This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2017.2732359, IEEE Access

A multimedia tool as an educational support for children in art learning: Looking the world through a Fauve eye

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***Abstract*—We introduce a computational tool that provides a space for metacognitive activities for the artistic development of young children or for students uninitiated in the visual arts. This interactive multimedia learning tool is based on the emulation of the particular characteristics of a reference painting upon a standard image. The color palette of a recognized image of a Fauve painter is mapped to the input image emulating the Fauve sight of the artist, which is characterized by the use of vivid colors. Filtering techniques are applied to the outcome, in order to emulate basic brushstrokes of the artist. In a playful way, the user can visualize and compare the input image with the outcome. The exercise can generate cogency in the user's mind by identifying the attributes of another image upon his own. This practice can establish cognitive links by association, as a complement to traditional cognitive means.**

***Index Terms*—Multimedia tool; visual arts education; digital image processing; painting emulation; Fauve movement.**

I. Introduction

Game-based learning is the result of understanding the use and value of technology in teaching. The incorporation of these digital tools is a creative step within the process of teaching and learning, which involves a reconstruction of professional practice. Studies examining the incorporation of these tools in teaching science also mention the benefits from the integration of these practices [1]. Educational policies around the world have imagined technology as a learning tool for transformation; however, this idea is not always envisioned in schools. A culture of using technology to better prepare students for their current and future digital lives is required in schools [2]. A child can have fun and, at the same time improve the skills and techniques needed to develop his art [3]. In this paper, we focus on providing a tool that contributes to the processes of teaching and learning in the area of the arts.

The art offers a form of spiritual consciousness, which is revealed through the heart and intuition [4], and is embodied in somatic forms of learning [3]. Furthermore, art is also valued as a way to communicate emotional, unconscious or unspeakable things [5] and to improve the "healthy" personalities [3]. Arts education teaches students how to interpret, criticize, and use the visual information and how to make decisions based on the same. Teaching or learning art, also promotes language development at different levels. In elementary school, students can talk about their own creations or about the feelings that are triggered when they see distinct styles of artworks. For very young children, making art or just talking about it, offers opportunities to learn words for colors, shapes and actions [6].

Learning to create and appreciate the visual aesthetic can be more important than ever for the development of the next generation of children as they grow. Nowadays, children need to learn more about the world, not just what they can learn through text and numbers. Art also improves the cognitive processes of children, and involves children in problem solving, thinking, and the use of symbolic systems to record thoughts, ideas and feelings [3]. Therefore, it is appreciated the importance of early learning about arts, as well as of the possible ways to facilitate this process. Dr. Kerry Freedman, Director of Art and Design Education at Northern Illinois University, says "Parents should be aware that children learn much more graphic sources now than in the past" [6]. This information consists of the signals they receive via images or three-dimensional objects from digital media, books and television. That is why we note that young children learn how to operate a smart phone or tablet, even before they can read, which means that they are processing this visual information.

Talking about art and its components, color is one of the most important pieces. 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 [7]. 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 colors, -but our ability to explain the meanings of these words goes no further! for the rest, we have either no idea at all of their use, or a very rough and to some extent false one" [8]. In other words, the language can determine the way we express the experience of color, but color and language are necessary 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 to the use and importance of

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color in the art it refers, we can mention that the color was projected for the first time since that the shape reached its limit at the post-impressionism. That is to say, when CÃĺ'zanne, Gauguin and Van Gogh, allowed the color and marks on the canvas bring out the power of expression [7].

Fauve painters were those who received teachings of Gauguin. Commanded by Matisse, fauvists captured the power of color taking it one step further [9]. The fauvist, despite being a short-living artistic movement, revolutionized the concept of color in art, since art used color as the vehicle for its expressive power and vitality essential to transmit the message. Particularly, the fauvist movement 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 Fauve vision was expressed in violent colors, involving and preferring the use of primary colors and complementary ones [10], but being a calm and relaxed vision at the same time [9].

Up to this point, it has been exposed the importance of arts education and its most significant component, color, and the relationship it keeps to one of the first and most outstanding artistic movements of the twentieth century and its main exponents. All this starts to make sense when we consider that through art you can help to build autonomous and innovative minds, because art spontaneously associates us to the cultivation of imagination, fantasy and creativity. This involves a particular type of experience, highly interesting, challenging, promising, and suggestive, that promotes the transformation of the mind, what is the product of metacognition [11]. Thinking about the understanding of art as a process that begins with the factual research, increases confidence in dealing with works of art. That is, from something less ambiguous, it allows the development of observational skills first and after, performing skills [12]. A work of art represents an expressive object made by a person, and hence unlike a tree, a rock, or other mere things, always it is something. Therefore, unlike trees or rocks, art requires interpretation [12]. The preceding ideas lead us to think that providing a didactic instrument for learning art can be very useful, and thus, contribute to the development of children in the early stages of studying arts.

Information and communications technology (ICT) is nowadays of great help in the development of content and tools that facilitate the teaching-learning process. Children currently have no difficulty in using ICT, being digital natives, these environments are familiar to them and are used naturally. Turning to the classroom, teachers face the challenge of holding back the energy of students, especially in early educational stages. Hence, those teachers search for tools that allow capturing the students' attention and provoke their participation in the dynamics that promote a more meaningful learning. This behavior is observed in the study of policies about learning games [13], which states that teachers involved with children from an early age of five to nine years, were convinced of the benefits of using digital games as a central component of their pedagogical approach.

It is also known that, if the process of learning and metacognition in a student is operated through proper stimuli, he will use his own capabilities to learn and understand his environment. In this way and if it is wanted to educate students and prepare them for life and work in the twenty-first century, it is necessary to create new ways to educate, not only within implementation of the new technology, it is also a matter of transforming simultaneously the existing social practices of teaching and learning [14].

Being aware of the situation, we introduce a computational tool that, on the one hand, can expand the range of instructional capabilities of a teacher of visual arts. On the other hand, the tool aims to be a stimulant link that allows the user to learn and appreciate art even unconsciously. The proposed computational environment can be used in a didactic way to improve the learning experience of arts in elementary school children. This premise is taken from studies in other areas, that show that the use of images and video captured on mobile phones under the supervision of teachers, improves the instruction, assessment of learning and correcting misconceptions in the students; thus, the use of the phone is used as a variety for learning, focusing in images to support learning [1]. In the same sense, another study carried out in an elementary school community [14], showed that learning practices, which are mediated by technology and are embedded in pedagogies of the XXI century, can resonate potentially in the lives of students and expand their opportunities to participate in meaningful and creative learning through time and space.

The main idea of our work is to present a tool that provides a space for student metacognitive activities, through a practical and interactive multimedia learning model. The relevance of this interactive multimedia tool, is based on studies of metacognition through self-regulation of multimedia learning [15] where the results point to the application of multimedia presentations more advanced and interactive, giving more space to metacognitive skills to students, as an addition to traditional cognitive means. In this way and in a playful and almost unconscious way, students can learn particular characteristics of artworks or artistic movements. The tool under discussion throughout this paper can facilitate the recognition and association of certain characteristics of the Fauve movement, by a process that users can do on their own. We have chosen to explore the Fauve trend, because this artistic tendency has very particular characteristics, with color as the core element in the artwork. Besides, taking advantage that color is the essence of painting and the element that is most likely to inspire emotional associations, and the fact that painting does not prescribe much intellectual effort for its judgment or perception, the computational environment aims to strengthen the first phase in which children approach to an artwork. We expect that the usefulness of the tool be manifest in the appreciation of students and teachers.

The rest of this paper is organized as follows. In Section II, the methodology for the implementation of the tool is introduced. Comments on some tasks from the digital image-processing domain, like the color transfer, color transformations and artistic effects, are included in this section. In Section III, experimental results obtained after the use of the developed software are given. Finally, some concluding remarks are included in Section IV.

II. Methodology

The tool performs an emulation of the real world using particular characteristics of the Fauvist painting; for this purpose, an input image is modified to look like an artwork of this movement. As mentioned before, color is the main element in the artistic trend and therefore, the key to the recognition and the metacognitive exercise for the students. For this reason, the tool is based on a method where the palette colors of a well-known image (called reference) of a Fauve painter is mapped to a standard image (the input), achieving in this way the emulation of the sight of the Fauve artist.

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

An RGB to CIELAB conversion is used to transform an input image to the CIELAB color space, where the main procedure takes place [16]. Then, images corresponding to the a^* and b^* channels are processed separately. Before the local color transfer process begins, each of the two frames is segmented by intensity using a three-level thresholding algorithm. Thus, at this point we have four independent images, two corresponding to the input and two for the target image.

A statistical color mapping procedure in then carried out between the corresponding three image categories in channel a^*. This algorithm stands as the core of our color transfer method. An analogous procedure is made with the images of the b^* channel. Afterwards, each of these two resultant images is converted back to RGB.

Color histograms are calculated for the two outcomes and for the target image. A comparison is then performed, 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 color 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. For this space, the Euclidean distance between two points in the space is proportionally uniform to the perceptual difference of the corresponding colors at the points. For the conversion from RGB to CIELAB, data are first transformed to the CIEXYZ color space [16]. 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 [17]. All images need to be transformed from sRGB to CIEXYZ, applying (1) where $\{r, g, b\} \in [0, 1]$ are the normalized color components

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

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):

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

$$a^* = 500 \left[f(X/X_n) - f(Y/Y_n) \right], \tag{3}$$

$$b^* = 200 \left[f(Y/Y_n) - f(Z/Z_n) \right], \tag{4}$$

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

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, shown in (6)-(8),

$$f_Y = (L^* + 16)/166, \tag{6}$$

$$f_X = f_Y + (a^*/500), \tag{7}$$

$$f_Z = f_Y - (b^*/200). \tag{8}$$

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

$$Y = \begin{cases} Y_n f_Y^3 & \text{if } f_Y > \sigma \\ f_Y - 16/116 & \text{otherwise} \end{cases} \tag{9}$$

$$X = \begin{cases} X_n f_X^3 & \text{if } f_X > \sigma \\ f_X - 16/116 & \text{otherwise} \end{cases} \tag{10}$$

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

whereas the inverse transformation is given by (12),

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

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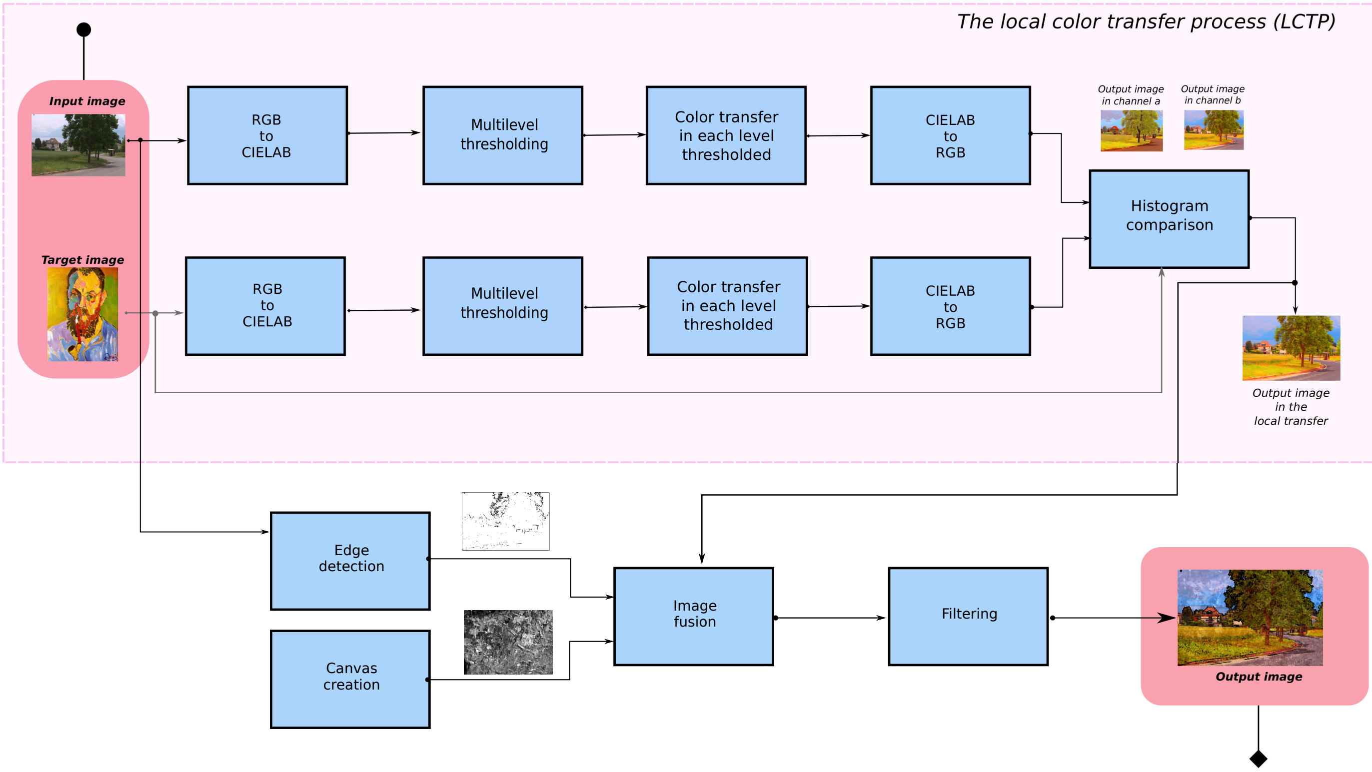

Fig. 1. Schematic diagram for the color transfer process.

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. Those pixels with gray values greater than a certain value T are classified as “object" pixels and are white-colored, while the others, with gray values lesser than T, are classified as “background" pixels, usually black-colored. Multilevel thresholding is a process that segments a gray level image into several distinct regions. 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".

In our study, we perform a simple 3-level thresholding algorithm. Here, the cumulative histogram for a color component is computed; this stands for a probability density function (pdf) of the image. For this task, we consider a thresholding in three levels; thus requiring the calculation of two thresholds. For the particular case where we use a chromatic component, the two thresholds corresponding to the intensity values that yield the 0.33 and 0.66 cumulative probability values, respectively. Figure 2 show the thresholded outcomes from input and tarjet images.

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 [18]. In this study, we use the proposal of Reinhard et al. [19] because of the method is simple and fast, computing only global statistics in the image.

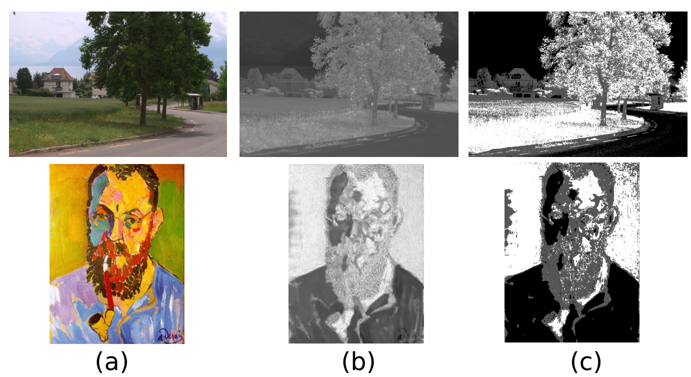

Fig. 2. a) Input and tarjet images. b) Color components for both images. c) The corresponding thersholded images from b).

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 distribution of data in order to transfer the color content between images, using a specific color space. 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 as follows

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

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

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

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

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. For the CIELAB space $i \in \{L^*, a^*, b^*\}$.

The transfer between the reference and the input for the corresponding channel is performed by the next general 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 three 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.

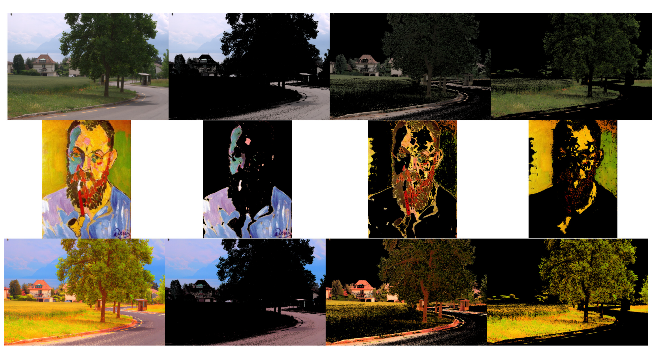

Fig. 3. Multilevel color transfer using the b^* component. First row exhibits the input image, second and third rows correspond to the target and the outcome, respectively. Left to right: The working image, followed by the first, second and third partitioned level.

D. Selection of the channel

We want to know which outcome is more similar to the target. For this reason, the colors in the outcomes must be compared against those colors in the target. 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. The metric that we use for the comparison of the histograms is the Euclidean distance $d_{L_2} = \sqrt{\sum_j((h_o(j)-h_t(j))^2}$.

For this metric, a lower value represents a better color transfer. The lowest value represents to the outcome more similar to the target, and this outcome will be used in the posterior stage.

E. Additional effects

Firstly, we consider the insertion of black edges in order to emulate one of the artistic effects. For achieving this effect, an edge detection is needed. For this particular task we consider useful the use of 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 grayscale image. Additionally, we apply a morphological dilation to the edges detected. 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 mimetic the effect of the artistic brush.

The images of the canvas, the edge image and the outcome from the color transfer, are fused. This fusion consists of a simple sum of the three images. Indeed, this fusion can be considered as a superposition among all of them, as shown in Figure 4.

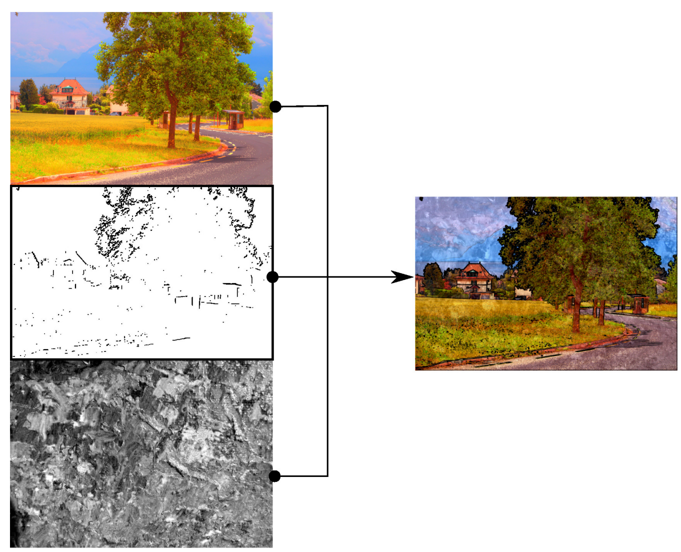

Fig. 4. Fusion of the outcome from the color transfer method, the edge image and the canvas image.

The final step for the simulation of the artistic effects corresponds to a filtering stage. In image processing, it is often desirable to be able to perform some kind of noise reduction on an image. Firstly, a mean filter is applied for blurring the

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image and, posteriorly, a median filter. Median filtering is very widely used in digital image processing because, under certain conditions, it preserves edges while removing noise.

III. Results

Once the algorithm and the digital image-processing development were completed, tests with the computational environment (interface) of the tool were carried out in order to test its operation. For this task, Fauvist paintings were used as the ”recognized” image (called reference). The Fauve paintings used as reference in experiments are given in Table I, www.henri-matisse.net(a-d), www.wikiart.org/en/andre-derain(e-h) and www.wikiart.org/en/maurice-de-vlaminck(i-l).

TABLE I
List of Fauve paintings used as references in our work.

Id.	Fauve 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

Within the same experimental testing of the tool and its interface, as the standard image (input) we use images from two databases used commonly in the image processing field. The first database is considered for having landscape images, the NIR-RGB scene data [20]. The second database is taken into account because of contains portrait images, the Berkeley segmentation dataset and benchmark [21].

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

In addition, we mention that the computational tool was developed using a commercial software package (MATLAB 2013a, The MathWorks Inc., Natick, MA, 2013), and each routine or function was implemented in the language of this package. The computational environment consists in an interactive visual interface, where the user can choose the input and the reference images and proceed with the color mapping. At the beginning, the program is executed in order to open the user interface. Once the interface is open (Figure 5), we can see the three sections that it contains: 1. Selection of a personal image, 2. Selection of the reference artwork and, 3. The emulation of the artwork over our personal image.

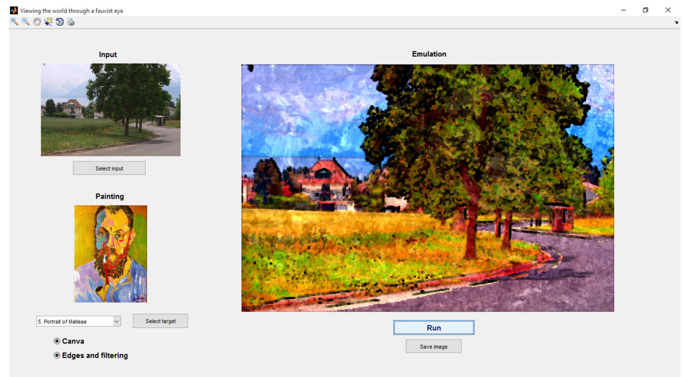

Fig. 5. Screenshot of the tool showing the outcome after processing an image using the âĂIJPortrait of MatisseâĂİ as reference.

In the top-left corner of the interface (Figure 5), we can find a ”Select input” button, which opens a window for searching the user’s personal image. In the bottom-left corner, there are two options: i) a pop-up menu with twelve predefined Fauve artworks (see Table I); and ii) a button for searching another reference image from disc. The latter option, although can add fun to the color transfer task, it can lead us away from our artistic purpose. The user can select between two additional options in order to modify the artistic effect on the resulting image. One option is for incorporating the canvas effect, and the other consists on the addition of black edges and filtering.

The tool is an interface that enables the selection of a user’s image file, and the choose of another image from a catalog of carefully-selected paintings, artworks highly representative of the Fauve art movement. Once the two images have been selected, we can run the algorithm for mapping, generating an interpretation of Fauvist artwork on the user’s image. That is, the color features are transferred from the reference artwork to the input image. At the end of the process, the outcome image appears, showing the artistic emulation, with a color content similar to the reference image. This resultant image allows us to identify the vision of the artistic movement, using pure, vivid colors. Additionally, it is possible to save the resultant image as a file. This procedure can be carried out a number of times, depending on the user. An example of results over different input images and using the same reference artwork are shown in Figure 6.

The distortion of the reality induced by colors allows us an artistic interpretation about the fauvist experience by sensations from colors. Otherwise, the interchange of images gives users the possibility of repeating this exercise for exploring the results. This action will strengthen the knowledge of the particularities about fauvist paintings. In Figure 7, we can see resulting images using the 12 reference images over the same input.

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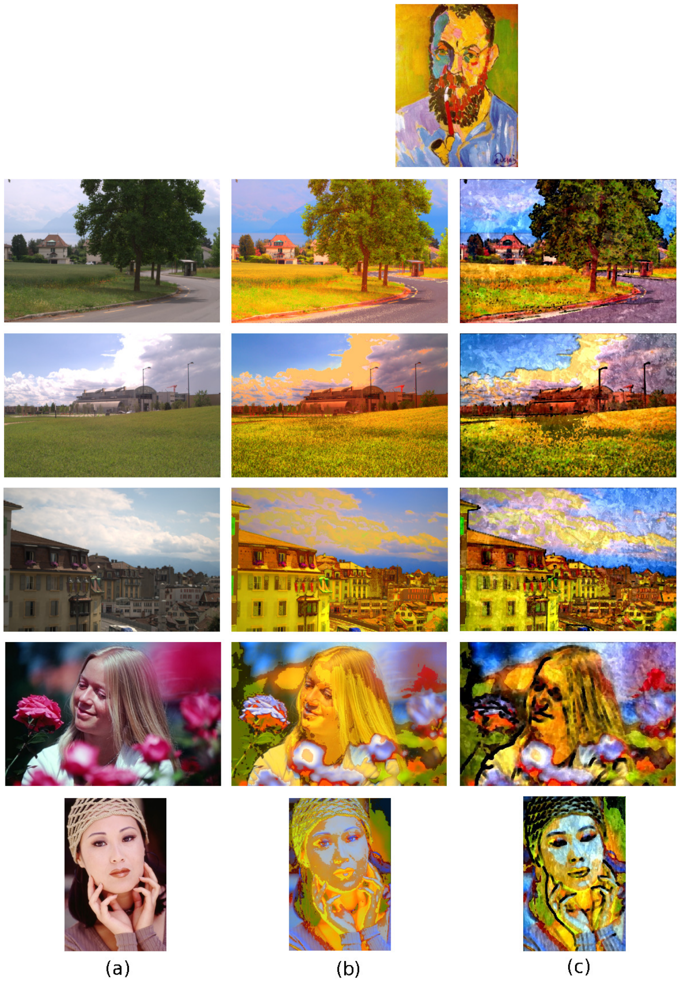

Fig. 6. Corresponding outcomes for different input images using the same reference; in column (b) we have the resultants of the color transfer method and, in (c) the same images but also including additional edges and canvas.

Studies relative to use of interactive multimedia tools in learning (Antonietti 2015), let us know that this tool can be used to establish cognitive links in the user, allowing him not only to imagine the artwork, but also look its appearance, and to recognize certain artistic features.

IV. Conclusions

A computational tool that supports in a playful way the approach to learning about Fauve artistic works and authors, has been discussed. Using it, the color palette of a recognized artwork of a Fauve painter is mapped to a personal image. Moreover, filtering techniques can be applied upon the outcome, in order to emulate basic brushstrokes of the artist. Once discussed the characteristics of the computational interface, we can say that the developed tool can be used in educational activities for the emulation of artworks and facilitate the learning of art. It serves as a vehicle for recognizing and learning the color features of the Fauve movement. Moreover, the use of the computational interface enables the user to discover new possibilities and get involved in an imaginary situation that compromises him emotionally. Besides, it is our intention that, once the user looks the attributes of an artwork reflected on his own image, this experience provokes his empathy and foster metacognitive processes allowing a meaningful learning, transcending the knowledge acquired. As said before, this tool can be used in educational activities of people uninitiated in visual arts or in the development of young children.

Acknowledgment

Jonathan Cepeda-Negrete thanks the Mexican National Council on Science and Technology (CONACyT), scholarship 290747 (Grant No. 388681/254884).

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This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2017.2732359, IEEE Access

Fig. 7. Corresponding outcomes for one input using different references (identified as in Table 1). Additional edges and canvas effects have been included.