Image Colorization Method Using Texture Descriptors and ISLIC Segmentation

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Abstract We present a new colorization method to assign color to a grayscale image based on a reference color image using texture descriptors and Improved Simple Linear Iterative Clustering (ISLIC). Firstly, the pixels of images are classified using Support Vector Machine (SVM) according to texture descriptors, mean luminance, entropy, homogeneity, correlation, and local binary pattern (LBP) features. Then, the grayscale image and the color image are segmented into superpixels, which are obtained by ISLIC to produce more uniform and regularly shaped superpixels than those obtained by SLIC, and the classified images are further post-processed combined with superpixles for removing erroneous classifications. Thereafter, each pixel of the grayscale image is assigned with a color obtained from the color image following a predefined matching metric based on the superpixels and the classes. Experimental results show that our proposed approach is effective and has a better colorization in naturalness compared with Welsh algorithm and unimproved SLIC strategy method.

Keywords Color transfer · Improved SLIC · Texture descriptors

1 Introduction

Colorization is a crucial technique by adding color to grayscale content. It is very useful for obtaining rich information from classic movies and monochrome photographs and images. A traditional category of colorization methods requires manually operation to add colors to grayscale images. On the contrary, another

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colorization approaches consist in transferring color from a pre-selected color image as a reference, which are called Exemplar-Based Methods [1].

Most of exemplar-based colorization approaches assume that the target grayscale pixels should be assigned to the color from reference color pixels which have similar intensities or similar neighborhood. Welsh et al. proposed a colorization technique, which relies only on matching the luminance values that is calculated by averaging its neighborhood pixels in the target image to those in the reference image, and transferring color accordingly [2]. However, mismatching may appear in difference region of the color image though the correspondence are with the same luminance value and similar neighborhood statistical characteristics. Therefore, some methods take account to the higher-level content of each pixel in addition to luminance. For, example, Irony et al. used a classification image obtained by supervised classifier and texture features to achieve convincing colorization [3]. Charpiat et al. exploited feature descriptors using Speeded Up Robust Features (SURF) incorporated into a probability estimation model to achieve colorization [4]. Gupta et al. presented a method that is employed a cascade feature matching scheme to seek matching pixels between grayscale and color images [5]. To summarize, the main underlying idea of these exemplar-based approaches is to find the best corresponding pixel (region) between the reference image and the target image, and to transfer the color accurately.

In this paper, we propose a new approach for example-based image colorization. To determine correspondences between reference image and target image, a series of statistical descriptors and a segmentation algorithm are employed. The main stages include classification and color transfer. The closest scheme of classification to our method is the approach of Irony et al. [3], which exploits K-nearest-neighbor (Knn) and linear discriminant analysis (LDA) with manually marked segmentation regions of reference images. In contrast to [3], we use SVM classifier based on statistical texture descriptors and SLIC segmentation to achieve classification images without manually marked regions. Meanwhile, we take the advantage of ISLIC to obtain the classification with more accuracy and more spatial consistency than that of SLIC.

The remaining of this paper is organized as follows. Section 2 describes the related techniques of our colorization solution in detail. Experimental results and analysis are shown in Sect. 3 before conclusions are given in Sect. 4.

2 Colorization by Example

2.1 Feature Space and Classifier

Luminance: Luminance is useful feature to provide information to guide correspondences, which has been demonstrated by Welsh et al. [2]. In this paper, the mean luminance of the grayscale image and that of the color image are utilized as a descriptor.

Entropy, homogeneity, correlation: the Gray Level Co-occurrence Matrix (GLCM) is an effective method to extract second order statistical texture features which can help to characterise the local structure in the scene. There are 14 features computed based on GLCM. According to them, entropy, homogeneity, correlation are uncorrelated and can be available for obtaining high classification accuracy. Entropy reflects the homogeneityfor scenes. Homogeneity, called Angular Second Moment (ASM), is to describe homogeneity of an image. Correlation is to measure dependence between the pixels at the specified position relative to each other. Those three features are employed in our work.

LBP feature: Different from the GLCM method that is greatly restricted by image scale, "uniform" LBP is an operator which is defined by invariant against any monotonic transformation for arbitrary quantization of angular space and spatial of the gray scale. It is a very formidable tool to analyze rotation invariant texture [6], and is also effectively used for image classification.

SVM: Once the feature space has been computed by label vectors, the supervised learning models are used for classification and regression analysis. SVM is an efficient and robust classifier with associated learning algorithms that analyze data to classify. It can perform linear and non-linear classification. The latter category, called kernel trick, can implicitly map the inputs into high dimensional feature spaces using kernel trick and achieve good classifications. In this paper, the SVM classifier is employed for naive classification and a radial basis kernel function is utilized.

2.2 Superpixels Extraction

Applying the SVM classifier for pixel-level may still lead to many non-discriminating and erroneous classifications. To avoid those misclassified pixels and to improve the efficiency of the classifier, the segmentation images are employed. Image segments are computed by superpixels that maintain strong spatial coherency to ensure the consistency of adjacent classification pixels.

SLIC is a simple and efficient segmentation approach, which produces a relatively regular lattice and possesses low computational complexity [7, 8]. In the SLIC method, the local K-means clustering based on the color and spatial distances is performed to extract superpixles. However, some small and isolated segments are generated because the number of superpixels is fixed.

To obtain relatively coherent superpixels and avoid over-segmentation of large homogeneous regions, the Sigma filter is employed to update the cluster centers which are calculated by only the pixels with the similar luminance values at the original center [8]:

$$\boldsymbol{\varphi}_j = \frac{1}{N}\sum_{i\epsilon\boldsymbol{\Omega}_j}\begin{bmatrix}\boldsymbol{C}_i\\ \boldsymbol{S}_i\end{bmatrix}, \tag{1}$$

$$\boldsymbol{\Omega}_j = \left(\left\| L_i - L_j \right\| < \alpha * \sigma_j\right) \cap \boldsymbol{G}_j, \tag{2}$$

where $\boldsymbol{C}_i$ and $\boldsymbol{S}_i$ represent the value of the jth cluster's color space and the centred location respectively. N is the number of pixels in $\boldsymbol{\Omega}_j$, which is a subset of the jth cluster and can be calculated in (2). L_i and L_j are the luminance value of pixel i and the mean luminance value of the jth cluster respectively. σ_j is the standard deviation of the luminance of all the pixels in the jth cluster $\boldsymbol{G}_j$ and α is a constant.

After iterative clustering, the obtained superpixels are further processed to produce a set of homogeneous segments $\boldsymbol{S}_{seg}$. The neighbour superpixels with similar statistical characteristics are merged to form larger segments as follow:

$$\boldsymbol{s}_i = \boldsymbol{s}_i \cup \boldsymbol{s}_j \mid \varepsilon < T, \tag{3}$$

$$\varepsilon = \sqrt{\left(\mu_i - \mu_j\right)^2 + \left(\sigma_i - \sigma_j\right)^2}, \tag{4}$$

$$T = \beta * \sigma_i, \tag{5}$$

where μ_i and μ_j, represent the mean luminance of the segments s_i and s_j respectively. β is a defined threshold.

In our work, we use the lαβ color space to segment image. Then, post-classifying is processed based on a small neighbourhood around each pixel in superpixels. It is assumed that (1) the centre pixel belongs to the class that all of the adjacent pixels belong to; (2) all the pixels in a superpixel are in the same class if 85% of the pixels in this superpixel belong to the same class.

2.3 Feature Matching and Color Mapping

For each target superpixel, we can seek a cross all reference superpixels combined with all features to find the corresponding superpixel which is most similar to the target one. Here, the candidate pixels in the matching superpixels must be in the same class according to the result of classification.

By this constricted condition, the most appropriate matching pixel can be found in the reference image. Using the matching pixel, color can be borrowed from the reference to the target image. The color mapping processing is the same as the method proposed by Welsh et al. [2].

3 Colorization Evaluations

Figure 1 illustrates the process of classification. The number of initialization superpixels is configured as 800, and $\alpha = 0.8$, $\beta = 0.8$ in our implementation.

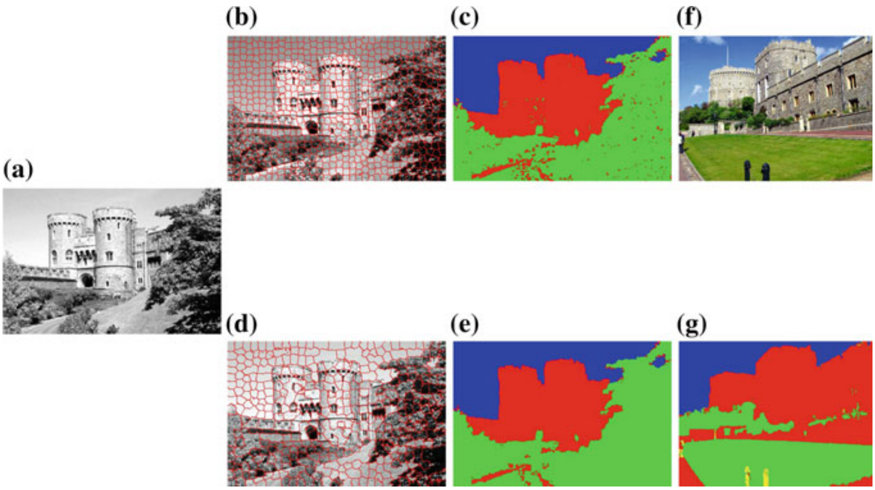

Fig. 1 Classification on **a** target image and **f** reference image; **b** and **d** superpixels by SLIC and ISLIC; **c** and **e** classifications combined with SVM classifier and superpixels based on SLIC and ISLIC; **g** classification of reference image based on our method

Clearly the naive SVM classifier combined with SLIC segmentation still leads to many erroneous classifications as shown in Fig. 1c. For example, some vegetation and building pixels are failed to discriminate. Classification through post-processing by ISLIC segmentation in Fig. 1e demonstrates a greatly improved result since most of the adjacent pixels in each superpixel are labeled to the same class. Figure 1g also shows a satisfactory classification result of the reference image based on our technique. Those results can provide accurate matching superpixels and classes between target and reference images.

After seeking colors using above segmentations and classifications, the final results after color transferring are obtain as shown in Fig. 2. We compare the colorization results of our method with that of the unimproved SLIC strategy and that of the approach proposed by Welsh et al. Due to the complexity of the image, the method by Welsh et al. yield uncorrected color in most regions shown in Fig. 2c since it is based only on direct luminance intensity matching. The methods for Fig. 2a, b produce comparable good results with successful mapping and colorization. However, there are some mistakes colorization in Fig. 2d which is based on unimproved method because of misclassification and mismatching. Improved colorization result in spatially continuity and consistency achieved by our approach is shown in Fig. 2e. It implies that our method has an advantage in creating spatially coherent color.

Figure 3 shows more results of colorization for different scenes. The human images are downloaded from the website for FDDB [9] (http://tamaraberg.com/faceDataset/). It can be observed that combining both texture descriptors and superpixels results in good performance on colorization. Compared with post-processing classification based on SLIC, our approach produces more robust

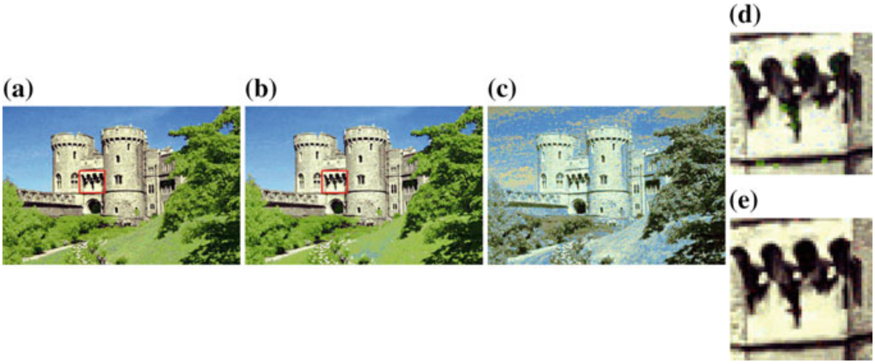

Fig. 2 Colorization results obtained by **a** texture descriptors + SLIC classification and **b** texture descriptors classification + ISLIC, **c** Welsh et al. method. **d** and **e** are the details information of *red rectangle* in **a** and **b**

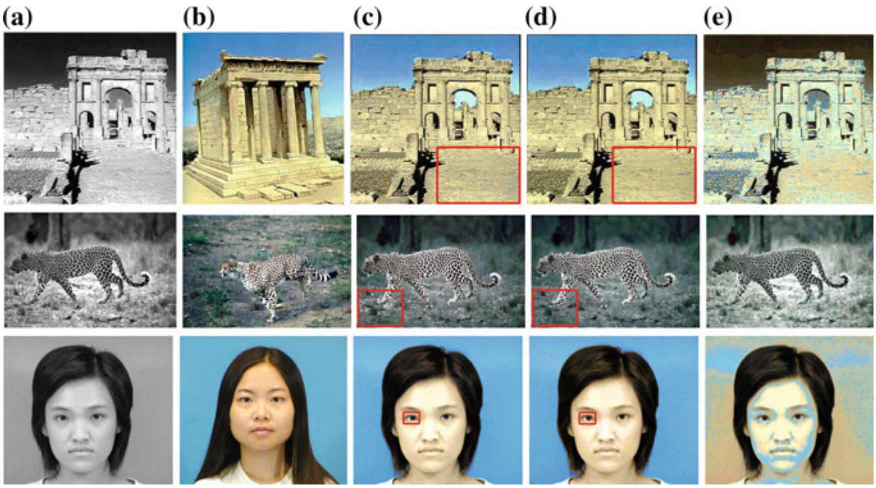

Fig. 3 Comparison with different colorization methods. **a** Grayscale images; **b** color images; **c**, **d** colorization obtained by texture descriptors + SLIC and texture descriptors + ISLIC; **e** colorization obtained based on Welsh et al. method

colorization. The details in red rectangle in Fig. 3c, d are demonstrated in Fig. 4. They clearly show that the resulted colorization of our method explicitly enforces spatial coherency. However, in some complex regions, our method also fails to transfer exact color information, such as the right forefeet of the tiger in Fig. 3d. The pixels are inaccurate at object boundaries or at thin image structures, which also result in incorrectly assigning colors. For example, the boundaries of the woman's eye in Fig. 4f take color from the background of the picture. The reason is that the categories of these pixels are difficult to discriminate based on the space features that we choose.

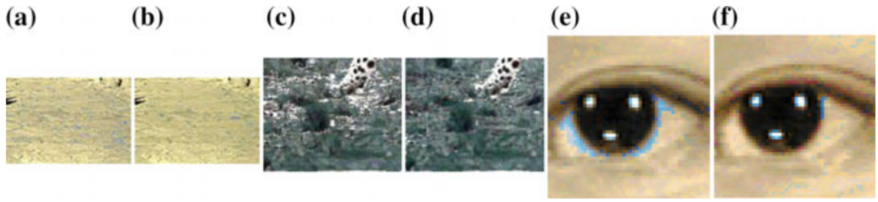

Fig. 4 Details of colorization results in *red rectangle area*. **a**, **c** and **e** Colorization obtained by texture descriptors + SLIC; **b**, **d** and **f** colorization obtained by texture descriptors + ISLIC

4 Conclusions

In this paper, we presented a new method for colorization grayscale images. This method exploits texture descriptors and segments images based on ISLIC to seek correspondences and to achieve colorize. Experimental results illustrate that our method develop sperceptually appealing colorizations. Additionally, comparisons among unimproved SLIC method and Welsh et al's method demonstrate that our method is more effective in colorization.

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