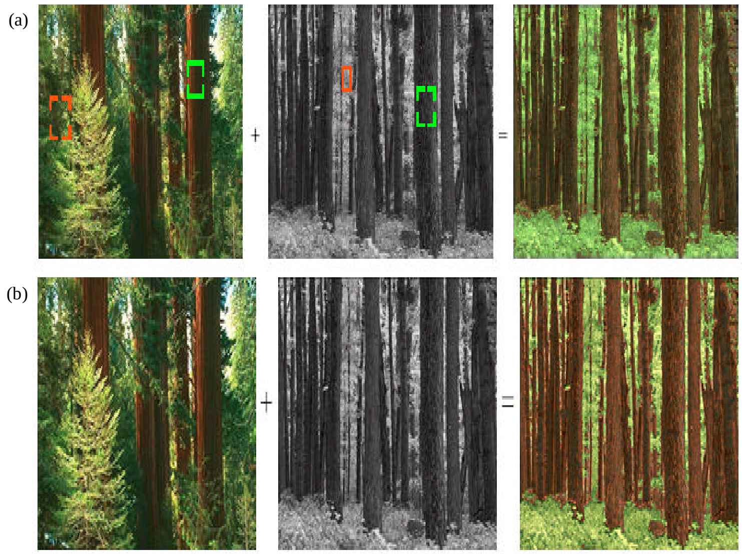

Fig. 1(a-b): Comparison of results of color transfer with and without interactive operation. (a) Color transfer results after users choose two groups of corresponding sample blocks interactively (Welsh *et al*. 2002), (b) Results of automatic color transfer

image color transfer algorithm with that of the algorithm proposed in this paper. As is shown in Fig. 1, our algorithm is close to the interactive algorithm without interactive operations. Moreover, the sample set chosen in our algorithm is a set of scattered points, thus the deficiency in choosing sample blocks during the interactive process can be avoided to some extent.

CONCLUSION

The automatic color transfer algorithm proposed in this paper is based on clustering. Interactive operation can improve the accuracy of color transfer to some extent, but it has low implementation efficiency and may not be accomplished when batch processing of multiple images is needed. In this paper, unsupervised learning clustering is used to divide the image data into a certain number of subset whose colors meet some similarity criteria. Then a number of sample points are taken out from each class to form sample sets and correspondence between the sample sets is established to transfer color. Experiments results show that our algorithm is close to the interactive algorithms in the results of color transfer though without interactive operation.

Since, only the luminance characteristic is used in establishing the correspondence between sample sets, some shortages may exist in our method. Thus, the way to establish better correspondence between sample sets may be considered in the latter work.

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