Watermarking of Color Images based on spectral modulation of viewing illuminant

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Introduction

In this paper we present a new method of watermarking devoted to color images. Watermarking technics generally sign images by introducing changes that are imperceptible to the human eye, but are easily recoverable by a computer program. The locations in the image where the signature is embedded are determined by a secret key in order to prevent possible attacks by pirates or alterations due to compression and coding transformations, or geometrical transformations.

Meanwhile a lot of methods have been proposed to watermark grey level images, only few methods have been devoted to color images. In [1], Kutter proposed a new method to watermark a color image based on amplitude modulation of the blue channel, depending on the value of the bit, and proportional to the luminance. Next, Kim et al. proposed in [2] an another method based on magnitude increase of the saturation component with the contrainst that the resulting color difference is acceptable to the human visual system.

The basic idea of this paper is to use the spectral radiance distribution of a secret illuminant to watermark the image. To reach this aim the secret illuminant used in place of the viewing illuminant is itself embedded, in some notches locations, by a watermark signal proportional to the spectral distribution of the studied image. The computation of notches locations is based on the analysis of the magnitude of the spectral histogram of the original image.

In order to obtain a good tradeoff between robustness and invisibility, the amplitude of the watermark signal is controled by the amplitude of color differences between the original image and the watermarked one. Besides, it appears that, even for large variation of the specified histogram, the transformed images look visually undistrorted.

The proposed process do not require to know neither the original image, neither the original viewing illuminant, to extract the watermark signal.

Spectral characterization of a color image

The main components involved in the image acquisition process are described by Figure 1. Let us denote $R(x, y, \lambda)$ the spectral reflectance of the object located at pixel location (x, y), then $S(x, y, \lambda)$ represents the *stimulus* seen by the camera :

$$S(x, y, \lambda) = I(\lambda) \times R(x, y, \lambda) \tag{1}$$

We have therefore :

$$R(x, y) = \int_{\lambda_{min}}^{\lambda_{max}} r(\lambda).I(\lambda).R(x, y, \lambda).d\lambda$$

$$G(x, y) = \int_{\lambda_{min}}^{\lambda_{max}} g(\lambda).I(\lambda).R(x, y, \lambda).d\lambda$$

$$B(x, y) = \int_{\lambda_{min}}^{\lambda_{max}} b(\lambda).I(\lambda).R(x, y, \lambda).d\lambda$$

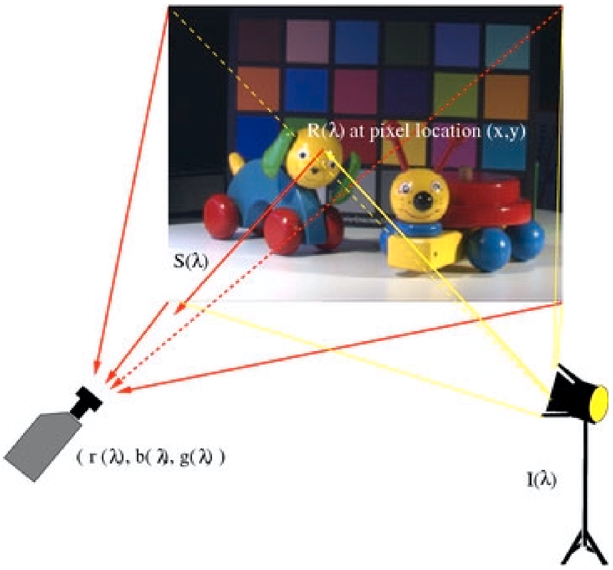

Figure 1: Schematic view of the image acquisition process. The camera response depends of the spectral radiance of the illumination $I(\lambda)$, of the spectral sensitivity $r(\lambda), g(\lambda), b(\lambda)$ of the r, g, b sensors, and of the spectral reflectance $R(\lambda)$ of the objects in the scene.

In our study, we have considered that the studied image has been acquired under a given illuminant, for example an illuminant with a $D65$ spectral radiance. That is, if the spectral radiance of the viewing illuminant is unknown, we suggest to use a *color constancy model*, such as those described in [3–8], to predict its spectral properties from spectral reflectance of the regions of the image.

It is well known that the appearance of a scene, or an image, may change considerably when the illuminant change [9–11]. Such a phenomenon is illustrated by Figure 2. That is, it is sometime difficult to predict changes in color due to changes in the viewing illuminant, one important for this being metamerism. To be abble to predict correctly these changes in color, we need to know the spectral reflectance of the objects of the scene (i.e. to work with multispectral images), and to use a *color appearance model* such as those proposed by Hardeberg [11]. That is, for color images an another heuristic process can be used. This process is described by the scheme illustrated by Figure 3.

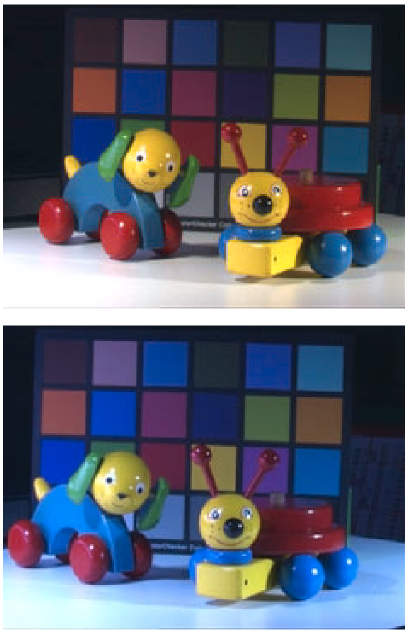

Figure 2: *Example of color appearance change due to a spectral radiance change of the viewing illuminant.*

This process require to know, or to predict, the channels response of the camera used and to know the coefficient of each matrix involved by the conversion transformations.

Step 1 : Watermarking of the spectral radiance distribution of viewing illuminant

The first step of our watermarking scheme consists of substituting to the viewing illuminant an another secret one, i.e. consists of simulating a change of viewing illuminant. Consequently, the colors of the image studied change according to the change of spectral radiance of the viewing illuminant. In order to illustrate this effect, we have simulated in Figure 4 a change of viewing illuminant from the $D65$ spectral radiance to the C spectral radiance.

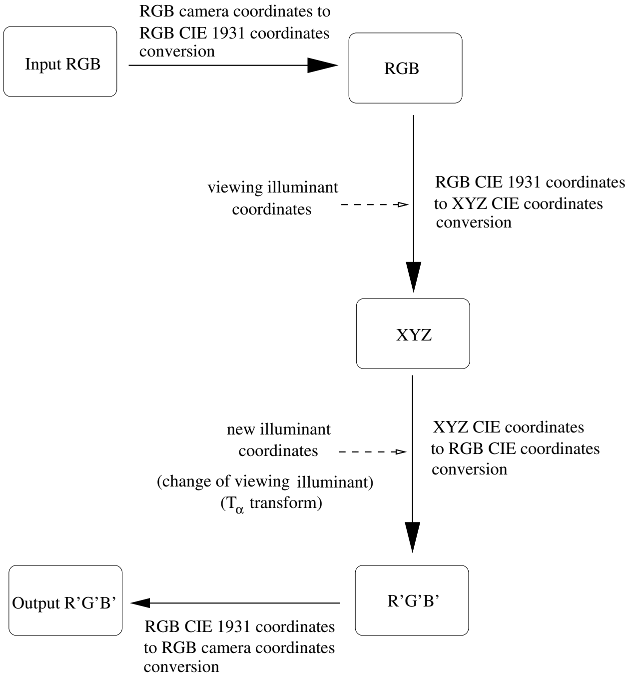

Figure 3: *Change of RGB color coordinates according to change of viewing illuminant coordinates.*

Let us note T_α the linear transformation which substitutes to the viewing illuminant $I_{D65}(\lambda)$ an another secret one $I_\alpha(\lambda)$, and T_α^{-1} the inverse transform which substitutes to the secret illuminant the original one. The new illuminant $I_\alpha(\lambda)$ is defined by using a secret procedure.

In this study, we have used the following transformation, which links illuminant $I_{D65}(\lambda)$ to illuminant $I_C(\lambda)$, to define the illuminant $I_\alpha(\lambda)$:

$$I_\alpha(\lambda) = (1-\alpha)\, I_{D65}(\lambda) + \alpha\, I_C(\lambda) \qquad (2)$$

This linear transformation depends of the parameter α which is given by a secret key.

More generally, whether we want to watermark some color areas of an image and not other ones, we suggest to use a secret procedure to define, to simulate, a new illuminant for which the spectral radiance will be maximal for each spectral wavelength corresponding to hues to take into account, and for which the spectral radiance will be minimal for other cases.

Let us note T_α the transform which enables to simulate the change of viewing illuminant required, thus :

$$I_\alpha(\lambda) = T_\alpha(I(\lambda)) \qquad (3)$$

We denote $R'G'B'$ the new RGB color coordinates of pixel (x, y) resulting of this change of illuminant.

Hue-to-spectral characterization of a color image

Step 2 : RGB-to-$YCrCb$ transformation

In this study, we have choosen the $YCrCb$ color space because $YCrCb$ is the color space used in the JPEG image compression standard and in the MPEG video compression standard [12]. In this color space Y represents the luminance component and $CrCb$ represent the chrominance components. These components are computed by means of the two following transformations [2, 12] :

$$\begin{aligned} Y &= 0.299R + 0.587G + 0.114B \\ R - Y &= 0.711R - 0.587G - 0.114B \\ B - Y &= -0.299R - 0.587G + 0.986B \end{aligned}$$

$$\begin{aligned} Y &= 16 + 235\,Y \\ C_b &= 128 + 112\left(\tfrac{0.5}{1-0.299}(R - Y)\right) \\ C_r &= 128 + 112\left(\tfrac{0.5}{1-0.299}(B - Y)\right) \end{aligned}$$

Let us note T_2 the RGB-to-$YCrCb$ transformation (see figure 5), and T_2^{-1} the inverse transformation. We consider that the RGB data are gamma-corrected and has a range of 0 to 255.

Step 3 : $YCrCb$-to-H transformation

Let us note H the phase of a point in the $CrCb$ plane, from the Cr axis, and S the magnitude of a point from origin of the $CrCb$ plane. Then H and S represent the Hue and the Saturation components of RGB data. They are given by :

$$\begin{aligned} H &= arctan\left(\tfrac{Cr}{Cb}\right) \\ S &= \left(Cr^2 + Cb^2\right)^{1/2} \end{aligned}$$

Let us note T_3 the $YCrCb$-to-YHS transformation (see figure 6), and T_3^{-1} the inverse transformation.

Step 4 : H-to-D_w transformation

Let us note T_4 the H-hue to D_w dominant wavelength transformation (see figure 6), and T_4^{-1} the inverse transformation.

Step 5 : scaled-space representation of the histogram $d(\lambda)$ of the D_w dominant wavelength componant

In order to select the most significant peaks of the histogram $d(\lambda)$ representative of the D_w-dominant wavelength componant, we have used a scale-space strategy which consists first to apply a scale-space Gaussian filter to the 1-D histogram $d(\lambda)$, and next to compute from the extrema of the derivatives, and from the intervals bounded by the extrema, a pair of thresholds (the upper and the lower) for each peak location [13, 14].

Let us note $g(\lambda, \tau)$ the Gaussian function used to smooth the 1-D signal $d(\lambda)$, and τ the standard deviation of this function.

Let us note $D(\lambda, \tau)$ the scale-space representation of the signal $d(\lambda)$, then :

$$D(\lambda, \tau) = d(\lambda) \; * \; g(\lambda, \tau) \qquad (4)$$

$$D(\lambda, \tau) = \int_{-\infty}^{\infty} d(u) \, \frac{1}{(2\pi)^{1/2}\,\tau} \, exp\left[\frac{-(\lambda - u)^2}{2\tau^2}\right] du$$

where “$*$” represents a 1-D convolution.

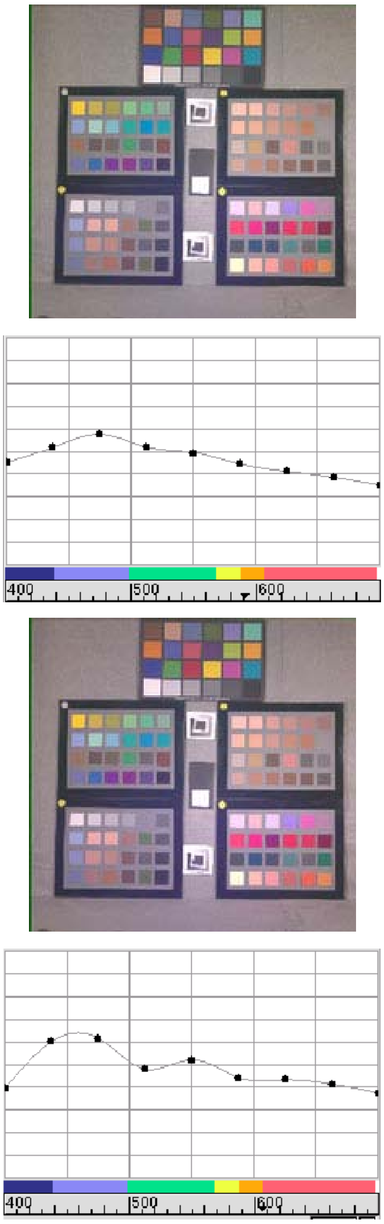

Figure 4: *Change of viewing conditions from illuminant D65 to illuminant C.*

Then, by computing the first and second derivatives of the signal $D(\lambda, \tau)$, and the zero-crossings defined by the following equations :

$$\frac{\supset D(\lambda, \tau)}{\supset \lambda} = d(\lambda) \; * \; \frac{\supset g(\lambda, \tau)}{\supset \lambda} = 0 \qquad (5)$$

$$\frac{\supset^2 D(\lambda,\tau)}{\supset \lambda^2} > 0$$

we locate easily the valleys of histogram $d(\lambda)$ [13, 14].

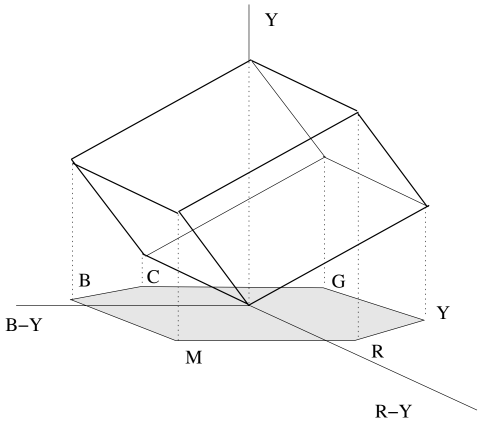

Figure 5: Color solid in the $Y\ R-Y\ B-Y$ color space. Projection of the $Y\ R-Y\ B-Y$ solid in the $R-Y\ B-Y$ plane.

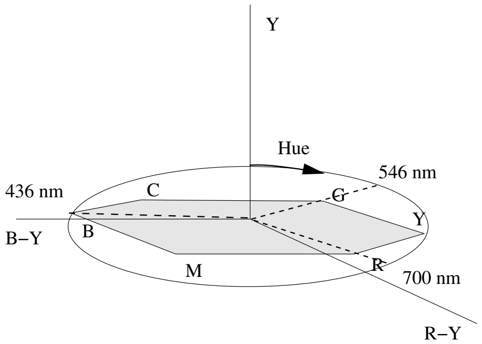

Figure 6: Chrominance hexagon of the YC_bC_r color solid. Projection of the $R-Y\ B-Y$ chrominance hexagon on the H hue component. Projection of the $R-Y\ B-Y$ chrominance hexagon on the D_w dominant wavelength componant.

Step 6 : selection of notches locations in the D_w dominant wavelength componant

The scale-space extrema at a certain τ_0 partition the λ-axis into several intervals. Let be nsp_1 the number of significant peaks determined by the scale value τ_0, and nsp_2 the subset of most significant peaks selected among these meaningful peaks. In order to determine the most significant peaks of the set of meaningful peaks extracted, we use the strategy proposed by Ohlander [15].

In this study, the parameters τ_0 and nsp_2 are two secret keys of the proposed approach.

The upper up and lower lo values of the first derivative $D'(\lambda,\tau)$ of the signal $D(\lambda,\tau)$ correspond to the λ-values where the sharpness is the higher, i.e. where the wavelength contrast is maximal.

Let us note $C_\tau(\lambda)$ the contrast function corresponding to the signal $D(\lambda,\tau)$, defined by :

$$C_{\tau,\beta}(\lambda) = \beta \times \left(|D'(\lambda,\tau)| - 1/2 \left(\frac{up + lo}{2} \right) \right) \quad (6)$$

where β represents the magnitude given to the signal $C_{\tau,\beta}(\lambda)$.

The parameter β is an another secret key of the process. The upper value of $C_{\tau,\beta}(\lambda)$ corresponds to the λ-values where the wavelength contrast is maximal. The lower value of $C_{\tau,\beta}(\lambda)$ corresponds to the λ-values where the wavelength contrast is minimal. By definition, the mean value of $C_{\tau,\beta}(\lambda)$ tends toward 0.

Watermarking of color image from spectral radiance distribution of viewing illuminant

Step 7 : Watermark signal embedded to the spectral distribution of viewing illuminant

The next step of our watermarking process consists of embedding the watermark signal $C_{\tau,\beta}(\lambda)$ into the spectral radiance distribution of the illuminant $I_\alpha(\lambda)$. The magnitude of this embedded signal is determined by the parameter β. The modifications are either additive or subtractive, and verify the following condition to be invisible :

$$C_{\tau,\beta}(\lambda) < \gamma\,\%\, I_\alpha(\lambda) \quad (7)$$

The value γ is selected such as to offer best trade-off between robustness and invisibility. In our study, γ is equal to 10. Besides, it appears that, even for large variation of the specified histogram, the transformed images look visually undistrorted.

Let us note T_7 the transform which embeds the watermark signal into the spetral radiance distribution of illuminant $I_\alpha(\lambda)$, thus :

$$I_{\tau,\beta,\alpha}(\lambda) = T_7(I_\alpha(\lambda)) = I_\alpha(\lambda) + C_{\tau,\beta}(\lambda) \quad (8)$$

We denote $R_eG_eB_e$ the new RGB color coordinates of pixel (x, y) resulting of this embedding based on spectral modulation of viewing illuminant.

Through an embedding of a watermark signal into the spectral radiance distribution of the viewing illuminant, we have thus realized an embedding of a watermark signal into the original image. Indeed, as shown in equation (1), the color appearance of an object (of a region) depends obviously of its spectral reflectance but also of the spectral radiance of the viewing illuminant. In watermarking the viewing illuminant, we have thus watermarked indirectly the original image. In order to illustrate this effect, we have simulated in Figure 4 an embedding of the C illuminant by an amplitude modulation of its spectral radiance distribution. We can observe that the degradations resulting of this watermarking process are acceptable to the human visual system, i.e. these degradations are invisibles (compare image given by Figure 4 with watermarked image given by Figure 7).

Figure 7: Example of watermark signal embedded to the spectral distribution of the viewing illuminant $I_{\tau,\beta,\alpha}(\lambda) = I_\alpha(\lambda) \pm 10\ \%\ I_\alpha(\lambda)$ *with* $\alpha = 1$.

Step 8 : Inverse change of illuminant to retrieve the original illuminant

The last step of our watermarking process consists of computing the inverse transform T_α^{-1}, in order to retrieve the original illuminant used to acquire the original image, i.e. the viewing illuminant $I(\lambda)$. This transform is used to obtain a watermarked image with the same color appearance as the original one. This last step can be defined by :

$$I_{\tau,\beta}(\lambda) = T_\alpha^{-1}(I_{\tau,\beta,\alpha}(\lambda)) \tag{9}$$

We denote $R_f G_f B_f$ the new RGB color coordinates of pixel (x, y) resulting of this “inverse” change of illuminant.

Magnitude of the watermark signal versus its degree of visibility

In order to assess color differences between the RGB coordinates (i.e. the original image) and the $R_f G_f B_f$ coordinates (i.e. the watermarked image), we use the $YCrCb$ color space, because in the $YCrCb$ color space color differences are proportional to color difference perceived by the human visual system [2].

Measurement of color differences from $YCrCb$ color space

Color difference in $YCrCb$ color space is defined by :

$$\Delta E_{CrCb} = \sqrt{(Y - Y_f)^2 + (Cr - Cr_f)^2 + (Cb - Cb_f)^2} \tag{10}$$

To assess color differences between the original image and the watermarked image, we use the PSNR measure based on the computation of the Mean Squared Error (MSE) measure defined by the following equations :

$$PSNR = 10\ \log_{10} \frac{255^2}{MSE} \tag{11}$$

$$MSE = \frac{1}{n.m} \sum_{x=1}^{n} \sum_{y=1}^{m} \Delta E_{CrCb}\,(x, y) \tag{12}$$

The tradeoff between robustness and invisibility

According to differents studies, we can consider that if a color difference ΔE_{CrCb} is lesser than 3 then this difference is none noticeable to the observer [2, 16]. On the other hand, if a color color difference ΔE_{CrCb} is bigger than 6, but lesser than 6, then this difference is perceptible to the human visual system, but nevertheless acceptable. If the color difference ΔE_{CrCb} is bigger than 6 then this difference is visible, and the two colors involved are considered as differents colors. We have used the same thresholds to analyse, from the MSE measure, the degree of visibility of our watermark process, and to adjust our parameters $\beta$and τ.

Through an iterative process, we have progressively amplified the amplitude of additive and subtractive modifications corresponding to transform T_7 (see step 8 of the process), in increasing the value of γ with an increment of 2% (the γ value is initially fixed to 4%) until having a MSE measure bigger than 6.

The interest of such an iterative process is that it enables to adjust automatically the value of the parameter β of the watermark process, this in order to obtain a good tradeoff between robustness and invisibility.

Perspectives

The next step of our work will consist to study the robustness of the secret procedure used to specify the illuminant $I_\alpha(\lambda)$ in regards to the notches locations of spectral distribution of $C_\tau(\lambda)$. Likewise, we will study if changes in spectral histogram of the transformed images can be easily detected from any image attack process. Protections against attacks will be reinforced by using a regional watermarking procedure based on color distribution of regions.

We will analyse also how to recover the embedded watermark signal from an image in using inverse, but not symmetric, functions of the embedding functions.

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References

[1] M. Kutter, F. Jordan, and F. Bossen. Digital signature of color images using amplitude modulation. In *Proc. SPIE*

Storage and Retrieval for Image and Video Databases, volume 3022, pages 518–526, San Jose, California, 1997.

[2] H. S. Kim, H. K. Lee, H. Y. Lee, and Y. H. Ha. Digital watermarking based on color differences. In *Proc. SPIE Internet Imaging II*, volume 4314, pages 10–17, San Jose, California, 2001.

[3] L. T. Maloney and Brian A. Wandell. Color constancy : a method for recovering surface spectral reflectance. *J. of the Optical Society of America*, 3(1):29–33, 1986.

[4] A. C. Hurlbert, W. Wen, and T. Poggio. Learning colour constancy. *Journal of Photographic Science*, 42:89–90, 1994.

[5] B. V. Funt. Linear models and computational color constancy. In *Color Imaging Conference : Color Science, Systems and Applications*, pages 26–29, Scottsdale, Arizona, November 1995. IS&T and SID Proceedings, 3rd CIC.

[6] G. D. Finlayson, P. M. Hubel, and S. D. Hordley. Colour by correlation. In *Color Imaging Conference : Color Science, Systems and Applications*, pages 6–11, Scottsdale, Arizona, November 1997. IS&T and SID Proceedings, 5th CIC.

[7] G. D. Finlayson, S. D. Hordley, and P. M. Hubel. Colour by correlation: A simple, unifying approach to colour constancy. In *International Conference on Computer Vision*, pages 835–842, Kerkyra, Greece, September 1999. IEEE Proceedings, ICCV.

[8] B. V. Funt. Color constancy in digital imagery. In *International Conference on Image Processing*, page 27AS2.4, Kobe, Japan, October 1999. IEEE Proceedings, ICIP.

[9] D. H. Brainard and Brian A. Wandell. Asymetric color matching: How color appearance depends on the illuminant. *J. of the Optical Society of America*, 9:1433–1448, 1992. QC.0622 in MIT Humanities Lib.

[10] S. L. Hayden and D. P. Oulton. The quantification of small visual colour differences. *JSDC*, 110:104–111, March 1994.

[11] J. Y. Hardeberg, F. Schmitt, and H. Brettel. *Colour Imaging : Vision and Technology*, chapter Multispectral Image Acquisition and Simulation of Illuminant Changes. John Wisley, 1999.

[12] J. Gomes and L. Velho. *Image processing for computer graphics*. Springer Verlag, 1997.

[13] Y. W. Lim and S. U. Lee. On the color image segmentation algorithm based on the thresholding and the fuzzy c-means techniques. *Pattern Recognition*, 23(9):935–952, 1990.

[14] R. Schettini. A segmentation algorithm for color images. *Pattern Recognition Letters*, 14:499–506, 1993.

[15] R. Ohlander, K. Price, and R. D. Reddy. Picture segmentation using a recursive region splitting method. *Computer Graphics and Image Processing*, 8:313–333, 1978.

[16] J. Y. Hardeberg. Transformations and colour consistency for the colour facsimile. Master's thesis, Norwegian Institute of Technology (NTH), Trondheim, Norway, April 1995.