Fully automatic coloring of grayscale images

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Abstract

This paper introduces a methodology for adding color to grayscale images in a way that is completely automatic. Towards this goal, we build on a technique that was recently developed to transfer colors from a user-selected source image to a target grayscale image. More specifically, in order to eliminate the need for manual selection of the source image, we use content-based image retrieval methods to find suitable source images in an image database. To assess the merit of our methodology, we performed a survey where volunteers were asked to rate the plausibility of the colorings generated automatically for grayscale images. In most cases, automatically-colored images were rated either as totally plausible or as mostly plausible.

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1. Introduction

Adding color to grayscale images and movies in a way that seems realistic to most human observers is a problem that greatly challenged the motion picture industry in the 1980s and has recently attracted renewed interest within the computer graphics community [1]. While coloring of historic photos and classic movies has usually been done with the purported intent of increasing their visual appeal, there are certain coloring techniques—such as luminance-preserving pseudo-coloring—that have been specifically developed to facilitate the visualization of scientific, industrial and security images [2,3].

In any of those cases, the coloring problem amounts to replacing a scalar value stored at each pixel of a grayscale image (e.g. luminance) by a vector in a multi-dimensional color space (e.g. a three-dimensional vector with luminance, saturation and hue). Thus, this is in general a severely under-constrained and ambiguous problem for which it makes no sense to try to find an optimum solution, and for which even the achievement of reasonable solutions requires some combination of strong prior knowledge about the scene depicted and decisive human intervention. In this article, we present a methodology to color grayscale images in a fully automatic way that compensates the lack of human intervention by using a database of color images as a source of implicit prior knowledge about color statistics in natural images.

The invention of colorization—the process of ‘enhancing’ monochromatic movies through the addition of color—is widely attributed to C. Wilson Markle, whose company colorization, Inc., released the first full-length colorized movie in August 1985. Although colorization became a very profitable business by the late 1980s, the technology used at that time was painstakingly manual and, thus, expensive and time-consuming. For instance, the colorization of the classic movie Casablanca in 1988 took more than two months and nearly US $450,000 to complete, in a process that involved—among many other labor-intensive steps—researching historical wardrobe notes from the original movie’s set to discover the specific colors that the actors and actresses wore in most of the scenes [4]. Eventually, as the novelty of colorization wore off and audiences dwindled, such high costs grew unsustainable and colorization of classic movies became an unfashionable and generally unprofitable activity. In reality, colorization of artworks such as Casablanca has always been a very controversial subject with delicate moral, ethical and legal implications [5].

However, there are nowadays more ‘mundane’ applications that could benefit from fully automatic, inexpensive, efficient colorization techniques, even if these techniques turn out to be
somewhat less reliable than those used in the 1980s. For instance, some off-the-shelf camcorders that are widely used for recording of domestic videos have near-infra-red illumination and imaging capabilities. A fully automatic, real-time colorization software would be a tool of great interest to the users of these cameras, which could enhance the value the cameras’ near-IR features. Even techniques that work only with static pictures—such as those that we will present in this article—can be used to increase the visual appeal of scientific, educational and commercial presentations (and of some domestic pictures), by adding color to various types of single-band images, such as those obtained with X-rays, MRI, CT, ultrasound, electronic microscopy, and near-IR, thermographic and UV cameras.

In the real-time colorization scenario above, traditional techniques where segmented image regions are hand-colored one by one are grossly inadequate. An important step towards minimizing the amount of human intervention needed to color grayscale images was the recent work of Welsh et al. [1], who developed techniques to transfer the chromatic information from a source color image to a target grayscale image. Unfortunately, empirical evidence suggests that the degree of similarity between these source and target images has a strong influence on the quality of the results obtained. Thus, the quality of colorings obtained with the techniques developed by Welsh et al. is, in principle, still strongly dependent on human selection of an appropriate source color image for each given grayscale image.

Here, we move another step towards automatic coloring of grayscale images, with a methodology where source color images are automatically selected from an image database. More specifically, we designed, implemented and experimentally assessed four techniques to choose images from a database, without any human intervention, to be used as source images in color transferring. These techniques leverage on some of the most traditional ideas on the very active area of content-based image retrieval.

1.1. Related work

Content-based image retrieval is a scientific discipline that has experienced fast transformations in the last few years [6,7,8]. The early approaches to this problem were based on the use of predefined, non-selective (global) features such as color [9] and texture histograms [10] and color correlograms [11]. When this kind of feature is used, all pixels in an image contribute equally to determine the image’s signature, which results in algorithmic simplicity and computational efficiency. In this paper, we use approaches along this line, in order to show that even very simple content-based image retrieval techniques have the potential to generate good results when used as the basis for automatic image coloring.

Unfortunately, the global nature of these approaches makes them oversensitive to background clutter and, more importantly, it creates a large gap between the high-level concepts that human beings use to describe images and the low-level features that are measured directly from the images in order to construct their signatures [12,13]. Much of the recent research in content-based image retrieval has been directed towards the daunting task of closing this gap, by using highly-selective, spatially-localized features [12,14,15] and/or by employing feedback from users in order to assign weights to various available features in a way that is statistically optimal [13,16,17]. The use of these ideas and techniques within the context of automatic image coloring is a promising direction for future work.

In a broader context, our work is related to a recent surge of interest on the general problem of transferring properties from one image (or movie) to another. For instance, Hertzmann et al. [18] developed a technique that can learn various types of filtering transformations from pairs of images and then apply the learned filters to other images that, as a result of the process, inherit properties from the original images. In addition to this general technique, a variety of methods specifically tailored for transferring a single property such as radiometric texture [19], geometric texture [20], illumination [21] or motion [22] exist. In particular, Reinhard et al. [23] and Greenfield and House [24] have recently introduced methods for transferring color between images. However, they assume that the target images already contain chromatic information and one merely wants to change this information in some meaningful way, which is a problem that is in general easier than the one we address in this article.

This article is organized as follows: Section 2 discusses how content-based image retrieval and color transfer techniques can be combined to create a fully automatic image coloring system, Section 3 describes the four image retrieval techniques that we selected for evaluation in this context, Section 4 deals with the color transfer step, Section 5 describes the experiments and analyzes their results and Section 6 lists the conclusions and future works.

2. Overview of image coloring system

Figs. 1–3 illustrate the proposed methodology to color a grayscale image using information from a database of color images. Initially, it is necessary to index the database by performing some type of ideally semantics-preserving compression [25] of each image in the database into a signature vector that must be as small as possible, in order to maximize the efficiency of queries to the database later on. Since, these signature vectors will eventually be compared against those of the grayscale images passed as input in the queries, they are extracted solely from the luminance component of each color image in the database (Fig. 1).

Once signatures for all images in the database have been collected, the database is ready to start answering queries. Each grayscale image received in this phase is similarly reduced to a signature vector. Using a predefined similarity metric, this signature is then compared to those stored in the database index and the content of the database image with the most similar feature vector is returned (Fig. 2).

Finally, the color transfer process takes two images, the grayscale one passed as input in the query and the color one
returned as the query answer, and adds to each scalar pixel of the former, the chromatic components of an automatically chosen pixel of the latter. The actual results of this process, using one of the retrieval techniques described in Section 3, the color transfer process described in Section 4, and images from the database described in Section 5, is shown in Fig. 3.

3. Image retrieval techniques

In this article we study four techniques—luminance histogram, luminance subsampling, luminance + gradient histogram, and luminance + gradient subsampling—to select automatically the source image for color transfer. As explained in Section 2, all of them build database indices that depend exclusively on the luminance component of the database images. Thus, we start this section by describing a preprocessing step common to all these techniques: the decomposition of source images in a component that has only luminance information and two mutually uncorrelated chromatic components. Then, on separate subsections, we focus on the particular aspects of each one of these four techniques: the way in which they process the luminance information to create the image signatures. In a final subsection, we describe another common point among all techniques in study: the way in which they compare feature vectors, once all such vectors have been assembled.

3.1. Conversion to the \textit{l}ab color space

The \textit{l}ab color space was proposed by Ruderman et al. [26], as a result of an analysis of the statistics of human photosensor responses to natural images. More specifically, it was observed that while the responses on the bands of the three types of cones...
present in the human eye are strongly correlated, if these responses are converted to the \( la\beta \) space, the existing correlation disappears. Reinhard et al. [23] realized the implication of this for color transfer: by converting images to the \( la\beta \) space, each one of these channels can be altered independently, with low occurrence of undesirable cross-channel artifacts. In the case of transferring color for graylevel images we do not necessarily need independence between the two chromatic channels, but conversion to the \( la\beta \) space is still and effective way of decoupling luminance from all chromatic information.

In addition, the \( la\beta \) space has a property that is very useful in the case of image databases: because it is logarithmic, it is not affected by gamma correction [23], a non-linear transformation that is often applied to images to improve exhibition in monitors. Because this transformation has a parameter that may vary from image to image, it is prone to cause trouble in linear color spaces.

Thus, we preprocess every database image by converting it to the \( la\beta \) space, where the \( l \) component is a measure of luminance, \( \alpha \) measures variations in the green–red chromatic axis (with positive values meaning red and negative ones meaning green) and \( \beta \) measures variations in the blue–yellow axis (with positive values meaning yellow and negative meaning blue). More specifically, each image originally coded in the RGB space is initially converted to the LMS space, which corresponds to the bands of sensitivity of the human cones and was thus used by Ruderman et al. as the basis to define the \( la\beta \) space. This initial transformation corresponds to a multiplication by a \( 3 \times 3 \) matrix, as expressed in Eq. (1):

\[
\begin{bmatrix}
L \\
M \\
S
\end{bmatrix} = \begin{bmatrix}
0.3811 & 0.5783 & 0.0402 \\
0.1967 & 0.7244 & 0.0782 \\
0.0241 & 0.1288 & 0.8444
\end{bmatrix} \begin{bmatrix}
R \\
G \\
B
\end{bmatrix}.
\] (1)

The conversion from LMS to \( la\beta \) is then performed through the sequential application of the logarithmic transformation expressed in Eq. (2) and the linear transformation expressed in Eq. (3):

\[
\begin{bmatrix}
L \\
M \\
S
\end{bmatrix} = [\log L, \log M, \log S],
\] (2)

\[
\begin{bmatrix}
l \\
\alpha \\
\beta
\end{bmatrix} = \begin{bmatrix}
1/\sqrt{3} & 0 & 0 \\
0 & 1/\sqrt{6} & 0 \\
0 & 0 & 1/\sqrt{2}
\end{bmatrix} \begin{bmatrix}
1 & 1 & 1 \\
1 & 1 & -2 \\
1 & -1 & 0
\end{bmatrix} \begin{bmatrix}
L \\
M \\
S
\end{bmatrix}.
\] (3)

Finally, after the color-space conversion is finished, a 128-level quantization is performed on each channel.

### 3.2. Luminance histogram

The use of similarity between intensity histograms as a relevant criterion to perform content-based image retrieval is a well-established idea [9] that has been used in a myriad of works. Thus, its choice as one of the methods to be evaluated in the various image databases is a natural one. Formally, the histogram of an \( m \times n \) monochromatic digital image \( I \) is a discrete function that maps each value \( k \) in the image’s intensity range to the fraction of pixels in image \( I \) that have intensity \( k \)

\[
h_I(k) = \frac{|\lambda_I(k)|}{m \times n},
\] (4)

where \( \lambda_I(k) = \{(x, y): I(x, y) = k\} \), and \( I(x, y) \) is the intensity of pixel \((x, y)\) in image \( I \).

Here, we use this function to generate image signatures by applying it to the \( l \) channel obtained after the color-space conversion described in Section 2. The only precaution that we have to take is to perform a linear normalization of the channel before computing its histogram, to factor out fluctuations in the illumination conditions under which the various images were acquired and the effects of gamma correction [23]. Since, we defined that the \( l \) channel admits 128 possible values after the post-conversion quantization, its histogram will consist of a vector of 128 pixel counts, scaled to unit \( L_1 \) norm. Moreover, since the \( l \) band is uncorrelated with the chromatic bands, comparable histograms can be computed for the graylevel images received as queries, as long as they are preprocessed with a logarithmic transformation followed by a linear normalization.
Thus, for each image in the database, a signature that consists of the 128 values of its luminance histogram is created (Fig. 4). By comparing each of these signatures against the one obtained from a query image and selecting the best match, the color image that will be used as the source for coloring the query image is identified.

3.3. Luminance subsampling

Another quite intuitive and broadly-used way of compressing an image into a signature is plain subsampling. In this technique the properly preprocessed (i.e. quantized, linearly normalized) \(L\) channel is convolved with a low-pass filter, the resulting image is divided in a regular grid of 128 regions of the same size, and the mean intensity within each such region is computed. Contrary to histograms that are invariant to the positions and orientations of the various objects within an image, subsampling preserves information related to the spatial distribution of intensities within the image—which is widely regarded as an important piece of information in image retrieval [11]—but on the other hand it obliterates all clues about the existence or not of fine texture in an image. The process of creating signatures through luminance subsampling is illustrated in Fig. 5.

3.4. Luminance + gradient histogram

Texture is a property with high semantic content in many application domains [10]. In order to ameliorate the loss of this information in luminance histogram and, especially, in luminance subsampling, we considered the use of signatures that are computed not only from the luminance channel, but also from its spatial gradient.

One technique to generate these signatures uses what we call a luminance + gradient histogram. It starts by convolving the luminance image with a Sobel kernel, to estimate the image’s spatial gradient. Then, it computes histograms both for the luminance image and for its gradient, but this time considering a coarser quantization of only 64 values on each image, so that signature size does not need to be increased. The final signature for each image is then obtained simply by a concatenation of the normalized pixel counts from the two histograms, in a predefined order (Fig. 6).

3.5. Luminance + gradient subsampling

The last technique studied also aims at preserving information about fine textures in the image signatures, but it combines gradient extraction with subsampling rather than with histograms. Once more, the luminance image is initially convolved with a Sobel kernel, but now the pre- and post-filtering images are simply subsampled to a size of \(8 \times 8\) pixels each. The two 64-element vectors formed by the pixels of these
subsampled images are then simply concatenated to generate a signature that has the same number of bits than those generated by the other three techniques (Fig. 7).

3.6. Similarity metric

Regardless of which of the techniques described in the previous four subsections is used, the criterion used to compare the image signatures and thus to determine the best match is the same: the correlation between the query and database signature vectors, calculated using their internal product

\[
\text{match}(Q) = \arg\max_i \frac{q \cdot d_i}{||q|| ||d_i||},
\]

where \(Q\) and \(q\) are, respectively, the query image and its signature, and \(d_i\) is the \(i\)-th signature in the database.

4. Transferring color to grayscale image

Once an appropriate source color image has been selected for a given target grayscale image by one of the techniques described in Section 3, we use the method of Welsh et al. [1] to transfer the chromatic information from the source to the target image, while keeping the luminance of the latter unchanged.

Welsh’s technique compares small pixel neighborhoods on the luminance channels of the source and target images, in order to try to identify, for each pixel in the target image, a matching pixel in the source image that has similar neighborhood statistics. Thus it also requires a conversion of all database images to the \(la\beta\) color space. However, since this conversion is already done a priori, during the indexing of the database, this is actually a trivial requirement.

To speed up the pixel-to-pixel matching process, the method considers only a very sparse set of pixels in the source image—typically around 200 pixels selected by jittered sampling. The target image is scanned in scan-line order so that, for every one of its pixels, the source sample that is closest in terms of intensity value (50% weight) and intensity standard deviation within the surrounding \(5 \times 5\) neighborhood (50% weight) is selected as a match. To create better correspondence between the two images, luminance remapping [18] is performed. This linearly shifts and scales the luminance histogram of the source image to fit the histogram of the target image. Once the best source pixel is identified for a given target pixel, the \(\alpha\) and \(\beta\) values of the former are added to the latter, which eventually leads to the complete coloring of the target image. This approach reportedly works well on image pairs where luminance correspondence between neighborhoods is correlated with color correspondence.

However, since there are quite a few image pairs that, in spite of being semantically close, do not satisfy this requirement, Welsh et al. [1] also developed an interactive variant of their technique where pairs of matching source and target image swatches are hand-picked by a human operator. Once the target swatches are colored with the \(\alpha\) and \(\beta\) channels of the source swatches, colors can be propagated to the rest of the target image with texture synthesis techniques [27,28]. Obviously, this in general yields more convincing results than automatic coloring, but the need for human intervention eliminates the possibility of using this alternative process in real-time video applications, for instance. So, we did not perform any experiments involving manual selection of swatches. Nonetheless, there is nothing in this alternative scenario that prevents the use of any automatic source image selection technique that we have discussed so far. We simply regard this as a topic for future work.

5. Experimental evaluation

In order to assess the four techniques in study, we used them with the same database of natural images, developed at the Ecole Nationale Superieure de l’Electronique et de ses Applications (ENSEA), France. This database has 14 semantically distinct classes, with a total of 1200 color images of natural scenes (Fig. 8). The query images were also taken from the same database but, of course, each image submitted in a query was temporarily deleted from the database while the query was processed.

The tests were conducted in three phases. In the first phase, we observed the results produced by the four techniques on the coloring of a subset of the database. Based on these observations we made certain hypotheses about the behavior and appropriateness of the techniques for different types of images. In the second phase, these hypotheses were validated on queries with a distinct subset of the database, whose results were presented to over 40 volunteers, who were asked to grade them according to their plausibility. Finally, in the third phase, we tested the sensitivity of each technique in study with respect to the size of the signatures used to index the image database.
5.1. Preliminary experiments

More specifically, in the first phase we chose one image of each class. Since, classes have different numbers of images, a number \(i\) between one and six (the smallest number of images presented in a class) was randomly selected and the \(i\)-th image of each class was selected to be colored automatically. By observing the results obtained in this phase, we noticed that the methods that do not use information derived from the image gradient tended to work much better in uncluttered scenes, where there is a single object in the foreground and this object is clearly discernible from a mostly homogeneous background. We named the set of all database images that conform to this loose description the *homogeneous* group, and the set of images that do not conform to it (and thus have multiple objects on the foreground, or have a cluttered background, or are illuminated in an uneven way) the *heterogeneous* group. We also observed that the methods that do use image gradients tended to outperform their counterparts in these more complex, heterogeneous images.

5.2. Evaluation by volunteers

Based on this preliminary assessment, we selected 15 new query images from the database, at random. Seven of these 15 images were classified as *homogeneous* and eight of them were classified as *heterogeneous*. For each technique, and for each one of the 15 images, we obtained the resulting color-enhanced image by applying the color transfer method described in Section 4. We developed a web site to assess the plausibility of the resulting colored images. Each volunteer that accessed this site was asked to choose among four possible classifications for each image, as shown in Fig. 9. In addition each volunteer was also shown eight ‘placebo’ images that had real colors and had never been colorized, as well as eight images colored using randomly-chosen color sources.

From the votes cast for each image, we computed net statistics on the plausibility of the output of each method. As one can observe in Fig. 10, all four techniques produce images that are not as good as real color images but are still much better than those obtained by transferring color from a randomly selected source. Among the four methods, the ones that do not use gradients have a slight edge in plausibility.

If we look specifically at the images in the *homogeneous* group (Fig. 11), then the results generated with the luminance histogram are noticeably better than the ones generated with the other three methods. This is reasonable: since the homogeneous images do not vary much, spatial location of the colors within them matters less than in the *heterogeneous* group and the gradient carries little information.

An example of coloring of an image in this group is the picture with the set of fighter planes displayed in Fig. 3. Luminance histogram matching identifies the picture of a commercial jet as a good source for color transfer in a large part due to the blue background that corresponds to the sky. This blue hue is then correctly transferred to the query image’s background (notice the dark \(\alpha\) and \(\beta\) channels in most of the resulting image). Of the 41 people that evaluated this image, 29 votes were for *totally plausible*, 10 votes for *mostly plausible*. 

![Fig. 9. Partial screen capture from the coloring evaluation website.](image)

![Fig. 10. Breakdown of votes for each technique, on all 15 images.](image)
votes for *mostly implausible* and no one thought it was *totally implausible*.

In the *heterogeneous* group (Fig. 12), on the other hand, the high-frequency intensity variations that exist in the images are semantically relevant and, consequently, the techniques that use image gradients to construct signatures in general produce better results than those that do not use this kind of information.

Examples of how the luminance histogram and the luminance + gradient subsampling techniques perform on this type of image are given in Figs. 13 and 14, respectively. Because of the strong illumination in the background, luminance histogram matching returns the image of a polar bear, which generates a final coloring with very little saturation, evaluated as *totally or mostly plausible* by only 1 and 8 voters, respectively, out of a total of 42. Luminance + gradient subsampling, on the other hand, finds a picture that is not only of lions, but also has the same kind of non-uniform illumination, generating a more saturated coloring that is classified as *totally or mostly plausible* by most respondents.

In addition, in the *heterogeneous* group there are more images in which the spatial localization of various intensities has a high semantic content. A classic example of this type of image are the sunset scenes, which are generally composed of a small central region with very high intensities (the sun), a large top region with medium-to-high intensities (the sky) and a large bottom region with low intensities (the ground). For such images, subsampling-based techniques are more appropriate than histogram-based ones.

Examples of what happens when the luminance histogram and luminance subsampling techniques are used in the coloring of a sunset image are shown in Figs. 15 and 16, respectively. Matching based on the luminance histogram returns an image of a red car whose beams have roughly the same intensities as the sun in the query, and whose body looks like the sky in the query, intensity-wise. The resulting color transfer was evaluated as totally or mostly plausible by only three and 10 voters, respectively. Using luminance subsampling, on the
other hand, images with distinct spatial distributions of colors no longer match and the answer to the sunset query is another sunset image, which results in a color transfer that was totally or mostly plausible for 12 and 19 respondents, respectively.

Hence, because both spatial localization of intensities and intensity gradients matter in the heterogeneous group, the luminance + gradient subsampling—which is the only evaluated technique that incorporates both these pieces of information into image signatures—is the technique that performs better in that group.

5.3. Sensitivity to signature size

All experiments reported in Sections 5.1 and 5.2 were performed with signatures of a predefined, fixed size of 128 bytes. In order to verify if the results obtained can be generalized to signatures of other sizes, we performed additional experiments with signatures of smaller sizes (32, 64 bytes) and larger sizes (256, 512 bytes). The goal in these experiments was only to measure how much query results vary with signature sizes. Thus, in this last phase, human volunteers were not used.

More specifically, in this last round of experiments, each of the fifteen queries that had been made (per technique) with 128-byte signatures (Section 5.2) was repeated with each of the other four signature sizes mentioned above. In order to estimate the sensitivity of each technique with respect to the size of the signatures, we recorded—for each new query performed—the rank (among the 1200 images in the database) of the image that had been the top-ranked answer with the old signature size (128 bytes).

If all new ranks computed by a given technique in this experiment were equal to one, then the image-coloring results obtained with this particular technique would be invariant to the changes in the signature size considered. However, this ideal situation seldom occurs. Hence, for each of the four techniques tested, for each of the four new signature sizes considered, for each maximum rank \( K = 1, \ldots, 10 \), we computed the percentage of queries in which the formerly top-ranked image was still among the \( K \) top-ranked images after the change in the signature size. The values of this sensitivity metric for the luminance histogram, luminance subsampling, luminance + gradient histogram and luminance + gradient subsampling techniques are shown in Figs. 17–20.
ring with techniques from the very active area of content-based image retrieval, in order to use an entire image database as the color source, rather than an individual user-selected image. While this methodology still produces some grossly miscolored images, we have to stress that in many applications automatic coloring is not meant to replace techniques that rely on human intervention completely, but only to reduce the number of images where these more labor-intensive techniques have to be applied. For instance, if an image generated automatically is found to be mostly plausible, perhaps all that the user needs to do is to go ahead and change the color in one or two segmented regions manually, which will take much less time than a fully manual coloring of the entire image.

Moreover, we have found that different techniques are appropriate for different types of images. Thus, there is a lot of room for improvement if we look deeper into the vast literature on content-based image retrieval, and incorporate the various state-of-the-art techniques in this topic within the framework that we proposed here.

6. Conclusion

In the current article we have demonstrated that it is possible to color many grayscale images in a way that is completely automatic and looks plausible to most people. The proposed coloring methodology blends existing works on color transferring with techniques from the very active area of content-based image retrieval, to color many grayscale images in a way that is completely automatic and looks plausible to most people. The proposed methodology still produces some grossly miscolored images, we have to stress that in many applications automatic coloring is not meant to replace techniques that rely on human intervention completely, but only to reduce the number of images where these more labor-intensive techniques have to be applied. For instance, if an image generated automatically is found to be mostly plausible, perhaps all that the user needs to do is to go ahead and change the color in one or two segmented regions manually, which will take much less time than a fully manual coloring of the entire image.

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