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EXEMPLAR-BASED COLORIZATION IN RGB COLOR SPACE.

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ABSTRACT

This paper deals with the problem of image colorization. A model including total variation regularization is proposed. Our approach colorizes directly the three RGB channels, while most existing methods were only focusing on the two chrominance channels. By using the three channels, our approach is able to better preserve color consistency. Our model is non convex, but we propose an efficient primal-dual like algorithm to compute a local minimizer. Numerical examples illustrate the good behavior of our algorithm with respect to state-of-the-art methods.

Index Terms— Colorization, total variation, patches, optimization, variational methods.

1. INTRODUCTION

Image colorization is an old research field that started in 1970 with Wilson Markle (see details in Levin *et al.* [2]). It appeared naturally for restoration of old documents and movies. The objective is to transform a given gray-scale image (called *target*) into a colored one. As no color information is present in a gray-scale image, additional prior is needed. It can be done in two ways: with manual interactions or by giving a color image as an example.

In manual methods (following the work of [2]), the user defines colors on some points of the image and an algorithm is used to spatially diffuse the color. These methods have a main drawback: if the image represents a complex scene, the user has to draw a lot of seeds. In exemplar-based colorization methods, the color information is extracted from a color image, called source, selected by the user. Figure 1 shows an example of such a method where the final result is obtained with the approach introduced in this paper.

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(a) Source.

(b) Target.

(c) Our result.

Fig. 1. Exemplar-based image colorization.

The first exemplar-based method is the one proposed by Welsh *et al.* [3]. It is derived from the texture synthesis algorithm of Wey *et al.* [4] which uses image patch similarities on the intensity channel to provide colors. Such methods suffer from spatial consistency since each pixel is processed independently. Hence, Irony *et al.* [5] considered the diffusion step of [2] as a post-processing, in order to regularize the colors given by the exemplar-based approach. Recently, Gupta *et al.* [1] segments the image in order to guide the selection of examples and regularize the colors with [2]. The approach of Charpiat *et al.* [6] ensures a spatial coherency without a segmentation but involves many complex steps while Chen *et al.* [7] uses image matting. Finally, Bugeau *et al.* [8] presents a framework for exemplar-based colorization based on the minimization of a functional including a total variation (TV) regularization on the chrominance channels. Nevertheless their results are too drab, in particular near the contours, and a transformation in the YUV space is needed which can create colors that do not exist in the example images.

In this paper, we propose an extension of [8] that overcomes these issues. Our new model differs from the chrominance model [8] which suffers from a lack of coupling between the luminance Y and the chrominance channels (U and V) during the regularization. In our model the colorization is done directly in the RGB space with coupled channels. This permits to preserve colors, in particular near the contours. Up to our knowledge, our model is the first exemplar-based colorization algorithm using the RGB color space. Notice that the RGB space is only used in [9], [10], which are manual methods.

The paper is organized as follows: we first review the

chrominance model [8], then we present our new model with an efficient primal-dual like algorithm [11] minimizing the functional. Finally, the behavior of the method is presented with comparisons with the state-of-the-art methods.

2. REVIEW OF THE CHROMINANCE MODEL [2]

The authors of [8] chose to work in the YUV space in order to easily constrain the Y channel to be equal to the original target image. Hence, all the information present in the gray-scale image are preserved, *i.e.*, contours or textures. The method consists in only computing the two chrominance channels (U and V) of the colorized image. Together with the Y channel, it permits to recover a RGB image.

The method starts by extracting, for each pixel of the target image, 8 chrominance candidates c_i with $i = 1, \dots, 8$ by comparing patches around pixel and using different features (variance, cumulative histogram and magnitude of the DFT for different sizes of patches). To select one color between these 8 candidates, an energy-based method is proposed. To ensure the regularity of the resulting image u defined on the domain Ω , the model includes a TV regularization of the U and V channels. Let $u = (U, V)$ be the chrominance to compute and $W = \{w_i\}$ be the candidate weights, the model of [8] reads:

$$F_1(u, W) := TV(u) + \lambda/2 \int_{\Omega} \sum_{i=1, \dots, 8} w_i \|u - c_i\|^2 + \alpha \int_{\Omega} \sum_{i=1, \dots, 8} w_i (1 - w_i) + \chi_{u \in \mathcal{R}} + \chi_{W \in \Delta} \quad (1)$$

$$\text{where } TV(u) = \int_{\Omega} \sqrt{\sum_{C=U, V} \partial_x C^2 + \partial_y C^2} \quad (2)$$

$$\text{and } \Delta := \{(w_1, \dots, w_8) \text{ st } 0 \leq w_i \leq 1 \text{ and } \sum_i w_i = 1\}. \quad (3)$$

The set \mathcal{R} is the standard range for the chrominance and the characteristic function $\chi_{u \in X}$ is 0 if $u \in X$ and ∞ otherwise. The model is continuous, and the fidelity-data term is the transformation of a labeling problem into a continuous term by introducing a weight w_i corresponding to the probability of considering the color candidate c_i . The term $\int_{\Omega} \sum_{i=1}^8 w_i \|u - c_i\|^2$ makes the link between the candidate color c_i and the color u which will be retained. Each candidate is weighted, and the fidelity-data term can be close to a melting of two colors, which does not correspond to any color of the source image. To tackle this issue the weights w_i are forced to be close to 0 or 1 with the sum equal to 1. To this end, the term $\int_{\Omega} \sum_{i=1}^8 w_i (1 - w_i)$ is introduced. λ and α are parameters that weight the influence of the different terms of the model. The functional is not convex and may admit local minima.

3. RGB MODEL FOR COLORIZATION

The results presented in [8] are visually good but the methods still presents some drawbacks. The resulting images are drab

since if a strong regularization is used, the U and V channels become constant, and the image is close to a gray-scale one. Another problem which naturally arises is the lack of coupling in direction between color channels creating halos near strong contours. To couple the three color channels, we propose to work directly with the RGB space.

The chrominance model [8] is invariant with respect to the scene illumination but the method only retains the U and V values. The consequence is: with a given U and V , different colors can be obtained when varying Y (see Figure 2) and can produce colors with hues that are not present in the candidates data. It is therefore preferable to directly work with the three

Fig. 2. If U and V are constant, and Y variates, different colors are obtained.

channels. In this paper, we propose a RGB -model that is invariant with respect to the illumination. A main advantage of our approach is that a color space transformation at the beginning and the end of the algorithm is not necessary. In order to take into account all these elements, we introduce the following functional, where u is now a RGB image:

$$F_2(u, W) := TV_{RGB}(u) + \lambda/2 \int_{\Omega} \sum_{i=1, \dots, 8} w_i \|u - c_i\|^2 + \alpha \int_{\Omega} \sum_{i=1, \dots, 8} w_i (1 - w_i) + \chi_{u \in [0, 255]^3} + \chi_{Y(u) = I_g} + \chi_{W \in \Delta} \quad (4)$$

$$\text{where } TV_{RGB}(u) = \int_{\Omega} \sqrt{\sum_{C=R, G, B} \partial_x C^2 + \partial_y C^2}. \quad (5)$$

Two constraints are added to the original model: the colorized image should be between 0 and 255 and the second constraint is that the luminance of the colorized image should be the same as the target gray-scale image in order to preserve image textures. The luminance constraint is given by $Y(u) = A.u = I_g$ where $u = (R, G, B)$, I_g is the original luminance of the target image, and $A = (0.2990, 0.5870, 0.1140)$ allows recovering the luminance of a RGB color.

Minimization of the functional. In order to estimate a local minimum of (4), we consider a primal-dual algorithm [11] with respect to the variable u and a projected gradient update for the variable $W = \{w_i\}$ with time step $\tau_w > 0$. The process is summarized in Algorithm 1. The dual variable $Z \in \mathbb{R}^6$ is related to the TV regularization in the RGB space and P_B is the projection onto the unit ball of \mathbb{R}^6 . P_{Δ} is the projection onto the simplex Δ defined by (3) that can be computed using [12]. The term $(\|u - c_i\|)_i$ represents the array of the same size of W such that each weight is equal to $\|u(x) - c_i(x)\|^2$ for $i \in 1, \dots, 8$ and position $x \in \Omega$. Notice that if W is fixed, then the model is convex in u and the algorithm converges [13] if $24\tau\sigma < 1$.

The problem of luminance and range. The natural problem that arises when we want to implement the primal-dual algo-

Algorithm 1 Primal-dual like algorithm applied to (4).

- 1: $Z \leftarrow 0, W = 1/8$ and $u = \sum_i w_i c_i$.
 - 2: **for** $n \geq 0$ **do**
 - 3: $Z \leftarrow P_B (Z + \sigma \nabla u)$
 - 4: $W \leftarrow P_\Delta (W - \tau_w (\lambda (\|u - c_i\|^2)_i + \alpha (1 - 2W)))$
 - 5: $u \leftarrow P_G \left(\frac{u + \tau (\operatorname{div}(Z) + \lambda \sum_i w_i c_i)}{1 - \tau \lambda} \right)$
 - 6: **end for**
-

Algorithm 2 Algorithm computing projection P_G .

- 1: $X \leftarrow \frac{A}{\|A\|^2} (I_g - \langle X|A \rangle) + X$
 - 2: **if** $X \notin [0, 255]^3$ **then**
 - 3: **for** $i = 1 : n - 1$ **do**
 - 4: **for** $j = i + 1 : n$ **do**
 - 5: $\alpha \leftarrow \left\langle \overrightarrow{P_i P_j} | \overrightarrow{P_i X} \right\rangle / \left(\|\overrightarrow{P_i P_j}\|_2 \|\overrightarrow{P_i X}\|_2 \right)$
 - 6: **if** $\alpha > 1$ **then**
 - 7: $X_{i,j} \leftarrow P_j$
 - 8: **else if** $\alpha < 0$ **then**
 - 9: $X_{i,j} \leftarrow P_i$
 - 10: **else**
 - 11: $X_{i,j} \leftarrow P_i + \alpha \overrightarrow{P_i P_j}$
 - 12: **end if**
 - 13: **end for**
 - 14: **end for**
 - 15: $X \leftarrow \operatorname{argmin}_{X_{i,j}} \|X - X_{i,j}\|_2$
 - 16: **end if**
-

rithm is the projection of u onto its constraints through the operator P_G , *i.e.*, the computation of the proximal operator of $\chi_{u \in [0, 255]^3} + \chi_{Y(u) = I_g}$. This is equivalent to computing the projection onto the intersection of the cube $[0, 255]^3$ and the affine plane defined by $A.u = I_g$. There are four cases for this set. It can be a singleton, a triangle, a quadrilateral or a pentagon. To compute the projection we proceed in two steps. First, we compute the projection onto the plane, then we project onto the intersection of the cube and the plane. The projection of a point onto the intersection of the cube $[0, 255]^3$ and the affine plane defined by $A.u = I_g$ is given in Algorithm 2, assuming this intersection is a polygon defined by points P_1, \dots, P_n .

The main drawback of this projection is the change of hue of the color (the H channel of the HSI color space [14]) during the computation, because the plane $\{Y = \text{constant}\}$ is not orthogonal to the axis I oriented from the white to the black. In practice, the H channel is maintained constant during the projection by slightly modifying Algorithm 2 in order to consider an oblique projection that preserve the hue. For the sake of simplicity, this projection is not detailed here (see [15] or [16] for more details).

4. NUMERICAL RESULTS

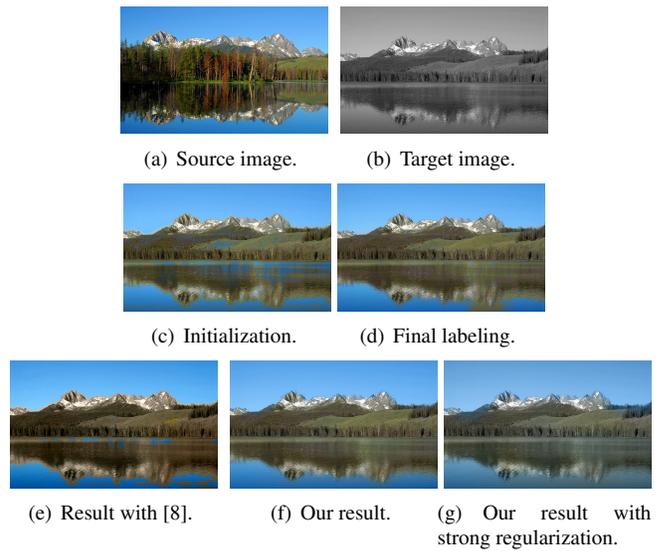


Fig. 3. Results with different regularization, with initialization and with data term at convergence. See text for details.

Figure 3 shows the details of a first colorization. Figure 3(c) is the initialization of the algorithm: $u = \sum_i c_i / 8$. The result obtained by our method is presented in Figure 3(f). Resulting colors are visually close to the ones of the source image (Figure 3(a)). Our approach improves visually the result obtained with the chrominance model [8] (Figure 3(e)). Indeed, the contours with our method are better preserved and we are able to recover some green on the hills. This confirms that the regularization term must couple all the three channels of color to have a good preservation of shapes. It is worth mentioning that our algorithm also provides a regularized labeling of the discrete original problem which is the choice of a candidate for each pixel. This is illustrated in Figure 3(d) that presents the labeling image $u = \sum_i w_i c_i$ after convergence of the algorithm. Finally notice that the images are drab when a strong regularization is used ($\lambda = 10^{-7}$), see Figure 3(g). If the regularization is weaker, the images are shinier and visually close to the obtained labeling (Figure 3(d)). In natural images a good parameter is about $7 \cdot 10^{-3}$.

The minimization of the functional with respect to u improves the quality of contours and prevents stains in constant regions of the image. Figure 4 shows experimental results compared to the state-of-the-art methods. On the left, the source and target images are shown. Our results are in the third column and other columns are results from [1], [5], [3] and [6] (these results have been directly taken in the article [1]). The results of [5] and [6] are not good although their algorithms need many steps. Due to the lack of regularization, images of [3] present artefacts where areas that were originally homogeneous now present irregularities. Our algorithm better preserves the homogeneous parts as the sky.

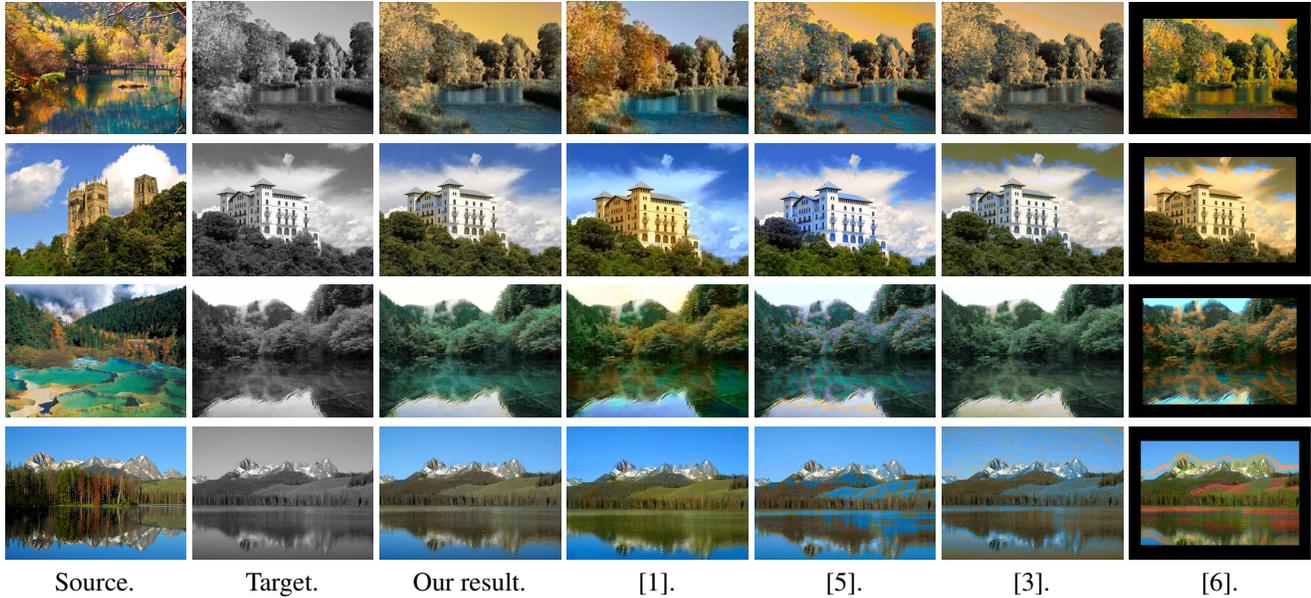


Fig. 4. Comparison with state-of-the-art methods. On the left, the source and the target images. Results of our method on four images, compared with the results of the state-of-the-art methods [1], [5], [3] and [6] (images taken from [1]).

The quality of our results are comparable to [1] whereas our algorithm is much simpler since local segmentation like superpixels [17] is not needed. Currently, our is faster, but we expect to speed-up it more with discrete optimization methods.

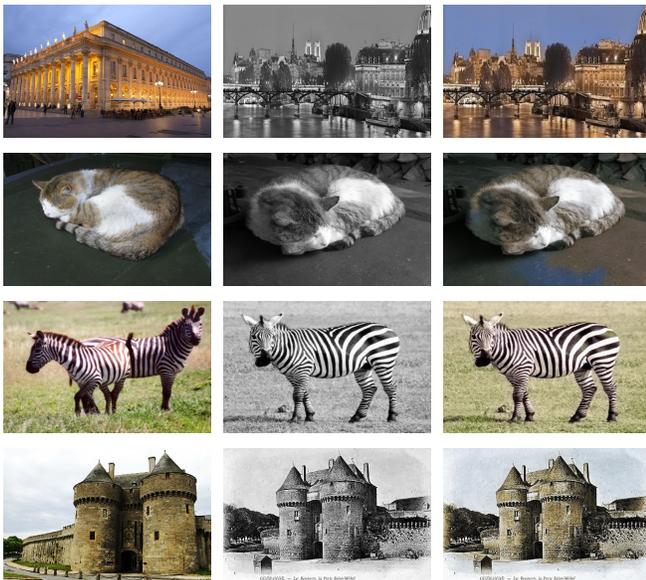


Fig. 5. Additional results.

Figure 5 present additional results. They show that our method is efficient and competitive in order to colorize gray-scale images with examples. Finally, Figure 6 highlight the influence of the source image on the colorization result. Us-



Fig. 6. Influence of the source image.

ing several source images could improve the quality of all the results and is directly feasible with the described method.

5. CONCLUSION AND FUTURE WORKS

In this paper a new model for exemplar-based colorization in the RGB color space has been described. The regularization is provided by the minimization of the coupled total variation of color channels. An efficient algorithm solving the proposed model has been given. This new approach extends and improves the chrominance model [8]. The resulting images are less drab, the color are better preserved and the contours are well colorized. In futur works, we plan to extend the method to integrate manual colorization, and to investigate the choice of good metrics for searching color candidates.

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