IMPROVING THE WHITE PATCH METHOD BY SUBSAMPLING

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ABSTRACT

In this paper an improvement of the white patch method, a color constancy algorithm, is proposed. The improved method is tested on several benchmark databases and it is shown to outperform the baseline white patch method in terms of accuracy. On the benchmark database it also outperforms most of the other methods and its great execution speed makes it suitable for hardware implementation. The results are presented and discussed and the source code is available at http://www.fer.unizg.hr/ipg/resources/color_constancy/.

***Index Terms*—** Auto white balance, color constancy, illumination estimation, MaxRGB, subsampling, white patch

1. INTRODUCTION

The ability of the human visual system to recognize the object colors irrespective of the illumination is called color constancy [1]. Achieving computational color constancy is important in processes like image enhancement and achieving it generally improves the image quality. The most important step in achieving computational color constancy is the light source color estimation, which is then used to perform chromatic adaptation, i.e. to remove the color cast and to balance the image colors as if they were recorded under white light. Under Lambertian assumption an image f is formed as

$$f_c(x) = \int_\omega I(\lambda)R(x,\lambda)\rho_c(\lambda)d\lambda \tag{1}$$

where c is the color channel, x is a given image pixel, λ is the wavelength of the light, ω is the the visible spectrum, $I(\lambda)$ is the spectral distribution of the light source, $R(x,\lambda)$ is the surface reflectance, and $\rho_c(\lambda)$ is the camera sensitivity of the c-th color channel. Under uniform illumination assumption, the observed color of the light source **e** can be calculated as

$$\mathbf{e} = \begin{pmatrix} e_R \\ e_G \\ e_B \end{pmatrix} = \int_\omega I(\lambda)\boldsymbol{\rho}(\lambda)d\lambda. \tag{2}$$

As both $I(\lambda)$ and $\boldsymbol{\rho}(\lambda)$ are often unknown, calculating **e** represents an ill-posed problem, which is solved with additional assumptions. Color constancy algorithms can be divided into two groups: low-level statistics-based ones like White-patch (WP) [2], Gray-world (GW) [3], Shades-of-Gray (SoG) [4], Grey-Edge (GE) [5], using bright pixels (BP) [6], using color distribution (CD) [7] and learning-based ones like gamut mapping (pixel, edge, and intersection based - PG, EG, and IG) [8], using high-level visual information (HLVI) [9], natural image statistics (NIS) [10], Bayesian learning (BL) [11], spatio-spectral learning (maximum likelihood estimate (SL) and with gen. prior (GP)) [12]. Although the former are not as accurate as the latter ones, they are faster and require no training requirement so that most commercial cameras use low-level statistics-based methods based on the Gray-World assumption [13] making them still important.

The white patch method has a great execution speed and low accuracy in its basic form. In this paper we propose the application of subsampling that improves its accuracy to the level of outperforming most of the color constancy methods in terms of accuracy. In terms of speed the improvement outperforms all of the mentioned methods. Due to its simplicity the improvement is suitable for hardware implementation.

The paper is structured as follows: in Section 2 the white patch method is described, in Section 3 the proposed improvement of the white patch method is described, and in Section 4 the experimental results are presented and discussed.

2. WHITE PATCH

The white patch method is a special case of the Retinex algorithm [14]. It assumes that for each color channel there is at least one pixel in the image with maximal reflection of the illumination source light for that channel and when these maximal reflections are brought together, they form the color of

the illumination source. Despite this being intuitively a good idea, performing the white patch method on images often results in poor illumination estimation accuracy, which can be attributed to even a single bad pixel, spurious noise [15], or limited exposure range of digital cameras [16]. To overcome the problems that cause the incorrect maximum, three preprocessing methods have been proposed: (a) removal of overexposed pixels, (b) median filtering, and (c) image resizing [15]. By testing the white patch method with this prior preprocessing methods on several image sets, it has been shown that its accuracy improves significantly and that it can outperform several other low-level statistics-based methods [15]. These preprocessing methods, however, do not guarantee that all too noisy or spurious pixels will be removed, thus disabling the full advantage of the initial assumption.

3. PROPOSED IMPROVEMENT

3.1. BASIC IDEA

One of the directions for a further improvement is to try to avoid the noisy and spurious pixels by exploiting some of the properties common to most images. One such property is the presence of many surfaces with pixels of uniform or slowly changing color. Since these pixels are supposed to be very similar, using one or few of them should be enough to represent the whole surface with regard to the white patch method, whose result depends on pixel color channel maxima. By disregarding the rest of the surface pixels there is a good chance to bypass the noisy ones as well, which are not so easily detected as the overexposed ones. Even though the noiseless pixels with the highest channel intensities might also be bypassed, approximate channel maxima should suffice because what matters are the ratios between the channel maxima, i.e. the direction of the maxima vector, and not its norm. One solution to get a smaller pixel sample is to subsample the image.

3.2. MOTIVATION

Estimating local illumination by using a relatively small pixel sample was shown to work well in the image enhancement Light Random Sprays Retinex algorithm [17] where there was no perceptual difference for images with illumination estimated for all pixels and with illumination estimated for 2.7% pixels with the rest being calculated using interpolation. Pixel illumination estimations were based on performing the white patch method on a relatively small number of neighborhood pixels selected with a random spray. Combining these pixel illumination estimations into a single global one was used in the Color Sparrow (CS) algorithm [18], which uses 9% of the image pixels to calculate 0.04% of the local pixel illumination estimations. This results in a very good accuracy and a great execution speed further justifying the use of a small pixel sample as the input for the white patch method. However, a serious drawback of CS is its unsuitability for hardware implementation due to the way it calculates the local illumination estimations by using distant neighbors.

3.3. THE PROPOSED METHOD

Motivated by the success of the mentioned Retinex based algorithms in using high subsampling rates without a significant loss of accuracy, we decide to use subsampling to avoid both the redundancy and the noisy pixels with a greater probability. To keep the procedure as simple as possible for hardware considerations, a random sample of N pixels evenly spread across the image is taken and the white patch method it applied to it, which results in a global illumination estimation.

In order to avoid the possibility of only one or more noisy pixels spoiling the whole sample, we propose not to use only one random sample, but M of them. After the white patch is applied to all of the samples, the final result is obtained as the mean of the individual sample maxima. This procedure introduces more stability and it also represents a subsampling generalization of the white-patch method and the original Gray World method: with M set to 1, a subsampling white patch is obtained, and with N set to 1, a subsampling Gray World algorithm is obtained. Unlike in CS, no noise removal is performed. The method is summarized in Algorithm 1 and a visual comparison with other methods is given in Fig. 1.

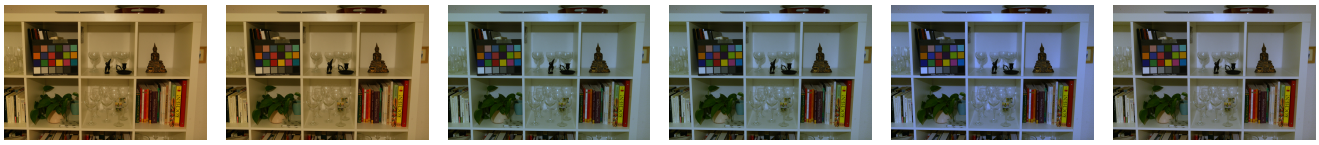
Algorithm 1 The Improved White Patch algorithm

```
I := GetImage()
e := (0,0,0)
for i = 1...M do
    m := (0,0,0)
    for j = 1...N do
        do
            row := RandU(1, I.rowsCount)
            column := RandU(1, I.columnsCount)
            p := I.GetPixel(row, column)
        while p is clipped
        for k = 1...3 do
            m_k := max(m_k, p_k)
        end for
    end for
    e := e + m
end for
e := Normalize(e)
```

4. EXPERIMENTAL RESULTS

4.1. USED DATABASES

The color formation model used in Eq. (1) is based on linear images and in digital cameras color constancy is generally implemented prior to conversion of raw data to device-



(a) (b) (c) (d) (e) (f)

Fig. 1. Example of color constancy algorithms application: (a) the original image, (b) the white patch, (c) the general Gray World, (d) 1st-order Gray-Edge, (e) 2nd-order Gray-Edge, (f) the proposed method.

Table 1. Angular error of selected low-level statistics-based methods, the proposed method, and selected learning-based methods on the ColorChecker (CC) database and new NUS databases (lower is better and median is more important)

	Low-level statistics-based methods									Learning-based methods						
Method	**proposed**	CD	GW	WP	SoG	GGW	BP	GE1	GE2	PG	EG	IG	BL	ML	GP	NIS
Dataset	Mean angular error (°)															
CC	3.95	**3.52**	6.36	7.55	4.93	4.66	5.33	5.13	3.98	4.20	6.52	4.20	4.82	3.67	3.59	4.19
Canon1	3.00	**2.93**	5.16	7.99	3.81	3.16	3.37	3.45	3.47	6.13	6.07	6.37	3.58	3.58	3.21	4.18
Canon2	2.94	2.81	3.89	10.96	3.23	3.24	3.15	3.22	3.21	14.51	15.36	14.46	3.29	2.80	**2.67**	3.43
Fuji	3.09	3.15	4.16	10.20	3.56	3.42	3.48	3.13	3.12	8.59	7.76	6.80	3.98	3.12	**2.99**	4.05
Nikon1	3.20	**2.90**	4.38	11.64	3.45	3.26	3.07	3.37	3.47	10.14	13.00	9.67	3.97	3.22	3.15	4.10
Oly	2.80	**2.76**	3.44	9.78	3.16	3.08	2.91	3.02	2.84	6.52	13.20	6.21	3.75	2.92	2.86	3.22
Pan	2.99	2.96	3.82	13.41	3.22	3.12	3.05	2.99	2.99	6.00	5.78	5.28	3.41	2.93	**2.85**	3.70
Sam	3.07	**2.91**	3.90	11.97	3.17	3.22	3.13	3.09	3.18	7.74	8.06	6.80	3.98	3.11	2.94	3.66
Sony	**2.91**	2.93	4.59	9.91	3.67	3.20	3.24	3.35	3.36	5.27	4.40	5.32	3.50	3.24	3.06	3.45
Nikon2	3.75	3.81	4.60	12.75	3.93	4.04	4.09	3.94	3.95	11.27	12.17	11.27	4.91	3.80	**3.59**	4.36
Dataset	Median angular error (°)															
CC	2.84	**2.14**	6.28	5.68	4.01	3.48	4.52	4.44	2.61	2.33	5.04	2.39	3.46	2.96	2.96	3.13
Canon1	2.03	**2.01**	4.15	6.19	2.73	2.35	2.45	2.48	2.44	4.30	4.68	4.72	2.80	2.80	2.67	3.04
Canon2	**1.77**	1.89	2.88	12.44	2.58	2.28	2.48	2.07	2.29	14.83	15.92	14.72	2.35	2.32	2.03	2.46
Fuji	**2.09**	2.15	3.30	10.59	2.81	2.60	2.67	1.99	2.00	8.87	8.02	5.90	3.20	2.70	2.45	2.95
Nikon1	**2.07**	2.08	3.39	11.67	2.56	2.31	2.30	2.22	2.19	10.32	12.24	9.24	3.10	2.43	2.26	2.40
Oly	1.93	**1.87**	2.58	9.50	2.42	2.15	2.18	2.11	2.18	4.39	8.55	4.11	2.81	2.24	2.21	2.17
Pan	**1.87**	2.02	3.06	18.00	2.30	2.23	2.15	2.16	2.04	4.74	4.85	4.23	2.41	2.28	2.22	2.28
Sam	**1.95**	2.03	3.00	12.99	2.33	2.57	2.49	2.23	2.32	7.91	6.12	6.37	3.00	2.51	2.29	2.77
Sony	**2.26**	2.33	3.46	7.44	2.94	2.56	2.62	2.58	2.70	4.26	3.30	3.81	2.36	2.70	2.58	2.88
Nikon2	2.78	**2.72**	3.44	15.32	3.24	2.92	3.13	2.99	2.95	10.99	11.64	11.32	3.53	2.99	2.89	3.51

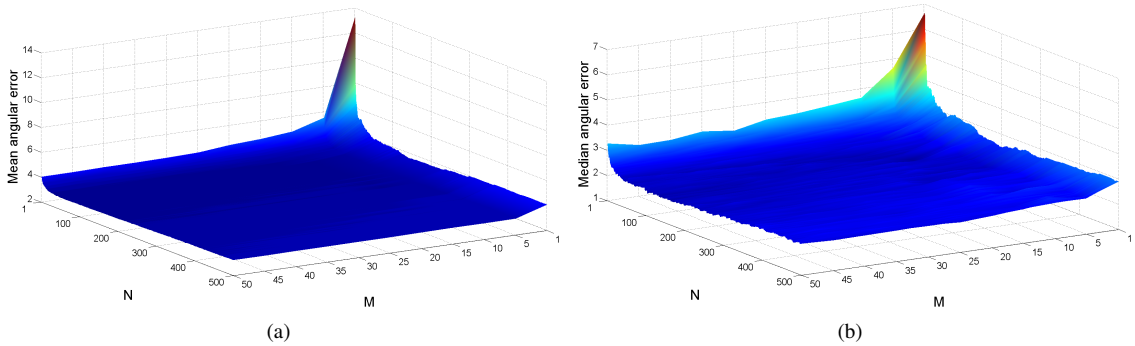
dependent RGB images [19]. Therefore the proposed method was tested on several color constancy benchmark linear image databases with assumed uniform illumination that were based on raw data: Shi's and Funt's linear version [20] of the ColorChecker (CC) [11] and nine new NUS databases described in [7] and available at [21]. Each NUS database was taken with a different camera: Canon EOS-1Ds Mark III (Canon1), Canon EOS 600D (Canon2), Fujifilm X-M1 (Fuji), Nikon D5200 (Nikon1), Olympus E-PL6 (Oly), Panasonic Lumix DMC-GX1 (Pan), Samsung NX2000 (Sam), Sony SLT-A57 (Sony), and Nikon D40 (Nikon2).

Each image in these databases contains a color checker, whose last row of achromatic patches was used to determine the illuminant of the image, which is provided with the images and serves as the ground-truth. Before testing an algorithm on these images, the color checker has to be masked out in order to prevent its influence on the algorithm. The illumination estimation of an algorithm for an image is then compared to the ground-truth illumination for that image, and a common error measure is the angle between the two illumination vectors. For comparison between algorithms over an image set the angular error's median should be used instead of the mean because the error distribution is often not symmetrical making the median a better descriptor [22].

4.2. ACCURACY

The proposed method was tested on all mentioned databases by using several combinations of values of parameters N and M. The influence of each parameter combination on the accuracy of the proposed method was calculated by applying it to all images of every database. The results for NUS Canon EOS 600D database are shown in Fig. 2. Graphs for all other databases are not shown because they have almost the same shape. The smoothness of the error curves indicates the stability of the proposed method.

In Table 1 for each database the best means and medians of errors for several color constancy methods including the proposed one are shown. The data for methods other than the



(a) (b)

Fig. 2. Influence of values of parameters N (single sample size) and M (samples count) on mean and median of the angular error for the NUS Canon EOS 600D database: (a) mean angular error, (b) median angular error.

proposed one was taken from [19], [23], [7], and [21] or was calculated by using the available source code. When the parameters N and M were learned using the cross-validation, the results did not differ very much from the best results as is the case with other low-level statistics-based methods, so the results reported here were achieved with no cross-validation used. For each database the proposed method clearly outperforms the white patch method in terms of accuracy. It also outperforms most of the other methods. For all databases the best median angular error is below $3°$, which was experimentally shown to be an acceptable error [24] [25]. As seen in Fig. 2 with changing values of parameters N and M the median error stays mostly below $3°$. It is interesting to mention that even for fixed $M = 1$ the value of N as low as 50 produces acceptable results as shown in Fig. 3.

It must be mentioned that the testing procedure for the NUS databases differed slightly from the ColorChecker database testing procedure, because the widely used results for ColorChecker in [19] and on [23] were calculated without subtracting the dark level [26]. For the ColorChecker database we also did not subtract the dark levels in order to be compatible with earlier publications. If the dark levels are subtracted, the mean and median errors for the proposed method on the ColorChecker are 3.39 and 2.07, respectively. On the other hand, the tests on NUS databases were performed correctly with dark levels subtracted.

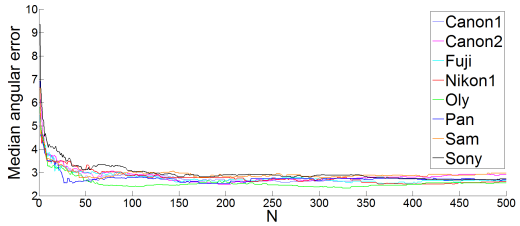


Fig. 3. Influence of value N on median angular error for fixed $M = 1$ on several NUS databases.

4.3. EXECUTION SPEED

The execution speed test was performed on a computer with Intel(R) Core(TM) i5-2500K CPU by using only one core. We used our own C++ implementations of several methods with all compiler optimizations disabled on purpose and used them with parameters [23] for achieving the respective highest accuracy on the linear ColorChecker (for the proposed method $N = 60$ and $M = 20$). Table 2 shows the execution speed superiority of the proposed method and a speed improvement of almost 99% with respect to the white patch method. The proposed method is by furthest the fastest one.

Table 2. Cumulative execution time for first 100 images of the linear ColorChecker database for several methods

Method	Parameters	Time (s)
Gray-World	-	1.3285
general Gray-World	$p = 9, \sigma = 9$	20.2154
1st-order Gray-Edge	$p = 1, \sigma = 6$	15.0224
2nd-order Gray-Edge	$p = 1, \sigma = 1$	10.5949
Color Sparrow	$N = 1, n = 225$	0.0357
white patch	-	1.3949
proposed method	$N = 60, M = 20$	**0.0148**

5. CONCLUSION

The proposed method represents a significant improvement of the white patch method by increasing its accuracy and execution speed. In terms of accuracy the proposed method outperforms most other color constancy methods, which is a significant result. Due to its simplicity and great execution speed the method is well suited for hardware implementation.

6. ACKNOWLEDGEMENT

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