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Colour balancing using sclera colour

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Abstract: Colour balancing is an image processing step employed in image signal processing pipeline to adjust colouration of images captured under different illuminations. Most of the existing colour balancing methods that make use of human faces and facial features use skin colour to estimate the chromaticity of the illuminant. This study examines how colour balancing can be performed exploiting the sclera colour extracted from the face automatically detected in the image. Sclera colour can provide enough and correct information to estimate the scene illuminant and reliably perform automatic colour balancing for face images. Experimental results suggest that, in terms of accuracy, the proposed method outperforms most other colour constancy methods on the experimental dataset collected as part of this research, which is a significant result.

1 Introduction

Colour constancy is one of the most amazing characteristics of the human visual system which ensures that the perceived colour of different objects remains relatively constant under varying illumination. An example is the white colour which is always perceived as white independently of the spectral characteristics of the light source illuminating the scene. A similar characteristic is highly desirable feature of many devices, e.g. digital cameras. This is achieved via colour balancing which is an image processing step employed in image signal processing (ISP) pipeline to adjust colouration of images captured under different illuminations [1]. Although various automatic and manual colour balancing methods exist, most users, however, prefer the former. The device then needs to dynamically detect the correlated colour temperature of the light source illuminating the scene and compensate for its effects, or determine from the image content the necessary colour correction due to the illumination. The colour balancing algorithm employed in ISP pipeline is thus critical to the colour appearance of digital images.

As computational colour constancy is an improperly posed problem, as its solution lacks uniqueness and stability, a number of different methods exist in the literature. Each method is based on different assumptions which are always needed. When these assumptions are not met, the algorithm's estimate of the illuminant can be weak. In other words, each of the existing colour balancing algorithms may fail under certain conditions. It has been demonstrated that the universal best and the universal worst algorithms do not exist: the best performing algorithm for a specific image depends on the image content. While there is a considerable body of work on computational colour constancy and extensive literature has been published, there is no unique classification of proposed methods. We follow classification of Gijsenij *et al.* [2], who did a comprehensive review of most popular colour balancing algorithms on several common datasets. They classified methods into three categories, being further divided into subcategories: static methods (low-level statistics-based methods and physics-based methods), gamut-based methods and learning-based methods (methods using low-level statistics, methods using medium and high-level statistics and methods using semantic information).

The most recent research area which has shown promising results aims to improve illuminant estimation by using convolutional neural networks based systems [3–5]. Also relatively simple features related to the colour statistics can be adequately used with appropriate machine learning techniques to give state-of-the-art accuracy [6, 7]. While these methods give competitive results, some of them are slower due to the complex features used, require a training dataset and have long training times.

Research area which has also shown promising results aims to improve illuminant estimation by using visual information automatically extracted from the images [8, 9]. Colour balancing methods that make use of human faces and facial features in the image as a source of information for scene illuminant estimation are mainly based on human skin. The idea that skin may provide a reference surface for illuminant estimation and thereby mediate colour constancy is not new [10]. Several implementations have shown that the diversity between the gamut of skin pixels of the detected faces and the skin canonical gamut can be affordably used to estimate the scene illuminant since skin colours tend to form a cluster in colour spaces [11, 12]. Recent implementation has shown that average skin colour can be effectively used to provide the reference patch against which other image colours are referenced [13].

In conducting the literature review for this research it was apparent that there is a shortage of prior research and data explicitly studying the relationship between sclera colour and illuminant estimation. Only one paper was found that proposes use of eyes for illumination estimation [14]. However, that paper was related to relighting faces rather than colour balancing.

In this paper, we examine how colour balancing can be performed exploiting the sclera colour extracted from the face automatically detected in the image. We propose use of average value of the segmented sclera colour for the scene illuminant estimation. The major steps in the proposed method are described in the next section: eye region detection, sclera segmentation, scene illuminant colour estimation and chromatic adaptation. The result of our work may contribute to colour balancing method, which either alone or in combination with other methods, will enable robust computational colour constancy in various environments for images containing faces.

The paper is structured as follows. In Section 2, the proposed method is described. In Section 3, experimental dataset is described. In Section 4, results are presented and compared against results of other methods. In Section 5, conclusions are derived and further research directions are proposed.

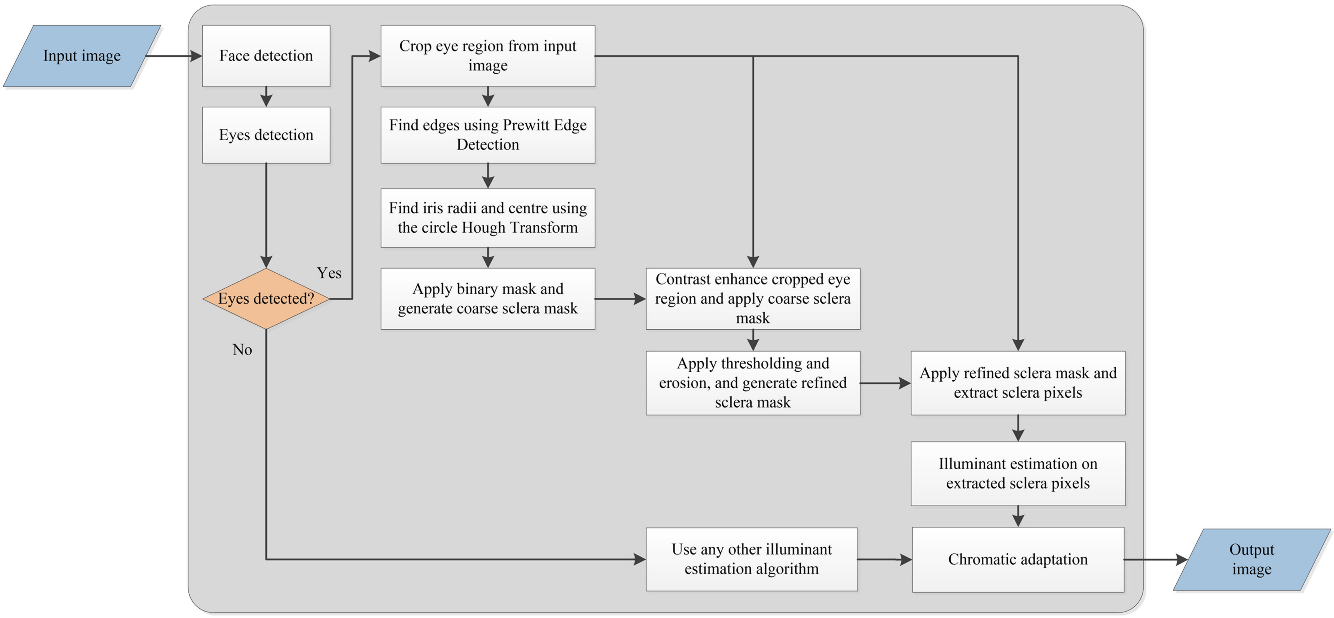

Fig. 1 *Operation flowchart of the proposed method*

2 Proposed method

The success of methods for accurate detection of human faces and facial features in images has accelerated development of face-related applications. Existing colour balancing methods that make use of human faces and facial features in the image as a source of information use skin colours to estimate the chromaticity of the illuminant. In this paper, we took a different approach and made use of sclera colours to estimate the chromaticity of the illuminant.

The sclera, also known as the white of the eye, is the most easily distinguishable part of the eye. It is nearly opaque white and colour constant in most humans. However, sclera colour can generally be different (than white) due to the different causes: age (more yellowish due to ageing), health (yellowish, reddish or some other colours due to different diseases) or ethnicity related (yellow-brown in some Afro-Americans due to larger levels of melanin pigment). Those cases were not considered in this work, but could be examined in future research. Despite those cases where sclera can have different colours, most of the time its colour is nearly opaque white in healthy humans, making it suitable for colour balancing. In comparison to skin, sclera is less affected by other confounding factors, e.g. pigment melanin (ethnicity), allowing a relatively simpler analysis. We demonstrated that sclera colour provides enough and correct information to estimate the scene illuminant and reliably perform automatic colour balancing for face images. The detailed flowchart of the proposed method is shown in Fig. 1.

From a computational perspective, automatic colour balancing is a two-stage process comprising of scene illuminant colour estimation and chromatic adaptation. For accurate scene illuminant colour estimation, pixels in the sclera region of the eyes were first segmented from the face image captured under varying illumination. Proposed scene illuminant colour estimation method is based on the measurement of the reference average sclera colour under the canonical illuminant. The illuminant estimation was then calculated as the ratio of the computed average colour of pixels of the sclera region and the reference average sclera colour. In addition, since the eyes are geometrically sunk compared with the forehead, the nose and the cheek in the face, the pixel values of the sclera region are mostly within the dynamic range of the digital camera regardless of the illuminant intensity. Chromatic adaptation was achieved through an independent gain regulation of the three colour signals, model also referred to as the von Kries hypothesis [15]. Finally, a new image was generated as if it had been taken under a canonical illuminant.

Proposed method is based on three assumptions:

- the illumination estimated on the face properly samples the illumination distribution in the scene;
- sclera colours form a sufficiently compact cluster in the colour space in order to represent a valid clue for illuminant estimation;
- sclera colour gives statistically equivalent colour balancing performance compared with those that would be obtained in the case of the classical von Kries white-patch normalisation (i.e. the reference patch is white) [16].

Furthermore, the method demands that at least one full frontal face is available within the image with both eyes clearly visible. If no face or no eyes are detected, any other state-of-the-art illuminant estimation algorithm can be used instead.

Contrary to some colour balancing methods which are computationally intensive, in this paper we propose a simple method based on the use of average value of the segmented sclera colour for the scene illuminant estimation. Face and eye recognition is technology incorporated into modern cameras and mobile devices. We built the proposed method on top of these technologies by adding method-specific operations. The proposed method does not require any colour constancy parameter tuning.

Practical justification of the proposed method comes from the fact that digital portrait images make up a significant portion of images taken. The recent development of mobile technologies, along with the proliferation of photo-sharing social media networks, has contributed to an increasing number of such images, particularly self-portraits or 'selfies'. Digital facial portrait images have become a common feature of the online everyday lives of most digitally connected people. Their rise will continue and will be applied to technology in practical terms.

2.1 Reference average sclera colour

Proposed method is based on the assumption that sclera colours form a sufficiently compact cluster in the colour space in order to represent a valid clue for scene illuminant estimation. Therefore, computation of the reference average sclera colour under the canonical illuminant was a crucial step. To determine the reference average sclera colour, colour calibration was applied to each image in self-collected experimental dataset in order to obtain standard, device-independent values. Colour calibration was constructed by imaging colour reference card that contains different coloured patches with published colour values for each patch [17]. Patches are selected to represent various natural objects, colours that are problematic for colour reproduction, additive and subtractive primaries, and a six steps greyscale. In our study, ColorChecker with published *XYZ* tristimulus values under the CIE standard

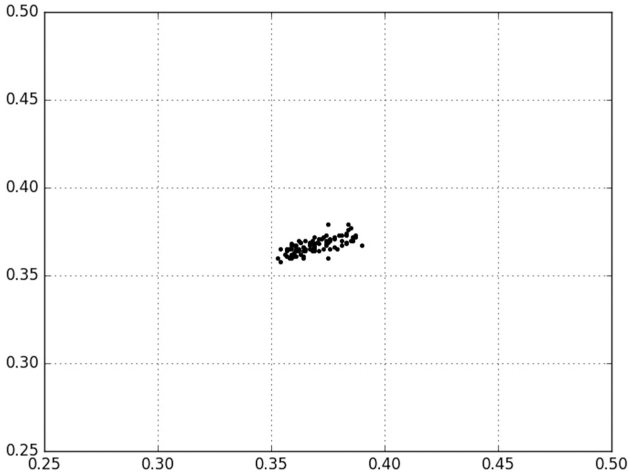

Fig. 2 *Sclera colours forming a compact cluster in xyY colour space*

illuminant D50 was used. Reference average sclera colour was determined based on colour calibrated images from self-collected experimental dataset by calculating average values for CIE XYZ over pixels in the sclera region.

To graphically represent the chromaticity of sclera colours, colour space transformation to CIE *xyY* colour space is used. Since the coordinates *x* and *y* indicate the chromaticity of a colour, a graph with *x* and *y* as its axes was used to plot points that indicate chromaticity. The average value for *x* and *y* is 0.369 and 0.367, with a relative standard deviation of 2.41 and 2.43%, respectively, indicating a small spread of values. Results show that, for a group of people involved in this study, sclera colours form a sufficiently compact cluster in the colour space, as can be seen in the enlarged graph in Fig. 2.

Research study on colours shows that sclera colour gives statistically equivalent colour balancing performance compared with those that would be obtained in the case of the classical von Kries white-patch normalisation (i.e. the reference patch is white) [16]. Accordingly, pixels in the sclera region can be used as a reference patch for scene illuminant estimation. Therefore, we call this method sclera patch (SP).

2.2 Eye region detection

The first step of the proposed automatic colour balancing method is detection of eye region in the image. There are two different approaches for eye region detection: detection of eyes in the whole image and detection of eyes in previously detected face region. Each of those approaches has its own advantages and disadvantages, including the percentage of true-positive detections and computational speed. The proposed method uses the latter approach. In this study, we use Matlab R2015a implementation of the Viola–Jones object detection framework [18]. Moreover, a set of rules was defined to accurately locate eyes in previously detected face region, i.e. symmetrical and geometrical properties of eyes in face region.

2.3 Iris localisation

The circular Hough transform can be employed to localise the iris region inside previously detected eye region and deduce its radius and centre coordinates. To accomplish this, a binary edge map is generated from the greyscale cropped eye region by using Prewitt's edge detection technique. The radius and centre coordinates of the circle that represents external iris border are determined by the circular Hough transform. The radius range of localised irises is known and expressed as a percentage of the eye region bounding box width. Our algorithm aims to detect irises of both eyes.

2.4 Sclera segmentation

To segment out the sclera pixels several operations are required. First, an eye-shaped binary mask is applied to each iris detected in the eye region. By using information about iris radii and centre of each eye, which were determined in previous step, binary masks are centred at approximated iris centres. These eye-shaped binary masks are further resized in order to adjust the region's height and the approximated iris radius. To detect only sclera pixels, circular shaped area representing the iris is discarded. Next, the resulting coarse sclera mask is applied to the contrast enhanced eye region. In order to enhance contrast between the white sclera, iris and the skin, a method proposed by Hsu [19] is used. To create the refined sclera mask and remove remaining iris and skin border pixels, binary thresholding and erosion are applied. Finally, sclera pixels are extracted by multiplying refined sclera mask and eye region of the original image.

2.5 Scene illuminant colour estimation

The computed average sclera colour is calculated from the segmented sclera pixels. Based on the aforementioned assumptions, the scene illuminant colour estimation is calculated as the ratio between computed pixel average colour of the sclera region $\bar{c}_{\text{sclera}}$ and the reference average sclera colour under the canonical illuminant ρ_{sclera}

$$I = \frac{\bar{c}_{\text{sclera}}}{\rho_{\text{sclera}}} \tag{1}$$

Once the illuminant $I = (Ix, Iy, Iz)$ has been estimated, each pixel in the image is colour corrected using the von Kries model.

2.6 Chromatic adaptation

Chromatic adaptation is based on a diagonal model of illumination change derived from the von Kries hypothesis [15]. The diagonal model states that the effect of moving from one scene illuminant to another can be modelled by scaling colour channels by independent scale factors. These scale factors can be written as elements of a diagonal matrix $\boldsymbol{M}$. Matrix maps *XYZ* tristimulus values that are taken under unknown scene illuminant u to their corresponding *XYZ* tristimulus values under the canonical illuminant c, such that the corresponding *XYZ* tristimulus values produce the same perceived colour

$$\begin{bmatrix} X_c \\ Y_c \\ Z_c \end{bmatrix} = [\boldsymbol{M}] \begin{bmatrix} X_u \\ Y_u \\ Z_u \end{bmatrix} \tag{2}$$

$$[\boldsymbol{M}] = [\boldsymbol{M}_A]^{-1} \begin{bmatrix} \rho_c/\rho_u & 0 & 0 \\ 0 & \gamma_c/\gamma_u & 0 \\ 0 & 0 & \beta_c/\beta_u \end{bmatrix} [\boldsymbol{M}_A] \tag{3}$$

To obtain $\boldsymbol{M}$, *XYZ* values are transformed into a cone response domain $[\rho, \gamma, \beta]$. In our work, the Bradford chromatic adaptation transform is used, which is regarded by most experts as the best one

$$\boldsymbol{M}_A = \begin{bmatrix} 0.8951 & 0.2664 & -0.0685 \\ -0.89 & 1.7135 & 0.0367 \\ 0.0389 & -0.0685 & 1.0296 \end{bmatrix} \tag{4}$$

3 Experimental dataset

3.1 Raw images

Images are considered unbiased if they have a known linear relationship to scene radiance. ISP pipeline in the camera introduces non-linearities through making model-specific and often proprietary operations, which change the colour, contrast and colour balance of images. These images are then transformed to a non-linear RGB colour space and compressed in an irreversible fashion to produce the image information expected by most operating systems and display drivers. As a consequence, pixel

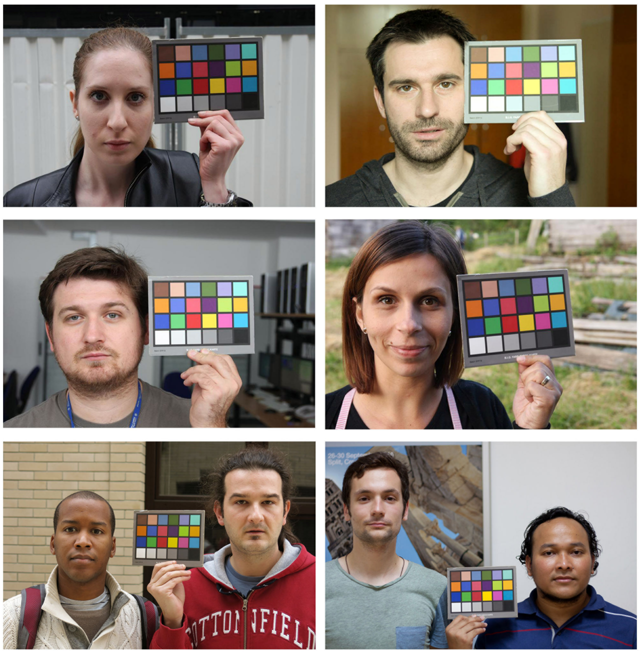

Fig. 3 *Example images from both datasets*

intensities are modified such that they are no longer linearly related to scene radiance. In order to determine the reference average sclera colour, raw format images are used. They contain unprocessed sensor data and have desired property of a linear relationship to scene radiance. This property makes it possible to obtain camera-independent images that can be quantitatively compared with no knowledge of the original imaging system. In [20], a simple yet effective approach is described for accessing the raw sensor data stored in a raw file and then applying the basic processing steps required to turn them into a displayable images linearly related to scene radiance.

3.2 Image dataset

To test the performance of proposed method, an experimental dataset was collected. We call this dataset Portrait dataset. It consists of raw format portrait images having a known colour reference card, allowing us to accurately estimate the actual scene illuminant for each image. Our dataset was captured using high-quality Canon EOS 60D and Canon EOS 6D DSLR cameras with all settings in auto mode and operated at their highest resolution. Images were stored as raw data and basic processing steps required to turn them into linear TIFF images were applied [20]. Dataset consists of 103 indoor and outdoor frontal view portrait images of a single person, taken under various lighting conditions. Participants were asked to hold a colour reference card in one hand. Dataset includes participants of different gender and age. To test the algorithm, three-fold cross-validation was used. Dataset was separated in two subsets, where 66.67% of the images were taken for reference average sclera colour calculation and the rest for evaluation.

To investigate whether variation among different races has any significant influence on the illumination estimation accuracy, we collected an additional dataset. Dataset consists of 17 frontal view images of two persons of different races. The same setup was used as in the Portrait dataset. For both datasets, colour reference card has been masked during all experiments to avoid biasing the algorithm. Example images from the two datasets are shown in Fig. 3. All images are available upon request.

In [13], the Milan portrait dataset was introduced. Dataset has been acquired in order to further evaluate the colour constancy algorithms using facial features on a larger number of images. The dataset includes portraits of a single person with a single colour reference card up to multiple persons with multiple colour reference cards. Unfortunately, at the time of writing this paper, that dataset was still unpublished and thus we could not test the performance of the proposed method by using that dataset.

4 Experimental results

4.1 Sclera segmentation error rates

Before reporting experimental results of the illuminant colour estimation, we have to evaluate segmentation accuracy of the proposed sclera segmentation method. In order to evaluate the method, Portrait dataset was used. Viola–Jones face detection algorithm achieved face detection accuracy of 97.09% and eyes detection accuracy of 96.12% on the aforementioned dataset.

Sclera segmentation error rates were obtained by comparison to the manually segmented results as the ground truth. Manual segmentation was performed on randomly chosen subset of 40 images by three experienced operators. The proposed method can generate four possible segmentation results: correctly matching (true positive: TP), correctly not matching (true negative: TN), incorrectly matching (false positive: FP) and incorrectly not matching (false negative: FN). The false positive error rate EFP is calculated as the ratio between the number of pixels falsely assigned to the final region and the correct number of pixels in that region. The false negative error rate EFN is calculated as the ratio between the number of pixels falsely assigned to the final region and the correct number of pixels in that region. The obtained EFP error rate was 0.9%, while EFN error rate was 11%. As we took a very conservative approach to assure that non-relevant regions (iris, eyelashes, upper and lower eyelid) are not segmented, which in turn degrade the average sclera colour measurement, high EFN error rate was expected. Note, however, that any other method can be employed for eyes detection and sclera segmentation, without changing other steps.

4.2 Performance evaluation

To test the proposed algorithm, different benchmarking algorithms were considered against which the proposed algorithm was compared. Algorithms considered were white patch (WP) [21], improved white patch (IWP) [22], grey world (GW) [23], shades of grey (SoG) [24], general grey world (GGW) [2], first-order grey-edge (GE1) [25], second-order grey-edge (GE2) [25], colour rabbit (CR) [26] and colour sparrow (CS) [27]. Source code for aforementioned benchmarking algorithms is made available on-line by the respective authors. Unfortunately, the source code for skin-based algorithms was unavailable at the time of writing, making a reliable comparison between the various algorithms using facial features very difficult. Performance evaluation of the algorithms was performed on the Portrait dataset.

The illuminant white point and an algorithm's estimate of the white point are *XYZ* triplets. To evaluate accuracy of the proposed algorithm, angle between the actual scene illuminant white point and an algorithm's estimate of the white point was measured for all images in the dataset. Colour space transformation to CIE RGB colour space was used. The angle between the two RGB triplets was used as error measure, as suggested in [28]

$$e_{\text{ANG}} = \arccos\left(\frac{\rho_w^{\mathrm{T}}\hat{\rho}_w}{\parallel \rho_w \parallel \ \parallel \hat{\rho}_w \parallel}\right) \tag{5}$$

Angular errors are often not normally distributed but rather skewed resulting in a non-symmetric distribution. Hence, the mean value of the errors is a poor summary statistic [28]. To summarise the distribution, several more appropriate statistics of these errors were reported: the median, the trimean and the max. The median gives an indication of the performance of the method on the majority of the images, while the trimean gives an indication of the extreme values of the distribution. The max gives an indication of the maximum value of angular errors. Table 1 indicates accuracy for the proposed and several other colour balancing algorithms applied to the Portrait dataset, in terms of the mean, median, trimean and max of angular errors. Angular error of 1° with respect to the ground truth was not found to be noticeable, while an angular error

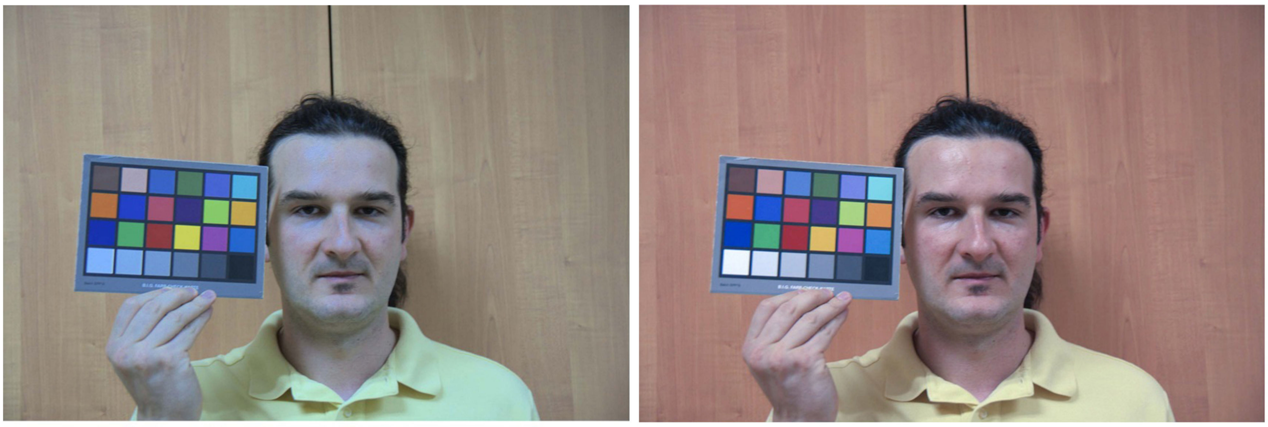

Fig. 4 *Example results of GE2 (angular error 11.76) and SP (angular error 4.40)*

Table 1 Angular error statistics obtained on the Portrait dataset

Algorithm	Mean	Median	Trimean	Max
WP	8.57	7.07	7.72	17.79
IWP	3.82	2.3	2.99	9.78
GW	4.2	3.64	3.71	11.18
SoG	3.77	2.73	3.23	9.07
GGW	3.77	2.73	3.23	9.07
GE1	3.09	2.19	2.63	7.18
GE2	2.6	1.97	2.22	8.88
CR	3.35	2.22	2.58	8.84
CS	3.8	2.37	3	10.08
SP	2.71	2.11	2.23	6.67

Fig. 5 *Original image and colour balanced images using left and right person's sclera colour*
(a) Original image, ***(b)*** Colour balanced image using left person's sclera colour, ***(c)*** Colour balanced image using right person's sclera colour

of 3° was found noticeable but acceptable [29]. Results suggest that the proposed SP method outperforms most other colour constancy methods on the self-collected experimental dataset. In some cases benefit of the proposed method is significant. For example, when a single dominant colour is present in the image, the assumption of many colour constancy methods is not met. While this will cause failure for most methods, the error of the proposed method will be significantly smaller. An example of such a setup is shown in Fig. 4.

As stated earlier, we conducted an experiment to investigate whether variation among different races has any significant influence on the illumination estimation accuracy. Illuminant estimation was performed twice for each image. Each time sclera colour from only one person was used for illuminant estimation. An example of such a setup is shown in the paper in Fig. 5. The figure depicts original image which is not colour balanced and two colour balanced images by using left and right person's sclera colour for illuminant estimation, respectively. For this particular image, the difference of angular errors of 0.14° was calculated while the mean of 0.22° was calculated for the entire dataset. Preliminary results of the research indicate small variation in chromaticity of the sclera colour among participants. Consequently, that variation has no significant impact on the illumination estimation accuracy of the proposed method.

5 Conclusion

Colour constancy, the root problem of automatic colour balancing, is still recognised as a difficult problem and thus impossible to solve in the most general case. This paper proposes a method for colour balancing of images containing faces, based on the scene illuminant estimation from pixels in the sclera region of the eyes. The major steps in the proposed method are eye region detection, sclera segmentation, scene illuminant estimation and chromatic adaptation. Since the steps are independent of one another, each step is suitable for future improvement. The method requires that at least one frontal face is available within the image. If no face or no eyes are detected, any other state-of-the-art colour balancing algorithm can be used instead. In terms of accuracy the proposed method outperforms most other colour constancy methods on the experimental dataset collected as part of this research, which is a significant result. To summarise, the proposed method is simple, does not require any colour constancy parameter tuning and enables computational colour constancy in various environments for images containing faces.

Further research is required to provide detailed insight into how sclera colour is altered by age, health and race. Moreover, a large-scale portrait dataset with a colour reference cards included in each image is needed, to be used for evaluation of colour balancing methods that make use of facial features.

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