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Multilevel Color Transfer on Images for Providing an Artistic Sight of the World

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ABSTRACT This paper represents a twofold approach. On the one hand, we introduce a simple method that encompasses an ensemble of image processing algorithms with a multilevel color transfer approach at its core. On the other hand, the method is applied for providing an artistic look to standard images. The approach proposes a multilevel color transfer in a chromatic channel of the CIELAB color space. Once converted from red, green and blue, a specific channel on both images, input and target (reference), is thresholded in a number of levels. Later, the color transfer is performed between regions from corresponding levels using a classical color transfer method. In the application phase, the color palette of a recognized artwork of the Fauve movement is mapped to the input image, emulating the sight of the artist, characterized by the use of vivid colors. Filtering techniques are applied to the outcome, in order to emulate the basic brushstrokes of the artist. Experimental results are shown, visualizing and comparing the input images with the outcomes.

INDEX TERMS Digital image processing, painting emulation, visual arts, fauvism.

I. INTRODUCTION

Color is an important cue of our visual world and one of the most important features of images used in art, photography, visualization and computer vision tasks. If colors in an image are modified, it is possible to simulate distinct lighting conditions, alter the overall emotion perceived when looking at a scene, or achieve some stylistic and artistic effects [1].

Color transfer or color mapping is an image processing technique where dominant colors in a target image should be transferred to a source scene usually with distinct chromatic content. An ideal color transfer algorithm should keep the scene in the source image and apply the color style of the target image. This procedure is similar in a wide range of applications ranging from personal photo enhancement to movie post-processing in accordance with the user interest: making the appearance of renderings more realistic, creating artistic appearance, or the processing of medical imaging. Thus, it is not clear which methods are best suited for particular purposes, or even what can really be achieved with this kind of solution.

There are three main strategies used for color transfer between images: geometric-based methods, user-aided solutions, and statistical approaches. In geometric-based methods [2], the transfer of aspects of color rendition from one image to another can be facilitated by searching for corresponding features that are depicted in both images. By actively finding correspondences between pairs of images, the color transfer algorithm can better ensure that features that occur in both images end up having the same colors. When the structure and content of the input image is very different from that of the reference or example image, many automatic methods will fail to find a successful mapping. In such cases, it may be required the application of an input from the user in order to guide the correspondences between the source and reference; these methods are referred to as user-aided solutions [3]–[5]. When direct correspondences between image features are not available, approaches using statistical properties are often used to define a mapping between the two input images [6]–[12].

A global color transfer between images could not be adequate in some tasks due to the following problem. If the images considered in the transfer contain contrasted color regions, the global statistics combine the colors from these different regions. Therefore, the result will present colors which not necessarily correspond to the reference image. Local color transfer methods can correct the aforementioned errors to some extent, but cannot solve all problems without an efficient clustering method. All these methods segment the images in different regions or objects. Later, the color mapping is performed between segments or using predefined look-up-tables. The problem with these solutions is on the complexity used for the segmentation of regions. Example of these techniques are: Expectation-Maximization [13], manual selection of regions [14], dominant-colors extraction [15], [16], based on weighted coefficients [17] and segmentation by texture similarity [18]. Despite the large number of developed methods, there is still open and interesting research in this area in order to improve color transfer solutions.

At this point, we observe that a number of studies in the image processing field have been related to artwork analysis. Applications are mainly oriented to detection of brushstrokes [19]–[21], analysis of paintings for artist identification [22]–[24], and painting categorization [25], [26] including the learning of the painting styles [27], being the goal of the present work far from the scope of these applications. Concerning artwork emulation, we must refer to [28], a highly complex method yielding impressive results by the use of deep neural networks. We also have the commercial Prisma App [29] for transforming photos and videos into artworks.

Our application requires a color mapping between target and input images, without any knowledge about correspondence of color content or geometric features. We propose a simple and fast approach to artwork emulation. Our method is based on the Reinhard *et al.* [6] color transfer, considering its excellent previous results and its simplicity. That approach computes global statistical moments from both input and target images, in order to transfer them from target to input. Despite the simplicity of the method, this technique can be successful for a large variety of images, but the quality of the results relies on a careful selection of the reference image. For this reason, we propose a modification on the method, applying the transfer over local regions in a perceptual color space. Features of the CIELAB make it a natural choice for performing our task, as results obtained in [30] suggest, a fact that is corroborated in our exhaustive experimentation. Further comments about CIELAB will be given on Section 3A.

In our proposal, the source and target images are thresholded in multiple levels of a specific chromatic component. Then, the color transfer is performed between each corresponding level using the aforementioned method. Although there exist a number of works addressing the local transfer, our approach has the advantage of using simple and traditional image processing techniques.

Since color is one of the most important components of art, we focus on images created in the 19th century when color hue was used as the core of creation and inspiration. Therefore, it was considered to explore images from the Fauvism, because this artistic trend exhibits highly contrasted and saturated colors. We think the proposed methodology is well-suited for transferring features from artworks of the Fauve trend according to the following reasons. Firstly, fauvist painters segment their compositions in solid and well-delimited colors (degradation is not present). The multilevel thresholding, using a color component, produces segments well-delimited and the color transfer between them provides solid colors. Secondly, the Fauve trend presents as main feature the use of pure and unnatural colors. Because thresholding is an unsupervised method, it can segment objects or regions into two or more parts. This effect allows the creation of unnatural colors in such objects after the transfer. More comments on fauvist art will be given in the next section.

The rest of this paper is organized as follows. A description about art and the importance of color in the Fauve trend is presented in Section II. In Section III, the methodology for the implementation is introduced. Comments on some tasks from the digital image-processing domain, like the color transfer, transformations between color spaces and artistic effects, are included in this section. In Section IV, experimental results obtained after the application of the method show it is appropriate for the emulation of fauvist artworks. Finally, some concluding remarks are provided in Section V.

II. NOTES ON COLOR IN THE FAUVE TREND

Talking about art and its components, color is one of the most important aspects. It has been used since the first human aesthetic expression, and that is why it is said that color is one of the basic elements of artistic composition. Color relevance is established by the end of the nineteenth century, when it turned a fundamental issue for artists, and began to be seen, not as a component of the works, but as the core of creation and inspiration. Furthermore, color is considered as the essence of painting and this has value by itself. Colors inspire emotional associations; emotions that sometimes cannot be expressed in language [31]. In this sense, Wittgenstein observed: *"when we're asked "what do the words 'red', 'blue', 'black', 'white' mean?" we can, of course, immediately point to things which have these colours, –but our ability to explain the meanings of these words goes no further!"* [32]. For the rest, we have either no idea at all of their use, or a very rough and to some extent false one.

In other words, the language can determine the way we express the experience of color, but color and language are needed to determine the chromatic experience. This leads us to believe that colors are the result from the language through the influence of culture. Now, as it refers to the use and importance of color in the art, we can mention that the color was projected for the first time since the shape reached its limit at the post-impressionism. That is to say, when Cezanne, Gauguin and Van Gogh, allowed the color and marks on the canvas bring out the power of expression [31].

We have chosen to explore the Fauve trend, because this artistic movement has very particular characteristics, with color as the core element in the artwork. Fauvist painters were those who received teachings of Gauguin. Commanded by Matisse, the Fauvist captured the power of color taking it one step further [33]. The Fauvism, despite being a short-living artistic movement, revolutionized the concept of color in art,

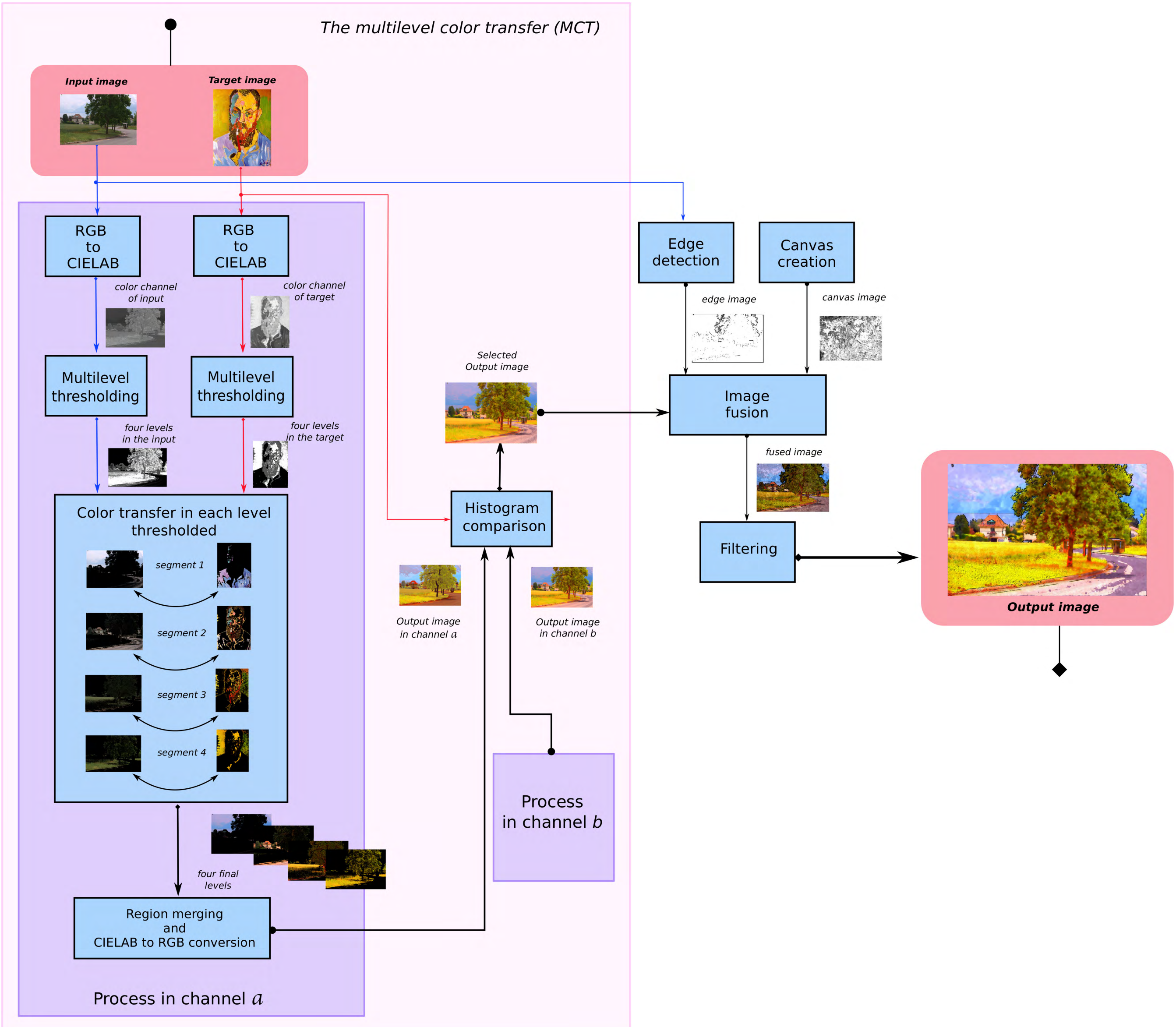


FIGURE 1. Schematic diagram for the color transfer process.

since fauvism used color as the vehicle for its expressive power and gave an essential vitality to transmit the message. Particularly, the Fauvism is considered the earliest of the so-called "isms" and, in this sense, is the key that opens the panorama of the vanguards of the twentieth century. The essence of this movement lays in the combination of bright colors, with a vivid appearance, but combining and balancing the masses. Therefore, the Fauvist vision was expressed in violent colors, involving and preferring the use of primary colors and complementary ones [34], but being a calm and relaxed vision at the same time [33].

III. METHODOLOGY

The method under discussion is based upon a number of algorithms related to the digital image processing field. Color transfer, multilevel thresholding, edge detection, and filtering, are some procedures used in this approach. The framework includes a number of processing blocks, shown in Figure 1 and described firstly in an algorithmic way, and later in detail.

A red, green and blue (RGB) to CIELAB conversion is used to transform an image to the CIELAB color space, where the main procedure takes place [35]. Thus, one chromatic channel in the CIELAB space is considered for continuing the processing. Before the local color transfer process begins, the chromatic image is segmented by intensity using a thresholding algorithm. The same procedure is performed on both, input and target images. A statistical color mapping procedure using the method by Reinhard *et al.* [6] is then carried out between the corresponding segments. This algorithm stands as the core of our color transfer method. Afterwards, the resulting image is converted back to RGB.

As said before, fauvist paintings mainly contain primary and complementary colors, exhibiting a pure and vivid appearance. With this in mind, a similar threshold and color transfer procedure is performed on both color channels and, after that, color histograms are calculated for the two outcomes and for the target image. A comparison takes place, in order to choose the resultant that best matches the color content of the target. The outcome more similar to the target corresponds to the outcome used in the posterior stage, where edges and a canvas effect can be added, obtaining the final image. A more specific description of the main building blocks in Figure 1 is given here.

A. COLOR SPACE TRANSFORMATION

Our procedure is carried out in the CIE 1976 (L^*, a^*, b^*) color space, a perceptually uniform color space better known as CIELAB. Unique features of the CIELAB color space are [36]: i) the Euclidean distance between two points in the space is proportionally uniform to the perceptual difference of the corresponding colors at the points; ii) the nonlinearity in the transformation equations, designed to model the compressive response typically found between physical energy measurements and perceptual responses; and iii) the combination of the signals into three dimensions corresponding to the light-dark, red-green, and yellow-blue responses of the opponent theory of color vision. For the conversion from RGB to CIELAB, data are first transformed to the CIEXYZ color space [35]. In order to transform an image from RGB to CIEXYZ, the RGB space needs to be determined. Here, sRGB is used because it is based in a colorimetric RGB calibrated space [37]. All images need to be transformed from sRGB to CIEXYZ, applying (1) where $\{r, g, b\} \in [0, 1]$ are the normalized color components

$$\begin{bmatrix} X \\ Y \\ Z \end{bmatrix} = \begin{bmatrix} 0.4124 & \text{‘}0.3576 & 0.1805 \\ 0.2126 & 0.7152 & 0.0722 \\ 0.0193 & 0.1192 & 0.9505 \end{bmatrix} \begin{bmatrix} r \\ g \\ b \end{bmatrix}, \quad (1)$$

The perceptual space transformations used in this study are applied to the CIEXYZ color space. Coordinates in the color space CIELAB are calculated from CIEXYZ using (2)-(5):

$$L^* = 116 f(Y/Y_n) - 16, \quad (2)$$

$$a^* = 500\,[f(X/X_n) - f(Y/Y_n)]\,, \quad (3)$$

$$b^* = 200\,[f(Y/Y_n) - f(Z/Z_n)]\,, \quad (4)$$

$$f(t) = \begin{cases} t^{1/3} & \text{if } t > \sigma^3 \\ t/(3\sigma^2) + 16/116 & \text{otherwise,} \end{cases} \quad (5)$$

where X_n, Y_n and Z_n are the coordinates of the reference white for the scene in CIEXYZ, t can be X/X_n, Y/Y_n or Z/Z_n, and $\sigma = 6/29$.

For the inverse transformation, three intermediate variables are required, f_Y, f_X and f_Z, as indicated in (6)-(8),

$$f_Y = (L^* + 16)/166, \quad (6)$$

$$f_X = f_Y + (a^*/500), \quad (7)$$

$$f_Z = f_Y - (b^*/200). \quad (8)$$

Finally, (9)-(11) are used to obtain the X, Y, Z values.

$$X = \begin{cases} X_n f_X^3 & \text{if } f_X > \sigma \\ f_X - 16/116 & \text{otherwise} \end{cases} \quad (9)$$

$$Y = \begin{cases} Y_n f_Y^3 & \text{if } f_Y > \sigma \\ f_Y - 16/116 & \text{otherwise} \end{cases} \quad (10)$$

$$Z = \begin{cases} Z_n f_Z^3 & \text{if } f_Z > \sigma \\ f_Z - 16/116 & \text{otherwise} \end{cases} \quad (11)$$

whereas the inverse transformation is given by (12),

$$\begin{bmatrix} r \\ g \\ b \end{bmatrix} = \begin{bmatrix} 3.2410 & -1.5374 & -0.4986 \\ -0.9692 & 1.8760 & 0.0416 \\ 0.0556 & -0.2040 & 1.0570 \end{bmatrix} \begin{bmatrix} X \\ Y \\ Z \end{bmatrix}. \quad (12)$$

B. MULTILEVEL THRESHOLDING

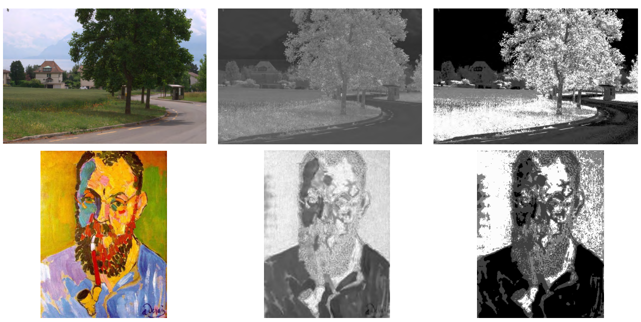
Thresholding techniques can be divided in two categories, bi-level and multi-level, depending on the number of image segments. In bi-level thresholding, an image is segmented in two different regions, according to the gray level of each pixel. Those pixels with gray values equals to or greater than a certain value T are classified as "object" pixels and they are white-colored, while the others, with gray values lesser than T, are classified as "background" pixels, and they are black-colored. Multilevel thresholding is a process that segments a gray level image into a number (higher than two) of distinct categories of regions. Each category encompasses pixels exhibiting a similar intensity to some extent. This technique determines more than one threshold for the given image and segments the image in regions with certain brightness, which corresponds to one "background" and several "objects".

We need to balance the chromatic content between the target artwork and the input image. With that purpose, we perform a color transfer between corresponding clusters of pixels. A first attempt to do that is automatically detecting the number of color clusters in the target, to say, using an adaptive algorithm (like MeanShift). Once we know the number of color levels, we can use that number to segment the input image using an algorithm designed to operate on a fixed number of levels (like k-Means or Otsu's). The aforementioned procedure results in a good segmentation according to the color content, but may yield unbalanced clusters, according to the number of pixels.

Our application must fulfill both color content and cluster size constraints. We found a simple but efficient solution, encompassing both requirements, and segmenting each image in clusters with a similar number of pixels and similar colors. For this task, we perform a thresholding algorithm, where the cumulative histogram for a color component is computed and normalized, obtaining a cumulative distribution function (cdf) of the image. From the cdf we calculate thresholds used to segment the image.

A question arises about the appropriate number of levels to use for segmenting the color channel. Despite the fact that increasing the number of levels at segmentation results in a better quality measure, we chose to use four levels for the following reasons. When using three levels for segmenting the channel, once applied the thresholding and the color mapping stages, there is a lack of detail in the outcome. That is shown as a merging of regions that should be apart, according to an observer perception. By contrast, when the segmentation is made using five levels or more, the color correspondence between regions is higher, and the outcome is perceived with more depth, luminosity and sharpness. Nonetheless, these features are undesirable for our purpose. In fact, the fauvist paintings are characterized by well-delimited and thicker color segments, with strong and nonfaded out colors. That implies whimsical color regions delimiting the masses but with a lack of volume and perspective. That is, using five segments or more, although we have a better color mapping, the outcome does not correspond to a fauvist look of the scene. Segmenting each color channel in four levels, results in a perception of well-defined vibrant colors, achieving that way a better correspondence with the look of fauvist artwork.

The intensity segmentation in four categories requires the calculation of three thresholds; those thresholds correspond to the values that yield the 0.25, 0.50 and 0.75 cumulative distribution values, respectively. In that case, each one of the four categories encompasses around 25% of the total number of pixels. At the same time, pixels within each category exhibit a similar color component. This procedure is performed on both, input and target images, resulting on a fast and robust segmentation. It is important to point out that the cdf approach takes into account intensities specific to the image. Thus, it yields a segmentation result that is in accordance with the actual color content of the scene. Figure 2 shows examples of thresholded outcomes.



(a) (b) (c)

FIGURE 2. a) Input and target images. b) b^* color channel for those images. c) The corresponding thresholded images from (b).

C. MULTILEVEL COLOR TRANSFER

Color transfer methods aim to recolor a given image or video by deriving a mapping between that image and another image serving as a reference [1]. In this study, we use the proposal of Reinhard *et al.* [6] because the method is simple and fast, computing only global statistics in the image (in our case, regions with similar intensity level).

The aim of this method is making a new image with a look similar to a reference image, named target. This means that it would be necessary to obtain some cues of the data distribution in order to transfer the color content between images, using a specific color space and pixels from a particular segment level. Only the average and standard deviation are used along each of the three color channels or components. Therefore, these measures in both images, source and target, are obtained. It is important to note that the averages and standard deviations are computed for each i channel separately. In equations (13)-(17), i stands for a specific channel in the CIELAB color space taking one of the 3 values $i \in \{L^*, a^*, b^*\}$

$$\mu_i^S = \frac{1}{M_S N_S} \sum_{x=1}^{M_S} \sum_{y=1}^{N_S} S_i(x, y), \tag{13}$$

$$\mu_i^T = \frac{1}{M_T N_T} \sum_{x=1}^{M_T} \sum_{y=1}^{N_T} T_i(x, y), \tag{14}$$

$$\sigma_i^S = \sqrt{\frac{1}{M_S N_S} \sum_{x=1}^{M_S} \sum_{y=1}^{N_S} \left(S_i(x, y) - \mu_i^S\right)^2}, \tag{15}$$

$$\sigma_i^T = \sqrt{\frac{1}{M_T N_T} \sum_{x=1}^{M_T} \sum_{y=1}^{N_T} \left(T_i(x, y) - \mu_i^T\right)^2}, \tag{16}$$

where the μ_i and σ_i are the respective mean and standard deviation, i is the channel index, M are the number of rows, and N are the number of columns of the image. Here, the signals T and S correspond to the target and source images, respectively.

The transfer between the reference and the input for the corresponding channel is performed by the following equation

$$O_i(x, y) = \frac{\sigma_i^T}{\sigma_i^S}(S_i(x, y) - \mu_i^S) + \mu_i^T, \tag{17}$$

where O represents the output image in the transfer. It is important to emphasize that this procedure is done between corresponding areas of an intensity level. In our case, for the four levels of each color component, separately.

Finally, we convert the O image back to RGB using the respective equations for the inverse transformation. Examples of images obtained in each step are given in Figure 3.

D. SELECTION OF THE CHANNEL

Colors for the a^* channel go from greenish to reddish, while colors for the $b*$ channel go from yellowish to bluish. Then, we perform the same color transfer procedure on both color channels, choosing the best outcome after that. For example, if images exhibit a large content of blue color, the $b*$ channel provides better results. Instead, if images correspond to a forest or sunset, the a^* channel is the best option.

Because we want to know which outcome is more similar to the target, the color content in the outcomes must be compared against that in the target. For that purpose,

FIGURE 3. Multilevel color transfer using the b^* component. First row exhibits the input image, second and third rows correspond to the target and the outcome, respectively. Left to right: The working image, followed by its four partitions.

we compare the corresponding histograms using as metric the well-known Euclidean distance $d_{L_2} = \sqrt{\sum_j((h_o(j) - h_t(j))^2}$. Firstly, the histograms of the target image (h_t) and the outcomes images (h_o) are computed. Later, the histogram from the target is compared with the histogram from the outcome image obtained using the color transfer in a^* channel. Analogously, the same histogram of the target is compared with the histogram from the image obtained using b^* channel. For this metric, a lower value represents to the outcome more similar to the target and that image will be used in the posterior stage. Other distance measures were also tried for selection of the better outcome, yielding similar results. For simplicity sake, we chose to use the Euclidean distance for calculations.

E. ADDITIONAL EFFECTS

A particular feature of the Fauve trend is that most of its artworks present dark contours in their figures. Thereby, we consider the insertion of black edges in order to emulate this artistic effect. For this particular task we consider the application of an edge detection step using the Sobel operator. This operator performs a 2-D spatial gradient measurement on an image and results on an emphasizing of regions of high spatial frequency that correspond to edges. Typically, Sobel is used to find the approximate absolute gradient magnitude at each point in an input gray-scale image. Additionally, we apply a morphological dilation to the detected edges. The dilation operation is commonly used for expanding the shapes contained in the input image. In our case, the edges are considered as the shapes. As the result, the edges will be markedly thicker. On the other hand, a generic canvas is used for imitating the effect of the artistic brush.

The image of the canvas, the edge image and the outcome from the color transfer, are fused. This fusion consists of a weighting of the three images. Indeed, this fusion can be considered as a superposition of the edge image over the outcome and adding of 25% of the canvas, as shown in Figure 4.

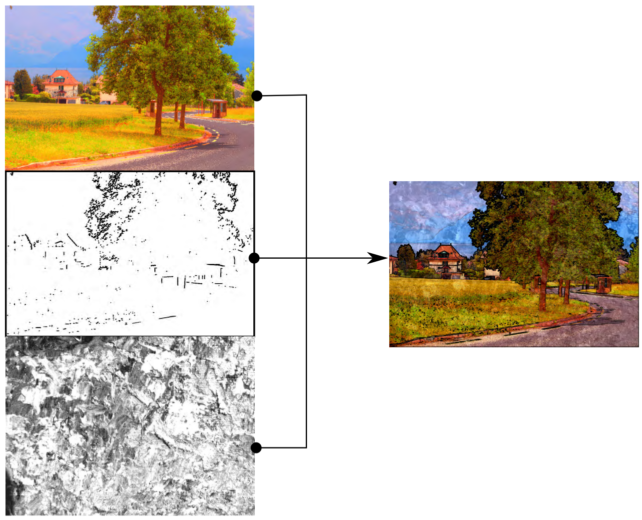


FIGURE 4. Fusion of the outcome from the color transfer method, with the edge image and the canvas image.

The final step for the simulation of the artistic effects corresponds to a filtering stage. Firstly, a mean filter is applied for blurring the outcome image and, posteriorly, a median filter is applied in order to suppress artifacts appearing as isolated pixels. The median performs this pixel removal without smoothing edges between adjacent regions.

These additional effects of edges, canvas and filtering, improve the artwork emulation and the identification of the sight of the artistic movement.

IV. RESULTS

Experiments were carried out in order to test the method and its results. For this task, fauvist paintings were used as the target image in experiments. Such references are given in Table 1, (a-d) [38], (e-h) [39] and (i-l) [40].

FIGURE 5. Corresponding outcomes for different input images in column (a) using the same reference target. In (b) the resultants of the global color transfer method (just for comparison); (c) resultants of the multilevel color transfer; (d) images from (c) after filtering and inclusion of edges and, (e) final outcomes adding a canvas.

Within the same experimental tests, as input we used images from two databases commonly used in the image processing field. The first database was considered for having landscape images, the NIR-RGB scene data [41]. The second database was taken into account because it also contains portrait images, the Berkeley segmentation dataset and benchmark [42]. We used six landscapes and four portraits.

When different algorithms are applied to an image, an objective measure is necessary for comparing the outcomes. In this study, we used a distance metric for calculating the similarity between the chromatic content of the outcome and the target image.

The comparison measure uses the histograms of the images. The histograms are compared by calculating the distance between them. We tested three different histogram distances: euclidean (d_{L_2}), Bhattacharyya (d_B) and chi-square (d_{chi-s}).

$$d_{L_2}(h_o, h_t) = \sqrt{\sum_j (h_o(j) - h_t(j))^2}, \tag{18}$$

$$d_B(h_o, h_t) = \sqrt{1 - \frac{1}{\sqrt{\mu_{h_o}\mu_{h_t}N^2}} \sum_j \sqrt{h_o(j) \cdot h_t(j)}}, \tag{19}$$

$$d_{chi-s}(h_o, h_t) = \sum_j \frac{(h_o(j) - h_t(j))^2}{h_o(j)}, \tag{20}$$

where h_o and h_t are the normalized color histograms from the output image, and from the target image, respectively. For the euclidean, Bhattacharyya and chi-square (d_{L_2}, d_B, d_{chi-s})

FIGURE 6. Corresponding outcomes for one input using different references (identified as in Table 1). Additional edges and canvas effect have been included.

distances, a small distance value corresponds to a better color transfer. In comparison tests, the intersection ($d_\cap$) distance was also considered,

$$d_\cap(h_o, h_t) = \sum_j \min(h_o(j), h_t(j)), \tag{21}$$

where the higher the distance, the better is the color transfer.

Examples of results over different input images and using the same reference artwork are shown in Figure 5. The corresponding measure for each outcome (only d_{L_2} is indicated). The outcomes from the multilevel color transfer reach a lower value (a better color transfer) compared to those obtained using the global approach.

The set of 10 source images was tested using the 12 target images. The distance measures were computed for all the outcomes. The mean was computed for all outcomes in each color transfer method, resulting in two mean values for each distance. Table 2 shows the computed values from

TABLE 1. List of Fauvist paintings used as reference in our work.

Id.	Fauvist painting
a	The green line (portrait of madame Matisse) Portrait 40.5 x 32.5 cm. Statens Museum for Kunst, Copenhagen 1905
b	Blue nude Portrait 92 x 140 cm. Baltimore Museum of Art, Baltimore 1905
c	Woman with a hat (madame Matisse) Portrait 81 x 65 cm. Private Collection 1905
d	Portrait of Andre Derian Portrait 39.5 x 29 cm. Tate Gallery, London 1905
e	Portrait of Matisse Portrait. Private Collection 1905
f	The Dancer, Portrait. Nationalmuseet, Copenhagen, Denmark 1910
g	The basin of London Portrait. 1906
h	Near Chatou Landscape 56.2 x 46.04 cm. Private Collection 1904
i	The River Seine at Chatou Landescape. Private Collection 1906
j	Chatou Portrait. Private collection, 1907
k	Restaurant de la Machine at Bougival Landscape 81.5 x 60 cm. Musee d'Orsay, Paris, France
l	Red Roofs Landscape 54.8 x 81 cm. Private Collection 1907

TABLE 2. Average values for the global and multilevel color transfer using different number of segments.

Distance	Global	Multilevel (n segments)			
		2	3	4	5
d_{L_2}	1.471	1.066	1.023	0.950	0.914
d_B	0.186	0.067	0.058	0.050	0.047
d_{chi-s}	10.925	1.565	1.081	0.962	0.903
$d_\cap$	1.948	2.235	2.266	2.320	2.345

each approach using the four distance measures. As we can appreciate, in all measures the best results are obtained using the proposed method.

Figure 6 depicts the application of our algorithm on the same input image using the 12 reference artworks as target. A direct comparison with methodologies such as [28] and [29] is not feasible because their source code is not available. Nonetheless, our results are an artistic interpretation of reality, induced by the distortion of colors. This particularity leads us to think that the method could be utilized as a tool that contributes to learning of art. Studies relative to the use of interactive multimedia tools in learning [43], point out that this kind of methodologies can be used to establish cognitive links. This allows not only the emulation of artworks but, by the look of their appearance, also the recognition of certain artistic features.

V. CONCLUSIONS

A multilevel color transfer to emulate artistic works has been discussed. A modification to a traditional color transfer method was proposed. Basically, a previous stage of multilevel thresholding was added, thus the color transfer is performed between each corresponding thresholded level. Also, filtering techniques can be applied upon the outcome, in order to emulate basic brushstrokes of the artist. The goal of this study has been to show that our approach using local transfer performs better than the classical method using the global statistics. As a result of the application of the method, the colors are mapped from a reference scene to a standard image provided by the user. We can say that the method works successfully in artwork emulation, especially of fauvist paintings; thereby, we consider this method can be used as a tool for contributing to the learning of art, or in other areas such as education through multimedia activities.

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