Color Transformation Method that Preserves the Impression of Texture in Virtual Makeover System

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Abstract. The algorithms of color transformation that preserves the impression of texture are used in virtual makeover systems, where maintaining the impression of unaltered texture is important in the process of transforming the color. The content of this paper covers the process of implementing the algorithm of digital picture color transformation with its main objective – minimizing its influence on the texture structure. The main idea of the presented algorithm is to determine the area in HSV space that consists of the original picture pixels and then, to move it towards the target color in such a way that every color is moved by the same vector, limited only by the fact that the transformation is not always possible. The analysis of the algorithm was conducted based on fragments of real face photographs. Its results were compared on the basis of measures estimated on the run length matrix and the co-occurrence matrix.

Key words: color, texture, color transform, virtual makeover, digital image processing

1. Virtual makeup and color spaces

Picture analysis methods are commonly used in virtual makeup systems, where a camera and screen function as a mirror, in which the process of putting on virtual makeup can be observed in real time. The quality of such applications' functionality depends on the algorithms of image processing and, in particular, their ability to change the color while maintaining the impression of image texture.

The color projection into a digital form is done through mathematical models that enable the description of the color using numeric parameters in coordinate system. The systems that enable this projection as well the descriptions of rules of such projections are color spaces [1, 2, 15, 16, 17, 18, 19]. There are a few different sets of parameters that can describe the same color, thus various color spaces. Two main approaches can be distinguished – sets based on trichromatic color vision theory, modeled on basis of the *physiology of human eyes* and sets in which the information on luminance and chromatic attributes of a color is independent, modeled on the basis of the *human perception of color*. The examples of color spaces are CIE XYZ – created by International Commission on Illumination CIE (fr. *Comission Internationale de l'Eclairage*), CIE RGB, RGB – Red, Green, Blue (for hardware applications), CMYK – Cyan, Magenta, Yellow, Kontur (for printing applications), HSV – Hue, Saturation, Value, HSL – Hue, Saturation, Lightness and CIE L$\alpha\beta$.

Choice of an optimal color space depends on its use. RGB model works best in applications that use light-emitting devices; HSV arranges the colors in a way that is intuitive for a human being, to simplify the interaction between users and colors; CIE L$\alpha\beta$ is a response to the need for perceptual uniformity of a color space. The decision on selecting the color space for a specific application should not be made hastily, as evidenced by studies on the accuracy of color matching done by users in a system based on RGB and HSV models [20], the results of which did not confirm the superiority of HSV space in the interaction with the user.

2. Color and texture

In the context of computer graphics, it is a great difficulty to provide a clear definition of the concept of texture. The definitions refer, among others, to *repetition of certain segments* of similar appearance and their distribution according to established rules, modeled on texture comparison from digital images to material specific to a particular group of real-world objects and surfaces (wood, sand, wool, etc.), or determined by a "change in the data at a lower level than is currently under consideration" [1, 2, 3, 4, 5, 6, 7, 18]. As there is no mathematical rule that would allow describing any chosen texture, finding the way to represent the textures digitally is one of the fundamental problems in terms of their processing. In addition to this problem there are four basic issues related to classic texture processing:

- *Classification* – identifying the object in the image, based on an analysis of texture that covers it;
- *Segmentation* – dividing the image into areas of different textures;
- *Detection of defects* – the process of deciding whether the texture of the image contains any irregularities;
- *Applying textures* – to objects in the image, in particular to modeled three-dimensional objects [7].

Due to the difficulty in describing the digital representation of texture, it is also problematic to compare them. Most commonly, in the process of comparing similarity of two textures, numerical measures and other parameters (e.g. geometrical) are used, which make it possible to describe the texture in such a way which enables distinguishing it from other textures at a certain level of probability. It relates to both the problem of *extracting* characteristic features of a texture and *selecting* such features that may be useful in the process of distinguishing (classifying) image textures (so-called *discriminative features*). Numerical measures corresponding to these parameters are defined as *descriptors*. The methods of texture description can be divided into structural (geometric – where the description of a texture consists of component definitions and the rules of their arrangement) and statistical (probabilistic – where the analysis is conducted at the level of individual pixels and their relations) [1, 2, 3, 4, 5, 6, 7, 8]. Geometrical methods include, among others: Grey Level Co-occurrence Matrix (GLCM) and Run Length Matrix (RLE).

Co-occurrence matrix is a tool to analyze three measures that characterize the texture structure: contrast i, entropy e and linear correlation of data c. Each of these measures belongs to a different group – they measure different features and there are no direct links between them (their values do not depend on one another), so that this collection should be sufficient to determine the characteristic features of every group of sample images.

Homogeneous pixel string matrix [6, 21], although very similar to the measure described above, is based on the analysis of components that form the texture. In this case, the elements considered are chains of pixels forming a single line of the same level of brightness. Run-length matrixes are determined for a given direction of θ (tilt of a chain) – usually: horizontal (0°) and vertical (90°), as well as two intermediate directions (45° and 135°). The elements of matrix R_{ij} contain information about how many times does a run of a specific length r and brightness g occur in the image.

Some statistical measures that may be obtained from run-length matrix are, for example, a reverse short run emphasis, long run emphasis, grey level non-uniformity, run-length non-uniformity and fraction of image in runs.

In addition, Pearson's correlation coefficient calculated for a random variable, which is the pixel brightness of two images, will determine the similarity of textures. The main advantage of this method is its independence from data presented in the image. Whatever the situation is, if the coefficient value is the same, it means that the level of similarity of textures will be the same as well.

3. Analysis of color textures

Methods of color texture analysis [2, 3, 9] are directly derived from those used for black and white images. A vast majority of commonly used methods in this field is practically identical for both groups of images. It involves presenting the color texture in greyscale and using tools for black and white image analysis in the processed image. Separating the color from the picture means removing chromatic features from the pixels of the image, leaving only the information about image brightness levels. The black and white texture that remains (understood as the distribution of pixel brightness on the surface of an object) can be further processed in accordance with the principles of tools created for greyscale images. Because texture and color of the objects are strongly related in nature, such treatment of data can be considered as lossy – it loses some information about the imaged objects. The conclusion is that the results of such analysis of an image may fall on a lower level than when analyzing both characteristics simultaneously. Note, however, that the classification of textures based on greyscale images provides good results.

4. The algorithm of color transformation

The basic premise of the algorithm of color transformation is to preserve the image texture in the most unaltered form possible. For this purpose, it is advised to transfer the colors in an unchanged structure from their color space into a new space, designated by a chosen target color. This way, any interrelationship between source image pixels should be preserved and restored in the image with changed colors.

Of the previously described color spaces it was decided to use the HSV space, abandoning RGB space (due to its lack of intuitiveness in use) and CIE L$\alpha\beta$ (due to a high degree of difficulty of calculations and the need for lossy conversion to RGB space, which could result in additional interferences). The structure of HSV space is the reason why it is often used in different aspects, due to its efficiency in use by color transformation algorithms. The idea of the algorithm created is therefore the designation of an area within HSV space consisting of source image pixels and moving it entirely towards the target color in such a way, that each color is shifted by the same vector, with the constraint that it is not always possible. Only in the case of changing the hue H, the algorithm will work correctly – irrespective of the type of transformation, shifting in the plane will show the correct value of the new parameter, because it forms a circle. Unfortunately, in the case of changes in the intensity S or brightness V, the vector may cause moving the pixels outside the boundaries of the space.

The first possible solution of this problem is to set the maximum values of a parameter, always if it exceeds its maximum, and resetting it if it moves beyond the lower limit of parameter value. The main disadvantage of this solution is the fact that in case of larger fragments of an image that are covered in shadow or in places with strong flares of light, using this method for the brightness parameter would result in the formation of large areas of uniform black and uniform white, respectively. Preserving the impression of the texture is impossible. Therefore, it is necessary to use a different procedure for the parameter V (which most strongly affects the texture).

The best seems to be to use the mechanism of slowing down the changes of obtained color brightness values of the source image, when they come to extreme values. Given the fact that human eye copes better with distinguishing light colors than dark ones, this proximity to extreme values for a centigrade greyscale can be 5 and 10 units for black and white respectively. Thus, if the brightness of the target pixel is less than 5 (especially if it is less than 0), its value would be between 0 and 5, proportionally to the difference between the brightness of the source pixel and minimal brightness of the image. It is the same in the case of the surroundings of a white point. However, because the texture is to remain unaltered, such smoothing should be done only if it is necessary, that is, when the chosen target color will cause the values to exceed the boundaries of the space.

The second important issue is *the choice of color space point* among those in the source image, for the one that would best characterize the *source* color for transformation. This color is needed to indicate the value of the translation vector which represents the transformation. Due to possible large areas of shadow or flare, it is best to use the average value of colors form the whole transformed image. In the case of using such measures as median or dominant, in extreme cases such deviations could completely undermine the effectiveness of the algorithm by choosing a completely bright or dark color as the point of reference.

Ultimately, the color transformation algorithm is as follows (qualifiers in subscripts are self-explanatory):

- Finding the average color values of the image (c_{avg}) as well as maximum ($v_{\max}$) and minimum ($v_{\min}$) brightness of the image.
- Finding the translation vector for the source color (c_{avg}) and its target (c_{tgt}) form: $W = [(H_{\text{tgt}} - H_{\text{avg}}), (S_{\text{tgt}} - S_{\text{avg}}), (V_{\text{tgt}} - V_{\text{avg}})]$.
- Determining the parameters of the new color for all pixels in the image:
  - hue: $H_{\text{new}} = H_{\text{old}} + W[H]$, if $H_{\text{new}} < 0°$, a full angle should be added to the resulting value; the same for $H_{\text{new}} > 360°$ - a full angle should be subtracted from the value;
  - saturation: $S_{\text{new}} = S_{\text{old}} + W[S]$, if $S_{\text{new}} < 0$, then $S_{\text{new}} = 0$; if $S_{\text{new}} > 100$, then $S_{\text{new}} = 100$;
  - brightness (value):
    - if $V_{\text{old}} + W[V] < 5$ and $v_{\min} + W[V] < 0$, then $V_{\text{new}} = 5\frac{V_{\text{old}}}{V_5}$, with $V_5 = 5 - W[V]$ (limit value, where slowing down the drop in brightness next to black color starts);
    - if $V_{\text{old}} + W[V] > 90$ and $V_{\max} + W[V] > 100$, then $V_{\text{new}} = 90 + 10\frac{V_{\text{old}} - V_{90}}{100 - V_{90}}$, with $V_{90} = 90 - W[V]$ (value, where slowing down the increase of brightness next to white color starts);
    - otherwise $V_{\text{new}} = V_{\text{old}} + W[V]$.

5. Solution implementation

In virtual makeup systems [10, 11, 12, 13, 14] the analysis is usually subjected to two separate aspects: face recognition, and more specifically identifying its parts, and color transformation, i.e. applying makeup. This study describes the mechanism of color transformation with the purpose of changing the color in the image and does not analyze the issue of face recognition. Since the transfer of cosmetics is a specialized process, the algorithms used in these systems are not commonly used in other areas. There are also

Tab. 1. The results of the algorithm on images of the facial skin.

Image	Transformation I		Transformation II		Transformation III	
		$e = 3{,}092$ $p = 0{,}992$		$e = 14{,}473$ $p = 0{,}969$		$e = 21{,}98$ $p = 0{,}435$
		$e = 0{,}312$ $p = 0{,}989$		$e = 5{,}861$ $p = 0{,}972$		$e = 14{,}362$ $p = 0{,}355$
		$e = 0{,}601$ $p = 0{,}981$		$e = 11{,}064$ $p = 0{,}922$		$e = 5{,}491$ $p = 0{,}692$
		$e = 0{,}419$ $p = 0{,}925$		$e = 2{,}821$ $p = 0{,}823$		$e = 10{,}66$ $p = 0{,}341$
		$e = 2{,}266$ $p = 0{,}975$		$e = 18{,}7$ $p = 0{,}888$		$e = 13{,}453$ $p = 0{,}598$
		$e = 0{,}913$ $p = 0{,}967$		$e = 6{,}212$ $p = 0{,}826$		$e = 8{,}472$ $p = 0{,}712$

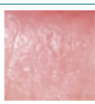
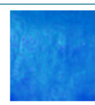
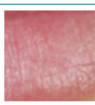
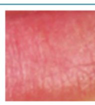
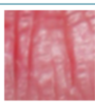
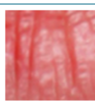
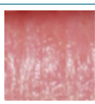
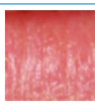
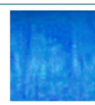
not many sources form which ideas and solutions can be drawn and a little number of publications on this type of color transfer exist.

The analysis of results generated by the algorithm was conducted for two characteristic surfaces on a face – the skin on cheeks (Tab. 1) and lips (Tab. 2). Each group is represented by six samples. For each sample the transformations performed were:

- a slight change of color – the target color is similar to the original one; gentle color, with weak features (Transformation I);
- change of brightness – target color is characterized by a high value of parameter V (Transformation II);
- change of intensity and hue – target color of an entirely different hue, darker and with high intensity (Transformation III).

In the analysis of values of the Pearson correlation coefficient p, a distinct influence of the modification of basic algorithm rules (resulting from the target values exceeding the acceptable ranges for HSV space) on the obtained results can be observed. The largest decrease in correlation was when a relatively homogeneous structure of the facial skin was also "flattened" by assigning the same value of intensity to a large number of

Tab. 2. The results of the algorithm on images of lips.

Image	Transformation I		Transformation II		Transformation III	
		$e = 10{,}697$ $p = 0{,}997$		$e = 6{,}9568$ $p = 0{,}987$		$e = 15{,}279$ $p = 0{,}739$
		$e = 5{,}096$ $p = 0{,}997$		$e = 28{,}43$ $p = 0{,}986$		$e = 30{,}14$ $p = 0{,}593$
		$e = 16{,}877$ $p = 0{,}995$		$e = 34{,}809$ $p = 0{,}99$		$e = 15{,}279$ $p = 0{,}739$
		$e = 16{,}816$ $p = 0{,}993$		$e = 35{,}773$ $p = 0{,}981$		$e = 31{,}109$ $p = 0{,}65$
		$e = 7{,}07$ $p = 0{,}996$		$e = 3{,}42$ $p = 0{,}983$		$e = 26{,}046$ $p = 0{,}926$
		$e = 43{,}246$ $p = 0{,}998$		$e = 65{,}823$ $p = 0{,}99$		$e = 67{,}895$ $p = 0{,}904$

pixels. This took place during Transformation III, because many pixel colors of the target image exceeded the maximum value of S parameter, which resulted in assigning a constant (maximum) value to them.

In other cases, the correlation between images is very high, especially in Transformation I. This conversion shows the situation in which the algorithm performs the color shift with the space in an almost unaltered configuration. There were no issues of exceeding the borders of the space. Therefore, there was no need for additional manipulation of brightness and saturation of color, which means that the differences between the color parameters are constant for each pair of corresponding image pixels. The correlation coefficient, however, is indicated for the image in greyscale. Because it is designated in accordance with the human perception (not based on parameter V itself), even such a direct transformation affects the perceived texture appearance.

The results obtained by the method of co-occurrence matrix e can not be compared in the same way, because their values strongly depend on the type of a presented image and must be considered in a broader context. However, when analyzing individual image samples, and keeping in mind the good results of using this method in texture classification, it should be noted that despite a substantial deformation of textures in Transformation III (where Pearson's correlation coefficient does not indicate a significant similarity with the original images), they are classified as more alike than the ones obtained in Transformation II (in spite of a high correlation of target and source textures).

Transformations II and III were selected in such a way that they present the critical points of the algorithm, i.e. those in which it is particularly exposed to texture deformations. In fact, such deformation can be observed both in obtained comparison results and in the presented output images. It should be noted, however, that these are extreme cases. Furthermore, these transformations did not lead to deformations, only to equalizing the surface structures. This makes it possible therefore to claim that the created solution conforms to the intent – the impression of texture is preserved.

6. Conclusion

The primary purpose of the algorithm of changing the texture colors is to minimize the loss of information about its structure (appearance). It is crucial in the case of virtual makeup, for the areas where cosmetics are applied not to look artificial. Based on the determined similarity measures, it was confirmed that the algorithm conforms to this intent. However, the primary objective of the virtual makeup system is the resulting visual effect. Therefore, in order to further develop the application, it is necessary to connect this tool to other components that form the virtual makeup system.

It should be noted that the proposed algorithm of transformation leads to flare effects when choosing the target color that is brighter than the original one. Although this effect is desired for some cosmetics (e.g. lip gloss), usually it is expected to bring the opposite effect (matting). Therefore, a modification of the algorithm to allow the manipulation of brightness parameter should be considered, to adapt it to the characteristics of the cosmetic. The structure of the algorithm allows for such modifications, because all the parameters of color channels, including their brightnesses, are processed separately.

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