A Novel Colour-Constancy Algorithm: A Mixture of Existing Algorithms

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ABSTRACT

Colour constancy algorithms attempt to provide an accurate colour representation of images independent of the illuminant colour used for scene illumination. In this paper we investigate well-known and state-of-the-art colour-constancy algorithms. We then select a few of these algorithms and combine them using a weighted-sum approach. Four methods are involved in the weights estimation. The first method uniformly distributes the weights among the algorithms. The second one uses learning set of images to train the weights based on errors. The third method searches for a linear combination of all methods' outcomes that minimise the error. The fourth one trains a continuous perceptron, in order to find optimum combination of the methods. In all four approaches, we used a set of 60 images. Each of these images was taken with a Gretag Macbeth colour checker card in the scene, in order to make quantitative evaluation of colour-consistency algorithms. The results obtained show our proposed method outperforms individual algorithms. The best results were obtained using the weights for linear combination and the trained continuous perceptron to combine the algorithms.

KEYWORDS

image processing, colour constancy, illumination invariance, weighted sum

1. INTRODUCTION

Colour constancy is a feature of colour vision systems. It allows the perception of objects' colour consistently under a varying illuminant. Human perception does this rather well, so the perceived colour of objects is almost independent of the illuminant. Colour constancy is a strong tool for colour machine-vision applications.

A model of digital colour sensor's signal is required for our study. We use the model presented in [1], where the colour signal is modelled by the objects' surface reflectance, scene geometry factor, and scene illuminant. This model assumes that the sensor's response can be approximated by delta functions [2]. Colour constancy is achieved by extracting the objects' surface reflectance. This extraction is a common approach used in the corresponding colour machine-vision systems.

The colour-constancy concept is very important for object recognition and analysis in computer vision applications. Many algorithms have been developed to address this problem in digital images [1], e.g. retinex algorithm, gamut mapping, grey world assumption. Practically each algorithm makes its own set of assumptions, e.g. uniform illuminant, presence of white patches, reflectance distribution, which is why it has certain advantages and shortcomings. Algorithms can be based on a scene illuminant assumption classified into two categories [1]: a) algorithms assuming a uniform scene illuminant (i.e., ambient light) that use a single transformation for the whole image; and b) algorithms that do not assume uniform scene illuminant and use a specific transformation for each image pixel.

Our main research interest is the detection of image regions with human skin and the analysis of minor colour variations due to reflectance in these areas, all under varying illumination conditions. We propose a novel colour-constancy algorithm that is a mixture of five well-known colour-constancy algorithms. Results of all five algorithms, i.e., five output images obtained by processing an input image by particular algorithms, are combined using weighted-sum approach. We will introduce four different methods to calculate these weights, ranging from a simple one to an intelligent learning-based method.

2. MATERIALS AND METHODS

2.1. Colour checker card

In this paper, a colour checker card is the tool to determine the weights for our proposed colour-constancy algorithm. This colour checker card is also used for an objective evaluation and comparison of obtained results.

A Gretag Macbeth ColorChecker chart is used in our study. This chart consists of 24 uniquely coloured patches [3]. Exact colour value for a particular patch can be either obtained from the manufacturer or can be measured by a spectrocolourimeter. We used colour values from the L*a*b* space provided by the manufacturer [4]. These values were then transformed to the RGB colour space using the transformation from [3].

2.2. Colour constancy algorithms

Five selected colour-constancy algorithms that we involved into our novel approach are overviewed in this section. The notation we use is as follows: the input image values are denoted by *C*, pixel positions by a vector $\mathbf{p}$, and the total number of pixels by *P*. The vector $\mathbf{p}$ is composed of two coordinates p_x and p_y. The value *C* of pixel $\mathbf{p}$ is defined as a product of reflectance function *R*, scene geometry factor function *G*, and scene illuminant function *I*:

$$C_W(\mathbf{p}) = R_W(\mathbf{p})G_W(\mathbf{p})I_W(\mathbf{p}) \tag{1}$$

where the index *W* denotes the different colour channels and reads R, G and B for red, green, and blue, respectively. The colour channels are processed independently. The colour channel index will therefore be omitted from all formulas and each calculation will implicitly be applied to each colour channel.

The result, i.e., the output image of any colour-constancy algorithm applied to the input image is denoted by *O*, and the applied colour-constancy algorithm is indicated by indexing the output image, e.g. O_i.

Random spray retinex (RSR) algorithm, developed by Provenzi et al. [5], is an implementation of the retinex algorithm, which was inspired by the research of human vision colour constancy and originally developed by Edwin H. Land and John J. McCann [6].

RSR estimates the illuminant locally. For each pixel $\mathbf{p}$, *S* random sprays are generated and marked as functions $s_i(\mathbf{p})$. The index *i* is used to identify individual sprays. A random spray is a selection of *L* pixels surrounding the current pixel, using a distribution function. In [5] a natural distribution function is suggested.

For each spray at pixel $\mathbf{p}$, the maximum pixel value $\max(s_i(\mathbf{p}))$ of the sprays pixels is determined. The illuminant is then predicted by averaging these maximum pixel values from the sprays.

$$I(\mathbf{p}) = \frac{1}{S}\sum_{i=0}^{S} \max\big(s_i(\mathbf{p})\big). \tag{2}$$

White patch retinex (WPR) colour constancy algorithm is a simplified implementation of the retinex theory [1]. It assumes a uniform illuminant. The illuminant is determined as the largest colour value found in the image:

$$I = \max\big(C(\mathbf{p})\big). \tag{3}$$

This algorithm has problems by fixing images with overexposed pixels. An enhancement of the WPR algorithm that tries to overcome this problem is presented in [1].

Grey world assumption (GWA) algorithm is a very popular colour-constancy algorithm. It is used as a basis for many other algorithms that incorporate its assumptions, such as local space average colour [7] and grey edge hypothesis [8].

The GWA assumes that the average scene reflectance under a perfectly white illuminant results in a neutral colour. Therefore the scene's single illuminant colour is estimated from the average image colour value or rather its deviation from the neutral value:

$$I = \frac{1}{P}\sum_{\forall \mathbf{p}} C(\mathbf{p}). \tag{4}$$

Acceptable results are obtained when this algorithm is applied on colourful images, while poor performance is expected for images that contain dominant single colour surfaces [1].

The shades of grey (SOG) algorithm is based on the GWA and uses the Minkwoski norm to describe a family of colour-constancy algorithms. The illuminant is estimated as:

$$I = \left(\frac{1}{P}\sum_{\forall \mathbf{p}} C(\mathbf{p})^m\right)^{\frac{1}{m}}, \tag{5}$$

where *m* is the parameter used to describe a particular algorithm. By setting the parameter *m* to 0, Eq. (5) describes the GWA algorithm. By setting *m* to ∞, Eq. (5) describes the WPR algorithm. Also by applying local smoothing to the image, the results of the algorithms can be improved. The local smoothing reduces the effects of image noise and overexposure.

Grey Edge (GE) algorithm is an extension of the GWA to image derivatives. In the case of the first order derivate the edges in images are obtained. The algorithm was proposed by [8]. A generalization of the family of algorithms, that cover WPR, GWA, and GE, was also introduced:

$$I^{t,m,\sigma} = \varphi\left(\int \left|\frac{\partial^t C_\sigma(\mathbf{p})}{\partial \mathbf{p}^t}\right|^m d\mathbf{p}\right)^{\frac{1}{m}}, \quad (6)$$

where m stands for the Minkowski norm order, σ for image smoothing parameter, and k for the image derivative order. The WPR algorithm can be expressed as $I^{0,\infty,0}$, the GWA as $I^{0,1,0}$, and the first-order GE algorithm as $I^{1,1,0}$. The σ parameter is used for image smoothing, which can reduce the influence of noise.

Local space average colour (LSAC) algorithm is also based on the GWA algorithm. Instead of a uniform illuminant, it assumes a slowly changing illuminant, which is predicted by 2-D low-pass filtering of the original image. Gaussian kernel κ can be used as the 2-D low-pass filter:

$$\kappa(\mathbf{p}) = e^{\frac{\mathbf{p}_x^2+\mathbf{p}_y^2}{2\sigma}}, \quad (7)$$

while the illuminant I is calculated as:

$$I(\mathbf{p}) = u^{-1}C(\mathbf{p}) * \kappa(\mathbf{p}) \quad (8)$$

where * stands for convolution. Constants u and σ in equation (8) denote the amplification and the size of kernel function, respectively. Constant σ depends on the maximal image dimension [1], [7].

After the illuminant has been estimated, image colour can be corrected. This is done without changing the image colour intensity, so that the normalized value $\hat{I}(\mathbf{p})$ is used instead of $I(\mathbf{p})$. The corrected image values are computed as:

$$O(\mathbf{p}) = C(\mathbf{p})\frac{\hat{I}_0}{\hat{I}(\mathbf{p})}, \quad (9)$$

where $\hat{I}_0$ stands for the canonical illuminant. A value $\sqrt{3}$ is used for $\hat{I}_0$, when the perfect white illuminant is considered. When the illuminant is estimated globally, $\hat{I}(\mathbf{p})$ in Eq. (9) is replaced by the constant $\hat{I}$. An index with image designation O denotes the algorithm used for the illuminant estimation. The RSR algorithm is associated with the index number 1, WPR with 2, GWA with 3, GE with 4, and LSAC with 5.

2.3. A mixture of existing algorithms

We are proposing a new colour-constancy algorithm as a mixture of five selected algorithms described in Section 2.2. Resulting images obtained by processing any input image by the five algorithms, are combined using weighted-sum approach.

The approach with mixing several methods has been proposed in [9]. The authors use a selection of algorithms that can be described by the Minkowski norm. They select the optimal colour-constancy algorithms for an image based on the set of features called natural image statistics. In contrast, our proposed method does not impose limitations on selected algorithms.

We will denote the results of a particular algorithm by O_n, where index n denotes selected colour algorithm; n = 1: RSR, n = 2: WPR, n = 3: GWA, n = 4: CCN , and n = 5: LSAC.

Proposed colour-constancy algorithm combines results of five selected algorithms through a weighted sum defined as:

$$O(\mathbf{p}) = \sum_{n=1}^{5} a_n O_n(\mathbf{p}), \; a_n \in \mathbb{R}, \quad (10)$$

where a_n is the n-th algorithm weight.

It has been shown a combination of several suboptimal algorithms, each executed under different illumination conditions, can, in general, boost the overall efficiency [10]. In this paper, we introduce four different methods to estimate the weights for linear combinations of more suboptimal algorithms, ranging from a simple to an intelligent learning-based method.

2.3.1. Uniform weights (M1 method)

The simplest way of combining selected colour-constancy algorithms is to assign each of them equal importance. Therefore, each weight a_n is set to $\frac{1}{5}$, i.e. $a_n = 0.2$, where $n \in [1, ..., 5]$. This method is denoted as M_1 method.

2.3.2. RMSE based weights (M2 method)

Weights for Eq. (10) are determined by learning procedures and are applied to the remaining three methods. A learning set consists of K randomly selected digital images, with a colour checker card integrated in the scene.

Another very simple way to determine the weights is by observing root-mean-square error (RMSE). It is calculated between the correct, i.e. expected, colour of particular patch q on the colour checker card (denoted by $c(q)$) and the actual colour of the same region (denoted by $O_{n,k}(q)$ and in our study determined as the mean colour of patch q), as obtained by the n-th selected colour-constancy algorithm on the k-th learning image. The number of all patches on the colour checker card is denoted by Q. The RMSE calculation is formally written as follows:

$$E_{n,k} = \sqrt{\sum_{q=1}^{Q} \left(c(q) - o_{n,k}(q)\right)^2} \tag{11}$$

We set the following rule for the M_2 method: the bigger the RMSE of selected algorithm, the lower weights it gets. At the end, a sum of weights is normalized to 1, thus preventing the output to be outside of allowed range of values.

We calculate the sum of RMSEs for each selected colour-constancy algorithm through all K learning images. This cumulated error is denoted by E_n for the n-th algorithm. Finally, the weight for the n-th algorithm, a_n, is determined as

$$a_n = \frac{E_n^{-1}}{\sum_{i=1}^{5} E_i^{-1}}. \tag{12}$$

2.3.3. Weights determined optimally in the least squares sense (M3 method)

In this method, we compare the correct colour of particular patch q from the colour checked card and the actual colour of the same region, obtained by the n-th selected algorithm on the k-th learning image. Each colour channel is observed separately. The following system is constructed:

$$\mathbf{b} = \mathbf{A}\mathbf{x}. \tag{13}$$

Column vector **b** consists of $3QK$ elements, where consecutive threesomes represent R, G, and B colour channels for particular patch on the colour checker card and for the selected learning image (note that there are 3 colour channels, Q patches on colour checker card per learning image, and K learning images). The values of **b** are the correct colour values of the patches provided by the manufacturer. Column vector **x** consists of five unknown weights a_n. Matrix **A**, with dimensions of $3QK \times 5$, is constructed as follows: each column of matrix A copies the column vector **b,** except that specific colour values are obtained by applying selected colour-constancy algorithms to a learning image; e.g., column 3 is obtained by applying the GWA algorithm on K learning images.

Eq. (13) is solved in the least squares sense:

$$\mathbf{x} = \mathbf{A}^{-1}\mathbf{b}. \tag{14}$$

2.3.4. Weights determined by continuous perceptron (M4 method)

In this method, weights for Eq. (10) are determined by supervised learning using a continuous perceptron (see [10]). A single-neuron continuous perceptron topology is applied. This neuron has five inputs and five synaptic weights. Each weight is associated with an appropriate input, whereas inputs are related to selected colour-constancy algorithms, e.g. input 4 is used for the CCN algorithm. Synaptic weights of this perceptron actually coincide with weights a_n as defined by Eq. (10). A sigmoid transfer function is assigned to this neuron output [10].

Synaptic weights a_n are determined in the learning phase. K learning images are used to define a learning set L. The learning set consists of $3QK$ pairs, whereas the first part of each pair describes a resulting colour channel out of five selected colour-constancy algorithms as obtained for one of colour-checker-card patches and for one learning image. This corresponds to one row of matrix **A** as defined in Section 2.3.3. The second part of the learning-set pairs contains the correct or expected values of the same colour channel and the same patch, which corresponds to an element of vector **b** as defined in Subsection 2.3.3. The global learning procedure was applied with learning time limited to a maximum of 1000 steps.

3. RESULTS

Results obtained by proposed colour-constancy algorithm are evaluated and compared to other algorithms in this section. We verified the efficiency of the four proposed methods for the calculation of weights (see Section 2.3). We also reveal the results of the five colour-constancy algorithms that were mixed in our novel approach (see Section 2.2).

The following settings were applied for the RSR algorithm: the spray radius was equal to the length of image diagonal, the number of points per spray was 500, while the number of sprays was set to 20. Other four algorithms do not have free parameters.

Our colour-consistency algorithm was evaluated on 60 images. For the experiments, 65 images were actually picked up from the Gehler image database [11], of which 5 images were randomly selected and moved to the learning set. All images contain the Gretag Macbeth colour checker card and human faces. Firstly, we convert the images from RAW to PNG format by using the UFRaw program, whereas a constant colour temperature of 3500 and all other default values were applied [12]. Afterwards, the images were rescaled to a width of 640 pixels with locked aspect ratio by using Gimp program. A cubic interpolation was applied.

Obtained results can be visually inspected in Fig. 1. Results for four different input images are exemplified. Row (a) shows original images. Rows (b)–(e) depict resulting images, so that rows (b), (c), (d), and (e) stand for the methods M_1, M_2, M_3, and M_4, respectively. Table 1 shows the weights as calculated by the four proposed methods described in Section 2.3.

Quantitative assessment of colour-consistency results was done by comparing the Gretag Macbeth colour checker card in each tested image to expected colours. The RMSE was calculated for every image. The mean RMSE values and standard deviations calculated over all 60 testing images are gathered in Table 2.

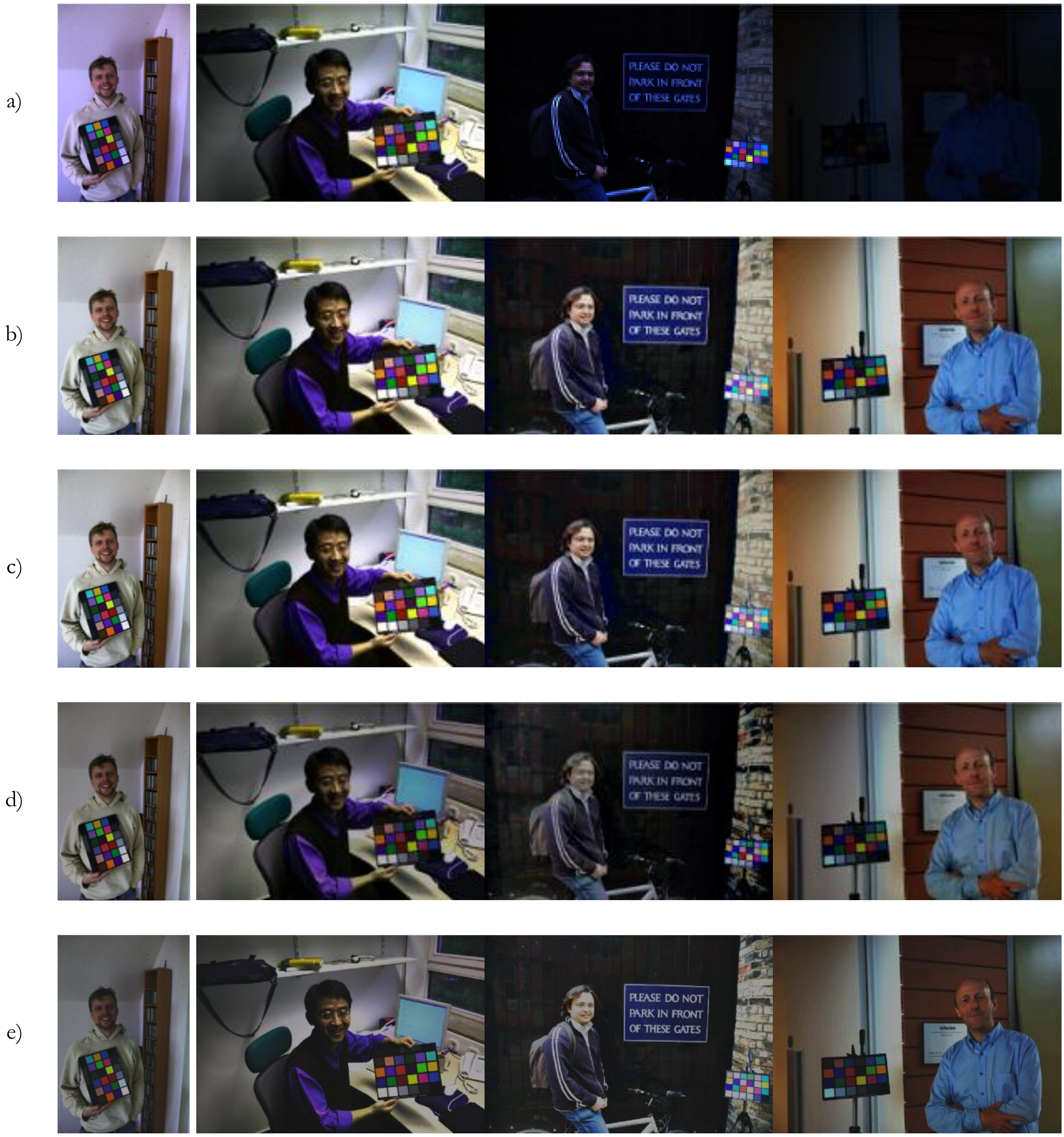

Fig. 1: Obtained results. Row (a) depicts original images, rows (b)-(e) present results of the proposed colour-constancy algorithm by using the four proposed methods for calculating weights: M1, M2, M3, and M4, respectively.

	a_1	a_2	a_3	a_4	a_5
M_1 method	0.20000	0.20000	0.20000	0.20000	0.20000
M_2 method	0.1770	0.1820	0.2153	0.1717	0.2540
M_3 method	0.2316	−0.5424	0.0053	0.7017	0.2739
M_4 method	0.7975	−0.1509	0.2116	2.2286	−0.0150

Table 1: Estimated weights a_i for Eq. (10). Four different methods were used to calculate these weights, i.e., M_1, M_2, M_3, and M_4.

	Mean ± Std
Original	112.60 ± 29.52
M_1 method	88.98 ± 44.17
M_2 method	84.89 ± 41.29
M_3 method	68.36 ± 29.36
M_4 method	72.38 ± 26.75

Table 2: Mean RMSE values and standard deviations calculated over all 60 testing images: row 2 contains values for original images, while rows 3–6 present results of our algorithm based on four proposed estimations of weights.

	Mean ± Std
Original	112.60 ± 29.52
WPR algorithm	113.08 ± 60.70
GWA algorithm	129.50 ± 75.82
CCN algorithm	102.03 ± 23.42
LSAC algorithm	137.15 ± 66.07
RSR algorithm	77.70 ± 39.31

Table 3: Mean RMSE values and standard deviations calculated over all 60 testing images: row 2 contains values for original images, while rows 3-7 contain results obtained by the WPR, GWA, CCN, LSAC, and RSR colour correction algorithms, respectively.

Row 2 in Table 2 shows RMSE values for the original image, while rows 3–6 contain the RMSE values and standard deviations for our proposed algorithm with the four different weight-calculation methods, i.e., M_1, M_2, M_3, and M_4. For a comparison reason, the RMSE values and standard deviations related to five selected colour-constancy algorithms used in our mixture are shown in Table 3. It can be seen that only the RSR algorithm results are comparable to the results of our method, while the results of other four selected algorithms are outperformed by our algorithm.

4. DISCUSSION AND CONCLUSION

Results from Table 2 and Table 3 confirm the suitability of the proposed concept for colour constancy. Proposed novel colour-constancy algorithm performs best with the weights determined by the M_3 method. Acceptable results are also obtained by the M_4 method. Comparing the results of our proposed method with the results of five selected colour-constancy algorithms, it is evident that only the RSR algorithm performance is comparable to our algorithm, while all other algorithms, i.e., WPR, GWA, CCN, and LSAC, have much higher RMSE values.

Our experiments with a variety of testing images proved that optimised mix of colour-consistency results obtained by suboptimal algorithms significantly boost performance and overall efficiency. An interesting conclusion can also be drawn about the way the mixing weights are estimated. Even when the weights were optimised by a learning approach, such as by the M4 method, with a small learning set (we used just 5 learning images), estimations were robust. Apparently, there is enough space for improvements, in particular with bigger and more representative learning sets.

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REFERENCES

[1] Ebner M (2007) Color constancy. John Wiley & Sons Ltd, West Sussex

[2] Bernard K, Ciurea F, Funt B (2001) Sensor sharpening for computational colour constancy. Journal of the Optical Society of America 18:2728–2743

[3] Pascale D (2006) RGB coordinates of the Macbeth ColorChecker. The BabelColor Company. http://www.babelcolor.com/download/RGB%20Coordinates%20of%20the%20Macbeth%20ColorChecker.pdf. Accessed 26 April 2012

[4] XRite ColorChecker Classic colorimetric data. http://xritephoto.com/documents/literature /en/ColorData-1p_EN.pdf. Accessed 26 April 2012

[5] Provenzi E, Fierro M, Rizzi A, De Carli L, Gadia D, Marini D (2007) Random Spray Retinex: A New Retinex Implementation to Investigate the Local Properties of the Model. IEEE Transactions on Image Processing 16:162–171

[6] Land E, McCann J J (1971) Lightness and Retinex theory. Journal of the Optical Society of America 61:1–11.

[7] Ebner M (2009) Color Constancy Based on Local Space Average Color. Machine Vision and Applications 11:283–301

[8] van de Weijer J, Gevers T, Gijsenij A (2007) Edge-Based Color Constancy. IEEE Transactions on Image Processing 16:2207–2214

[9] Gijsenij A, Gevers T (2011) Color Constancy Using Natural Image Statistics and Scene Semantics. IEEE Transactions on Pattern Analysis and Machine Intelligence 33:687–698

[10] Marsland S (2009) Machine Learning. Taylor & Francis group, Boca Raton

[11] Gehler P, Rother C, Blake A, Minka T, Sharp T (2008) Bayesian Color Constancy Revisited. Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition 1–8.

[12] UFRaw documentation. http://ufraw.sourceforge.net/Guide.html. Accessed 26 April 2012