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Example-based image colorization via automatic feature selection and fusion

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ABSTRACT

Image colorization is an important and difficult problem in image processing with various applications including image stylization and heritage restoration. Most existing image colorization methods utilize feature matching between the reference color image and the target grayscale image. The effectiveness of features is often significantly affected by the characteristics of the local image region. Traditional methods usually combine multiple features to improve the matching performance. However, the same set of features is still applied to the whole images. In this paper, based on the observation that local regions have different characteristics and hence different features may work more effectively, we propose a novel image colorization method using automatic feature selection with the results fused via a Markov Random Field (MRF) model for improved consistency. More specifically, the proposed algorithm automatically classifies image regions as either uniform or non-uniform, and selects a suitable feature vector for each local patch of the target image to determine the colorization results. For this purpose, a descriptor based on luminance deviation is used to estimate the probability of each patch being uniform or non-uniform, and the same descriptor is also used for calculating the label cost of the MRF model to determine which feature vector should be selected for each patch. In addition, the similarity between the luminance of the neighborhood is used as the smoothness cost for the MRF model which enhances the local consistency of the colorization results. Experimental results on a variety of images show that our method outperforms several state-of-the-art algorithms, both visually and quantitatively using standard measures and a user study.

1. Introduction

The aim of example-based image colorization is to transfer the chrominance information from a reference image with color to a target grayscale image. It is an important research topic in image processing, and has many applications in different areas, such as heritage restoration [1] and image stylization [2,3]. However, it is ill-posed and difficult because the common grayscale information between the reference and target images may not be sufficiently distinctive for reliable transfer. Most existing image colorization methods use feature matching: given a reference image with color information, the target grayscale image will be colorized by finding correspondences from the reference image based on feature similarity. Therefore, choosing suitable features is key to the colorization performance. In the pioneering work by Welsh et al. [4], luminance features are used to find the correspondences. However, such features perform poorly for non-uniform (e.g., textured) regions, leading to artifacts in the colorized images. More recent work has used many advanced texture features for image colorization, such as Gabor wavelets [5], SIFT [6], SURF [7], etc. To improve results, most existing methods use multiple features as a combined vector for matching, which implies that individual features contribute *equally* to region matching across the entire image. However, a specific type of feature is often more effective for certain types of regions. It is thus beneficial to treat regions *differently* according to their local characteristics. For example, pixels in uniform regions are more suitable to be matched by intensity features whereas texture descriptors should be used for highly non-uniform regions. An example is shown in Fig. 1. We can see that the intensity feature is suitable for the sky region but not the castle (Fig. 1(f)), whereas the texture descriptor performs well for the non-uniform castle regions but produces erroneous matches in the uniform regions (Fig. 1(g)). Combining these two features improves the result (Fig. 1(i)), but numerous matching errors remain

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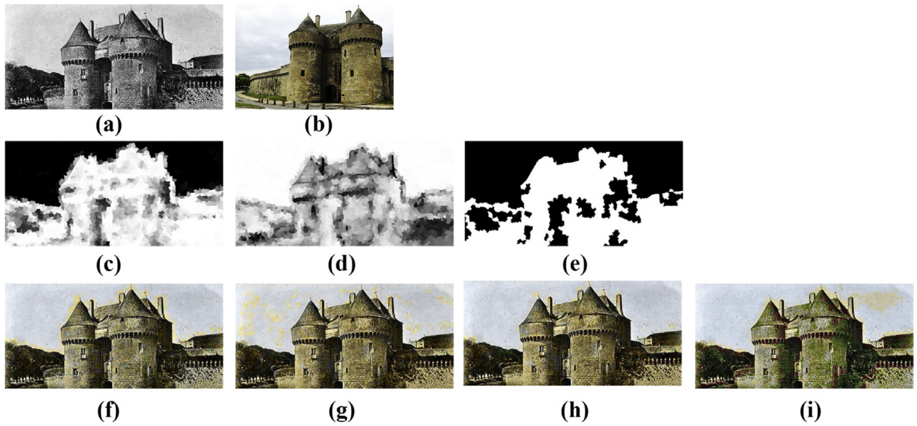

Fig. 1. Illustration of automatic feature selection for colorization. (a) target grayscale image, (b) reference color image, (c)(d) probability maps of uniform and non-uniform regions (black to white for 0 to 1), (e) the optimal label image learned by an MRF model (black: uniform, white: non-uniform), (f)(g): colorization results using intensity feature and SURF texture feature respectively, (h) colorization result using our proposed automatic feature selection and fusion, (i) the result using direct combination of intensity and SURF texture features.

which lead to the green tint on the castle and the yellow tint in the sky. Our automatic feature selection and fusion is effective at avoiding such problems (Fig. 1(h)).

In this paper, we propose a novel image colorization method via automatic feature selection within a Markov Random Field (MRF) framework. To the best of our knowledge, this is the first work that exploits automatic feature selection and fusion for image colorization. Specifically, image regions can be generally classified as being uniform or non-uniform. In uniform regions, the luminance of pixels is evenly distributed, so the intensity distribution can represent these regions well, whereas in non-uniform regions, texture feature descriptors are effective to represent the patterns. Based on the learned distribution of intensity deviation for uniform and non-uniform regions, the probability of a given region being assigned a uniform or non-uniform label is estimated using Bayesian inference, which is then used for selecting suitable features. Instead of making individual decisions locally, we further develop an MRF model to improve the labeling consistency where the probability is used for the label cost and similarity between the luminance of the neighboring regions for the smoothness cost. The MRF model can be efficiently solved by the graph cut algorithm, enhancing the local consistency of the colorization result. Finally, the colorization results are obtained by transferring corresponding chrominance information from the reference image to the target grayscale image.

The main contributions of the paper are summarized as follows: (1) We propose a novel approach to improving image colorization by local feature selection and fusion. (2) We develop a novel algorithm that classifies local image regions into uniform and non-uniform regions and which allows suitable features to be applied. An MRF framework guided by Bayesian probability inference is further proposed to improve locality coherence. (3) We perform extensive experimental analysis both visually and quantitatively, which shows that the proposed method outperforms state-of-the-art methods.

The rest of this paper is organized as follows. We review work most relevant to this paper in Section 2, and then describe the proposed algorithm in detail in Section 3. Experimental results are shown in Section 4 and finally conclusions are drawn in Section 5.

2. Related work

In general, existing image colorization methods can be divided into three categories: user-scribble based methods, example-based methods and methods that use a large number of training images. User-scribble based methods are semi-automatic, and they often require substantial user interaction as input. In the pioneering work by Levin et al. [8], some color scribbles on the target image are required as input, and then the color will be propagated based on least squares diffusion. However, there are obvious color bleeding effects around edges due to the isotropic nature of the diffusion. In order to better preserve the edge structure, an adaptive edge detection based colorization algorithm was proposed in [9]. To make the color region boundaries more consistent with human judgement, a saliency guided colorization technique was proposed in [10]. The approach first generates a saliency map of the reference and target images to predict the visual attention of human viewers, softly segmenting the images into foreground and background regions. Color transfer is then performed first to the foreground and then the background using a weighted color transfer algorithm. In [11], a fast colorization method based on the geodesic distance weighted chrominance blending was proposed. Thanks to the use of the luminance-weighted chrominance blending model and efficient intrinsic distance computation, the method is efficient for both image and video colorization. However, for all these scribble-based methods, it is time-consuming and the quality of colorization results highly depends on the appropriateness of user scribbles.

Compared with user-scribble based methods, example-based methods can be fully automatic without any user interaction. For example-based methods, typically only one reference image with color information is needed, and the target grayscale image is colorized automatically. The pioneering work by Welsh et al. [4] first finds the best matching sample in the reference image for each pixel in the target image, and then the chrominance information is transferred to the target grayscale image from the color reference image by the matching results to form the colorized images. Most of the existing example-based colorization algorithms follow this framework involving the steps of feature matching and color transfer. As feature matching is critical to the quality of results and the proposed method, Welsh's method resorts to manually specified swatches when automatic matching fails to produce satisfactory results.

In order to improve the feature matching performance, different features or different combinations of features have been proposed. Ying and Ji [12] proposed using a more extensive neighborhood descriptor computed using co-occurrence matrix based texture features. To reduce artifacts caused by outliers, the edit-nearest-neighbor method [13] is used to try to remove the outliers. While the paper presents examples showing im-