Texture Classification across Illumination Color Variations

Rahat Khan, Damien Muselet, and Alain Trémeau

***Abstract*—Accounting color information in the texture description can help in the context of classification but the instability of color across illumination variations remains a problem since most practical applications are more likely to face varying illumination conditions. That is why we analyze the impact of such variations on the most classical texture features and we show that, from their structures, these features are not far from the lowest invariance degree required by most of the applications. Hence, applying classical color normalization on these features leads to unnecessary invariance that tends to decrease their discriminative power. Consequently, in this paper, we propose a feature transformation model and a deduced normalization step. We show that the resulted texture features do not depend on the illumination variations while preserving the maximum of the discriminative information. Our classification results outperform the existing texture descriptors available in the literature.**

***Index Terms*—Texture, color, illumination invariance, classification.**

I. Introduction

The human visual system is able to perceive colors as unchanged even if the illumination color is varying but what seems very easy for our brain is still a puzzle in the field of digital image processing. To deal with this problem, many different but related research areas have been emerged. Illumination invariant texture description is one of these areas and has been shown useful in many different applications e.g. face recognition, content based indexing and retrieval. In this paper, we specifically address the problem of color texture classification across illumination temperature variations. For this purpose, we consider images of color textures acquired with the same viewpoint and the same scale factor but under different illumination colors.

Different solutions can be found in the literature and we propose to distinguish two main approaches. The first one consists first, in applying a color normalization on the images such as the grey-world normalization [1], the comprehensive color image normalization [2] or the color constant color indexing approach [3] and second, in extracting classical texture features from the normalized images [4]. The second one consists in extracting directly specific invariant features from the images. Some of such invariant features exploit the rank measures [5] of the pixels [6], [7]. Healey et al. [8] have used spatial correlation function and shown that in case of change in the illumination conditions, the change in the structure of the correlation function is linear and they have solved the problem by proposing an adapted distance function. In another work, Hanbury *et al.* [9] have employed mathematical morphology to address the problem. Finlayson *et al.* [10] have proposed a method known as angular color indexing and have shown that inter-band color vector angles of the laplacian edge map of each color band are invariant to illumination changes. Color ratio [3] histograms have also been tested by [4] as a potential invariant texture descriptor. Finaly, Muñiz *et al.* have used color ratio with gabor features, wavelet and co-occurrence matrices and shown improved results [11].

In the context of texture recognition, the aim is not to normalize the colors of the images so that these images look as if they had been acquired under a canonical illumination but rather to extract discriminant invariant features from the images. In order to be highly discriminative, we argue that these features must be as less sensitive as possible to illumination variation while preserving the maximum information about the material properties. In this sense, we have to make a trade-off between invariance across illumination changes and discriminative power of the resulted features. For example, a normalization that would be perfectly invariant to illumination colors would consist in setting all the colors to a single one (for example R = 1, G = 1 and B = 1 for all the pixels). This normalization would provide features that are perfectly invariant to illumination variations but that are not at all discriminative. Thus, the optimal normalization, with respect to discriminative power, would be this which removes only the effect of the illumination on the colors without removing any information from the material properties.

In this paper, we show that the classical texture features, which are based on frequency decomposition, remove a part of the effect of the illumination color variation. Consequently, when these features are used, it is very important to account this removal so that it is not done a second time by a useless normalization step. Indeed, we have just said that the addition of superfluous normalization decreases the discriminative power of the resulted features.

Thus, three points have to be carefully analyzed in the context of color texture classification. First, we have to know how a change in the color of the illumination impacts the colors of the pixels. This is represented by, what we call a color transformation model. In the second section of this paper, we propose to present the most widely used color transformation models and to test them on a publicly available database. From this experiment, we deduce the most adapted color transformation model for our application and we show that this model can be explained in theory in

Manuscript received June 25, 2012; revised July 29, 2012.

The authors are with the Laboratoire Hubert Curien UMR CNRS 5516 Université Jean Monnet – Saint Etienne, France 42000.

DOI: 10.7763/IJCTE.2013.V5.648

the third section. Second, if we consider that this model holds, we have to evaluate the impact of an illumination color variation on the extracted features. This is represented by, what we call a feature transformation model. The main contribution of this paper is to show that for the classical texture features based on frequency decomposition, the feature transformation model is different from the color transformation model and that this difference has to be accounted by the normalization step. Third, we have to normalize the features according to this knowledge while taking care that no interesting information is removed. These last two points are presented in the fourth section. In the fifth section, experimental results show that the application of these recommendations provide very good results in the context of color texture classification.

II. Color Transformation Models in Practice

Classical color transformation models. Color transformation models describe how the intensities of Red, Green and Blue channels, commonly referred to as RGB, of a pixel in an image acquired under one illumination change to R'G'B', the intensities of the pixel "observing" the same elementary surface in an image of the same scene acquired under another illumination. These models are based on assumptions on the parameters of the color formation, i.e. the scene illumination, the reflective model of the object and the camera sensor responses [12]. This problem is very complex by nature but thanks to these assumptions it is generally agreed that linear models are good fit for color transformation models. In literature, three different linear models have been widely used: the Diagonal model [13], [14], the Diagonal-Offset model [15], [16] and the Affine model [17], [18] respectively defined by:

$$\begin{pmatrix} R' \\ G' \\ B' \end{pmatrix} = \begin{pmatrix} \alpha_R & 0 & 0 \\ 0 & \alpha_G & 0 \\ 0 & 0 & \alpha_B \end{pmatrix} \begin{pmatrix} R \\ G \\ B \end{pmatrix} \quad (1)$$

$$\begin{pmatrix} R' \\ G' \\ B' \end{pmatrix} = \begin{pmatrix} \alpha_R & 0 & 0 \\ 0 & \alpha_G & 0 \\ 0 & 0 & \alpha_B \end{pmatrix} \begin{pmatrix} R \\ G \\ B \end{pmatrix} + \begin{pmatrix} \beta_R \\ \beta_G \\ \beta_B \end{pmatrix} \quad (2)$$

$$\begin{pmatrix} R' \\ G' \\ B' \end{pmatrix} = \begin{pmatrix} \alpha_{RR} & \alpha_{RG} & \alpha_{RB} \\ \alpha_{GR} & \alpha_{GG} & \alpha_{GB} \\ \alpha_{BR} & \alpha_{BG} & \alpha_{BB} \end{pmatrix} \begin{pmatrix} R \\ G \\ B \end{pmatrix} + \begin{pmatrix} \beta_R \\ \beta_G \\ \beta_B \end{pmatrix} \quad (3)$$

There exists a lot of such models and the difference between them are the dependences of the parameters α and β. The literature is not unanimous when the color transformation model is in question [14]-[18]. In the introduction, we have underlined that the choice of the colour formation model is very important in the definition of the texture features. We have to select the model from which we will deduce a normalization whose aim is to remove the effect of the illumination on the colors without removing the information about the material properties. On the one hand, if we want to be sure to remove the impact of the illumination on the colors, we should choose the most complex model, i.e. the Affine model (eq. (3)), on the other hand, if we want to be sure to preserve all the information about the material property, we should choose the most simple model, i.e. the Diagonal model (eq. (1)). However, Finlayson *et al.* have shown that for best fit of the canonical color gamut, addition of the offset terms to the Diagonal model are necessary [16] and Gros *et al.* have suggested that Diagonal-Offset model is a good compromise between complexity and accuracy [15]. Consequently, the first intuition is to move to the Diagonal-Offset model (eq. (2)). In the next paragraph, we propose to validate this intuition on the outex database [19].

Validation on the outex database. To measure the performance of the three models on real images, we propose to test them on some texture image pairs of outex database [19]. From outex texture database, random pairs of images acquired under two different illumination conditions are chosen. Since the camera have not moved between the acquisitions, the same elementary surfaces are associated to the pixels with the same spatial coordinates in the two images. Using a least square approach, it is possible to find the best global transform between the colors of the corresponding pixels from the first image to the second one by using one of the three models. Then, this transformation is applied on the first image and we calculate the residual root mean square error (RMSE) between this transformed image and the second original image of the pair. By applying this on 10 pairs of images, we have evaluated the mean RMSE for each model. We have obtained 2.11 for the Diagonal model, 0.42 for the Diagonal-Offset model and 0.32 for the Affine model. As expected, this shows that when the complexity of the color transformation model increases (from Diagonal to Diagonal-Offset and to Affine), the residual error decreases, i.e. the invariance increases. Furthermore, the Diagonal model generates high errors comparing to the two other models whose errors are relatively close together. Since we know that the increasing of the complexity of the model can lead to a decreasing of the discriminative power of the resulted features, the best choice is the Diagonal-Offset model because it is the best trade-off between minimization of the residual errors (maximization of the invariance) and minimization of the complexity (maximization of the discriminative power). This is not a proof that the Diagonal- Offset model is the best in all situations, but this shows that this model also provides the best results for the Outex database. Furthermore, we obtain to the same conclusions as [15] and [16] who did experiments on other databases. In the next paragraph, we propose to show the theoretical meaning of this Diagonal-Offset model.

III. The Diagonal-Offset Model in Theory

Considering the Lambertian model, the color values $\{R_E, G_E, B_E\}$ of a pixel in an image depend on three different factors which are the spectral power distribution of the illumination $E(\lambda)$, the reflectance of the surfaces observed by the camera $S(\lambda)$ and the spectral sensitivity of the sensors $Q_R(\lambda)$, $Q_G(\lambda)$ and $Q_B(\lambda)$. Shaffer proposed to add a 'diffuse' light term $L_E(\lambda)$ in order to account the inter-reflections, the infrared sensitivity of the camera sensors and the scattering property of the lens [12]:

$$K_E = \int_{\lambda_1}^{\lambda_2} S(\lambda)E(\lambda)Q_K(\lambda)d\lambda + \int_{\lambda_1}^{\lambda_2} L_E(\lambda)Q_K(\lambda)\, d\lambda, \qquad (4)$$

where $K = \{R, G, B\}$. The integral is taken over the range of wavelengths λ_1 to λ_2 for which the sensor has non-zero sensitivity.

By assuming that each sensor Q_K, $K = \{R, G, B\}$ is sensitive to only one wavelength λ_K, we deduce that $\int_{\lambda_1}^{\lambda_2} QK(\lambda)d_\lambda = Q_K(\lambda_K)$. In practice, although this assumption does not hold perfectly it leads generally to adequate models [20], [3] and it can be improved by spectral sharpening [21]. This assumption transforms equation (4) into:

$$K_E = S(\lambda_K)\, E(\lambda_K)\, Q_K(\lambda_K) + L_E(\lambda_K)\, Q_K(\lambda_K) \qquad (5)$$

Then, if the spectral power distribution of the illumination changes from $E(\lambda)$ to $E'(\lambda)$,the color component of the same elementary surface is given by:

$$K_{E'} = S(\lambda_K)\, E'(\lambda_K)\, Q_K(\lambda_K) + L_{E'}(\lambda_K)\, Q_K(\lambda_K) \qquad (6)$$

From equations (5) and (6), we can obtain the color transformation model:

$$K_{E'} = \alpha_K K_E + \beta_K \ ,$$

where

$$\begin{cases} \alpha K = \dfrac{E'(\lambda K)}{E(\lambda K)} \\ \beta K = L_{E'}(\lambda_K) QK(\lambda K) - \dfrac{L_E(\lambda K) QK(\lambda K) E'(\lambda K)}{E(\lambda K)} \end{cases} . \qquad (7)$$

Thus, if we consider lambertian surfaces and narrow band sensors, the illumination variation can be modeled by the Diagonal-Offset model where the coefficients α_K and β_K depend only on the two spectral power distributions of the illuminations $E(\lambda)$ and $E'(\lambda)$ and on the sensitivities of the sensors. Since they do not depend on the analyzed pixel, this transform is the same for all the pixels in the same image. This characteristic is important for the normalization step.

IV. Illuminant Invariant Texture Features

Feature transformation model. In this section, we propose to determine the feature transformation model, i.e. how an illumination variation impacts the texture features. For this, we consider the classical texture features which are based on frequency decomposition. These features are based on the Discrete Fourier Transform (DFT), the Discrete Cosine Transform (DCT) or the Discrete Wavelet Transform (DWT).

From the last section, we have shown that, if we consider a pixel P_i in one image acquired under the illumination E and the pixel P_i' in a second image acquired under the illumination E' so that P_i and P_i' observe the same elementary surface, then the relation between their respective color components $K(P_i)$ and $K(P_i')$ is:

$$K(P_i) = \alpha_K \ K(P_i') + \beta_K\ , \quad K = \{R, G, B\} \qquad (8)$$

where α_K and β_K do not depend on the considered pixel.

Considering a set of N weights w_i so that $\sum_i w_i = 0$ and a set of pixels P_i in the first image, the weighted sum:

$$\begin{aligned} \Sigma_i\, w_i K(P_i) &= \alpha_K \Sigma_i\, w_i\, K(P_i') + \beta_K \Sigma_i w_i \\ &= \alpha_K\, \Sigma_i\, w_i\, K(P_i'),\ \ K = \{R, G, B\}, \end{aligned} \qquad (9)$$

does not depend on the parameterβ_K.

This means that a weighted sum of the component levels of some pixels in an image transforms the Diagonal-Offset model into a Diagonal model if the sum of the weights is 0. We know that the frequency decomposition used by the classical texture features like DFT, DCT or DWT is based on weighted sums of the component levels of some pixels so that the sums of the weights are 0. Thus, by using these features, we transform the Diagonal-Offset color transformation model into a Diagonal feature transformation model. The only part of these features which preserves the β_K is the one which represents the lowest frequencies. Consequently, the normalization of these kinds of texture features consists in removing only the α_K which represent the diagonal coefficients of the transformation matrix. Since these coefficients are constant over the whole image, one good way to remove them is just to normalize the energy of the texture features, i.e. to divide the coefficients of the features by the mean value of the non-zero frequencies (because zero frequency coefficients still depend on the β_K). The complete normalization is illustrated with the Fourier Transform in Fig. 1. It is worth mentioning that we can replace the Fourier transform here with any other frequency decomposition transforms.

Invariant Features. To demonstrate the effectiveness of our normalization method, we have chosen two classical texture descriptors for feature extraction. Both of them are filtering based techniques and different in design, but exploit frequency decomposition transforms. They are, namely, Gabor filtering and local linear transform.

1) Gabor filtering: Gabor filters are used to model the spatial summation properties of simple cells in the visual cortex and have been adapted and popularly used in texture analysis [22] [23] [24]. In this paper, we have followed the approach proposed by Manjunath *et. al.* [24] to generate the filters. The idea of Gabor is to take the Fourier transform of the image, to multiply it with a Gaussian window centered at various frequencies, and to take the inverse Fourier transform of this filtered Fourier. Then for each filter, they extract two features from this resulted image: the mean of the absolute values of this image and the standard-deviation of the image. $\text{Gabor}_{4,6}$ considers 4 scales and 6 orientations, that constitutes a set of 24 filters. So, the dimensionality of the feature vector is 48 for one channel and 144 for 3 channels (color

images). We know that the sum of the weights of the Fourier Transform is equal to 0 for each frequency, except for the zero-frequency term. Consequently, the non-zero frequency components of the Fourier transform are insentive to the β_K from equation (7). So, our normalization consists just in dividing the Fourier transform by the mean value of all its component, except the zero-frequency component, before applying Gabor.

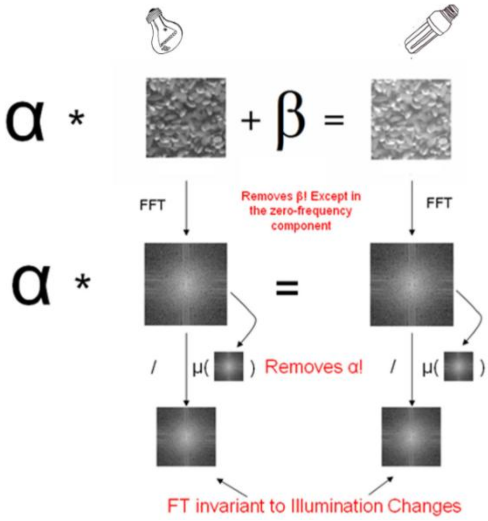

Fig. 1. Graphical representation of the complete normalization process. We use FFT for Fast Fourier Transform and FT for Fourier Transform. μ is the mean value.

2) Local linear transform: The original idea of Local Linear Transform(LLT) was proposed by Micheal Unser [25]. Unser proposed to characterize the texture by a set of statistical measures at the outputs of a filter bank of relatively small size. Each filter mask is tuned to capture a particular property of the texture. Drimbarean *et al.* [26] proposed Discrete Cosine Transform (DCT) to use with LLT. Except for the zero-frequency filter, the sum of the weights of each filter is 0. Consequently, the resulted features are insensitive to the β_K from equation (7). In order to remove the α_K and reach full invariance, we propose to divide each filtered image by its mean. Finally, we obtain 24 dimensional feature vectors for 3 channels.

V. Results and Discussion

For performance evaluation of our method, we are using 'Outex_TC _000014' test suite as a classification problem [19]. This test suite has 68 different textures under three different illuminations. The textures illuminated by 2856K incandescent CIE A light source are used as training data, while the textures illuminated by 2300K horizon sunlight and 4000K fluorescent TL84 are the test samples. We have selected the training and test sets as recommended on the webpage of the Outex database. Furthermore, we have employed k-NN classifier with $k = 3$ like most of the research works on this database. Unfortunately, we can not compare our results with those of Hanbury *et al.* [9] or those of Seifi *et al.* [7] because they have used a different way to select the training and test sets in Outex_TC _000014.

Table I shows the effect of our normalization on the classification result for both the features. From the results of Table I we can clearly see that our normalization method provides a huge improvement in the classification results. We also see that the Gabor features clearly perform better than the local linear transform features. So, for the rest of the experiments, we propose to present only the results provided by Gabor features.

TABLE I: Classification Scores Performed on OUTEX_TC_000014.

Feature	Without normalization	With our normalization
Gabor4,6	35.4%	64.9%
LLT	14.0%	51.4%

TABLE II: Classification Scores Performed on Outex_TC _000013.

Feature	Without normalization	With normalization
Gabor4,6	84.8%	84.8% (our normalization)
Gabor3,4	86.9%	84.0% (Z-normalization)

Table II shows that our normalization increases the invariance of the classical texture features based on frequency decomposition. That is one advantage of our normalization. The second advantage of this normalization is that it does not decrease too much the discriminative power of these resulted features. In order to prove that, we propose to use another test suite titled Outex_TC _000013 for which only one illuminant (incandescent one) was used for test and training sets and to compare the classification scores with and without normalization. Furthermore, we propose to make the same comparison (with and without normalization) with the Z-normalization which consists in normalizing the images so that the mean value of each channel is 127 and the standard deviation is 20. It is easy to show that this normalization also removes the α_K and β_K from the image. The results of this normalization are taken from [4] where the Gabor3,4 features were used. They are based on different filters than those of Gabor4,6 but usually provide similar results [4]. The results presented in Table II show that the application of our normalization does not decrease the results, because the accuracy remains the same before and after the normalization. This stable result shows that our normalization does not decrease the discriminative power of the texture features. However, the application of Z-normalization on Gabor3,4 filters decreases the results from 86.9% to 84.0%. This confirms our intuition that too much invariance decreases the discriminating power. Indeed, we know that Gabor filters cancel one part of the illumination impact on the colors since they remove the β_K (see equation (7)). Then we also know that the Z-normalization removes both the α_K and β_K. Consequently, applying Z-normalization before Gabor filters is like a "double illumination normalization" and this reduces the discriminative power of the resulted features.

TABLE III: CLASSIFICATION SCORES PERFORMED ON OUTEX _TC _000014.

Feature	Classification score
$Gabor_{4,6}$ RGB Our	64.9%
$Gabor_{4,6}$ RGB Greyworld	58.3%
$Gabor_{3,4}$ RGB	43.5%
$Gabor_{3,4}$ RGB Z-	62.4%
$Gabor_{3,4}$ L*a*b*	55.2%
Gabor Opponent Color	53.3%
3D Histogram of Invariant	42.7%
$LBP_{8,1}$ RGB	53.9%
$LBP_{8,1}$ RGB	43.8%
$LBP_{8,1}$ L*a*b*	60.1%
$LBP^{u2}_{16,2}$ L*a*b*	63.2%
$LBP_{8,1} + {}^{u2}_{16,2} + {}^{u2}_{24,5}$ L*a*b*	67.8%

TABLE IV: CLASSIFICATION SCORES PROVIDED ON LUMINANCE CHANNEL OF THE TEXTURES IN OUTEX_TC _000014TEST SUITE.

Feature	Classification score
$Gabor_{4,6}$ Our normalization	71.25%
$Gabor_{4,6}$	66%
$LBP^{u2}_{16,2}$	69.3%
$LBP_{8,1} + {}^{u2}_{16,2} + {}^{u2}_{24,5}$	69.5%

TABLE V: CLASSIFICATION SCORES FOR EACH ILLUMINATION SOURCES ON OUTEX_TC _000014 TEST SUITE.

$Gabor_{4,6}$ Our normalization	TL84	Horizon	Average
Color	74.4%	53.6%	64.9%
Luminance	69.2%	73.3%	71.25%

We propose now to compare the classification score of our normalized Gabor with those of classical texture features on the Outex_TC _000014 test suite where the illumination is changing between test and training sets. The results of all these features are extracted from [4]. In Table III: we can find the results for several Gabor feature normalized by some classical illumination invariant approaches, the histograms of the invariant color ratios from Funt *et al.* [3] and some variants of the well known Local binary Pattern (LBP). We can see that $LBP(_{8,1} + {}^{u2}_{16,2} + {}^{u2}_{24,5})$ provides the best results. However, the determination of the transformation from RGB to L*a*b* requires the knowledge of illumination conditions and sensor sensitivities.

These data are available for the outex database and the use of the L* a* b* color space is possible but for practical applications where the illumination conditions and the sensor sensitivity are unknown, the default transformation leads to less accurate results. We can see that Gabor features obtained from our normalization provide the second best results among all the classical texture features and classical illumination normalizations.

Finaly, we propose to test our normalization on grey-level images. Indeed, Table IV shows the classification scores by considering only the luminance channel of the textures of 'Outex_TC_000014' test suite. The luminance channel was calculated using $Y = 0.6534R + 0.3190G + 0.0277B$ as recommended by [4] for the sake of comparison. We can see from the results that Gabor features with our normalization provides the best results among all the methods. Indeed, we have shown that our normalization has to be applied independently on each channel, so in case of grey-level textures, we consider that the luminance channel is one channel and that it can be normalized exactly the same way.

Thus, in this section, we have shown that Gabor filters obtained after the application of our normalization provide very good results in the context of texture classification across illumination changes.

VI. CONCLUSION

In this paper, we have proposed a way to normalize the classical texture features based on frequency decomposition in case of illumination variations. For that, we have introduced a feature transformation model that represents the way how the texture features vary in case of illumination changes. This model is deduced from the Diagonal-Offset color transformation model whose efficiency has been assessed on a publicly available database and compared with two other well-known color transformation models. Then, we have shown that with this knowledge, we can design texture features which depends as less as possible on the illumination used for the image acquisition while preserving almost all the information about the material properties. The Gabor filters obtained after the application of our normalization provide very good results in the context of texture classification across illumination changes. We have not addressed the problem of rotation invariant features in our work, but there exist many modifications of these classical descriptors to make it invariant to rotation [28] [29]. This will be one of our future works.

REFERENCES

[1] G. D. Finlayson and E. Trezzi, "Shades of gray and colour constancy," in *Proc. of Color Imaging Conference*, 2004, pp. 37–41.

[2] G. FInlayson, B. Schiele, and J. Crowly, "Comprehensive color image normalization," in *Proc.of the 5th of European Conference on Computer Vision*, vol. 1, Frieburg, Germany, 1998, pp. 475–490.

[3] B. V. Funt and G. D. Finlayson, "Color constant color indexing," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 17, no. 5, pp. 522–529, 1995.

[4] T. Mäenpää and M. Pietikäinen, "Classification with color and texture: jointly or separately," *Journal of the Pattern Recognition Society*, November 2003.

[5] G. Finlayson, S. Hordley, G. Schaefer, and G. Y. Tian, "Illuminant and device invariant colour using histogram equalisation," *Pattern Recognition*, vol. 38, pp. 179–190, 2005.

[6] T. Ojala, M. Pietikäinen, and T. Mäenpää, "Gray scale and rotation invariant texture classification with local binary patterns," in *Proc. of European Conference on Computer VIsion*, 2000, pp. 404–420.

[7] M. Seifi, X. Song, D. Muselet, and A. Trémeau, "Color texture classification across illumination changes," presented at European Conference on Colour in Graphics, Imaging and Vision, 2010.

[8] G. Healey and L. Wang, "Illumination-invariant recognition of texture in color images," *Journal of Optical Society of America*, vol. 12, pp. 1877–1883, 1995.

[9] A. Hanbury, U. Kandaswamy, and D. Adjeroh, "Illumination-invariant morphological texture classification," presented at 7th International Symposium on Mathematical Morphology, 2005.

[10] S. S. C. Graham, D. Finlayson, and B. V. Funt, "Color angular indexing," presented at European Conference on Computer Vision, 1996.

[11] R. Muñiz and J. A. Corrales, "Pattern Recognition and Image Analysis," *ch Use of Band Rationing for Color Texture Classification*, Springer Berlin, pp. 606–615, 2003.

[12] S. A. Shaffer, "Using color to separate reflection components," *Thesis*, April, 1984.

[13] G. Finlayson, M. Drew, and B. Funt, "Color constancy: Generalized diagonal transforms suffice," *Journal of Optical Society of America*, vol. 11, pp. 3011–3020, 1994.

[14] G. D. Finlayson, M. S. Drew, and B. V. Funt, "Color constancy: enhancing von kries adaption via sensor transformations," *SPIE*, 1993.

[15] P. Gros, "Color illumination models for image matching and indexing," *IEEE Transactions on Pattern Analysis and Machine* Intelligence, 2000.

[16] G. D. Finlayson, S. D. Hordley, and R. Xu, "Convex programming colour constancy with a diagonal-offset model," preaented at International Conference of Image Processing, 2005.

[17] M. S. Drew, J. Wei, and Z.-N. Li, "On illumination invariance in color object recognition," *School of Computing Science*, Simon Fraser University, Vancouver, Canada., Tech. Rep., 1997.

[18] D. Slater and G. Healey, "What is the spectral dimensionality of illumination functions in outdoor scenes?" in *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, 1998.

[19] T. Mäenpää, M. Pietikäinen, J. Viertola, J. Kyllönen, and S. Huovinen, "Outex - new framework for empirical evaluation of texture analysis algorithms," in *Proc. 16th International Conference on Pattern Recognition*, vol. 1, 2002, Quebec, Canada, pp. 701 – 706.

[20] G. Finlayson, M. Drew, and C. Lu, "Intrinsic images by entropy minimization," in *Proc. of the European Conf. on Computer Vision*, 2004, pp. 582–595.

[21] G. Finlayson, M. Drew, and B. Funt, "Spectral sharpening :sensor transformations for improved color constancy," *Journal of the Optical Society of America*, vol. 11(A), pp. 1553–1563, 1994.

[22] M. R. Turner, "Texture discrimination by gabor function," *Biological Cybernetics*, vol. 6, no. 4, pp. 71–82, 2004.

[23] A. K. Jain and F. Farrokhnia, "Unsupervised texture segmentation using gabor filters," *Pattern Recognition*, vol. 24, pp. 1167–1186, 1991.

[24] B. Manjunath and W. Ma, "Texture features for browsing and retrieval of image," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 18, no. 8, pp. 837–842, 1996.

[25] M. Unser, "Local linear ttransforms for texture measurements," *Signal Processing*, vol. 11, pp. 61–79, 1984.

[26] A. Drimbarean and P. F. Whelan, "Experiments in colour texture analysis," *Pattern Recognition Letters*, vol. 22, pp. 1161–1167, 2001.

[27] R. Gershon, A. D. Jepson, and J. K. Tsotsos, "From [r,g,b] to surface reflectance: Computing color constant descriptors in images," *Perception*, pp. 755–758, 1988.

[28] L. M. J Zhang and T Tan, "Invariant texture segmentation via circular gabor filters," presented at International Conference on Pattern Recognition, 2002.

[29] S. Fountain and T. Tan, "Rotation invariant texture features from gabor filters," presented at Asian Conference on Computer Vision, 1998.

Rahat Khan is a PhD student in the university of Saint-Etienne. He is currently working on improving the bag-of-words approach by incorporating spatial and color information.

Damien Muselet is an Engineer (Ecole des Mines de Douai, France, 2001), receives his PhD in Automatic Control and Computer Science from the faculty of science at the university of Lille, France. He is currently assistant-professor in the faculty of science at the university of Saint-Etienne where he is teaching 3D-images, motion estimation, image compression and color science. He is a member of the image processing team of Hubert Curien Laboratory (UMR CNRS 5516). His research interests are object recognition across illumination changes in color images.

Alain Trémeau is a professor in Color Imaging at the Universite Jean Monnet, Saint-Etienne, France. Alain. Tremeau is member of the Laboratoire Hubert Curien, UMR 5516, a research laboratory working in Photonics and Optics, and in Computer Vision and Color Imaging Science. He is currently mainly focused on mathematical imaging and color science with reference to human vision and perception. He works also in color metric with regard to color appearance and rendering measurements. He has written numerous papers or book chapters on Computational Colour Imaging and Processing. He is the coordinator of the ERASMUS MUNDUS master CIMET devoted to Color in Informatics and Media Technology.