# Color Cat: Remembering Colors for Illumination Estimation

Nikola Banić and Sven Lončarić

***Abstract*—Having images look the same regardless of the scene illumination is a desirable feature called color constancy. In this paper the Color Cat (CC), a novel fast and accurate learning-based method for achieving computational color constancy is proposed. It learns and then uses the relationship between transformed color histograms and the regularity in the possible illumination colors. The proposed method is tested on a publicly available color constancy dataset and it is shown to outperform most of the other color constancy methods in terms of accuracy and computation cost. The results are presented and discussed. The source code is available at http://www.fer.unizg.hr/ipg/resources/color_constancy/.**

***Index Terms*—Chromaticity, color constancy, illumination estimation, image enhancement, linear regression, white balancing.**

(a) (b)

Fig. 1: The same scene (a) with and (b) without illumination color cast.

## I. Introduction

THE human visual system (HVS) can recognize colors of objects under different illumination and this ability is called color constancy [1]. Computational color constancy is an important part of image enhancement. The essential step in achieving it is the illumination source color estimation, which is then used to remove the illumination color cast through chromatic adaptation. Fig. 1 shows the same scene under illumination color cast and with the cast removed. By using the Lambertian assumption the image $f$ formation is given as:

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

where $c$ is a color channel, $x$ is a given image pixel, $\lambda$ is the wavelength of the light, $\omega$ is the visible spectrum, $I(\lambda, \mathbf{x})$ is the spectral distribution of the light source, $R(\mathbf{x}, \lambda)$ is the surface reflectance, and $\rho_c(\lambda)$ is the camera sensitivity of the $c$-th color channel. For uniform illumination, $\mathbf{x}$ is removed from $I(\lambda, \mathbf{x})$ and the observed light source color is given as:

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

Very often only the values of $f_c(\mathbf{x})$ are given and the values of $I(\lambda)$ and $\rho_c(\lambda)$ remain unknown. This makes the calculation of $\mathbf{e}$ an ill-posed problem. To solve it, additional assumptions are needed, which leads to different color constancy methods that are generally divided in two groups. The first group contains low-level statistics-based methods like White-patch (WP) [2], its improvements [3] [4], Gray-world (GW) [5], Shades-of-Gray (SoG) [6], Grey-Edge (1st and 2nd order (GE1 and GE2)) [7], Weighted Gray-Edge [8], using bright pixels (BP) [9], Color Sparrow (CS) [10], Color Rabbit (CR) [11], using color distribution (CD) [12]. In the second group are algorithms that require learning like gamut mapping (pixel, edge, and intersection based - PG, EG, and IG) [13], using neural networks [14], using high-level visual information (HLVI) [15], natural image statistics (NIS) [16], using a mixture of existing methods [17], choosing the most appropriate method by using low-level image properties [18] and scene semantics [19], Bayesian learning (BL) [20], spatio-spectral learning (maximum likelihood estimate (SL) and with gen. prior (GP)) [21], exemplar-based learning (EB) [22], choosing the most appropriate illumination from a predefined set [23]. Most of the digital still cameras use methods from the first group [24] because these are faster. The learning-based algorithms are slower, but more accurate.

In this paper we propose a novel fast and accurate learning-based method based on using transformed color histogram values as features and on the regularity of the possible illumination values. The method is named Color Cat (CC) and it outperforms most of the other methods in terms of accuracy and computation cost thus combining the best properties of the two main color constancy method groups.

The paper is structured as follows: In Section II some properties of the color and illumination distribution are shown, in Section III the proposed method is described, and in Section IV it is tested and the results are presented and discussed.



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## II. Color and illumination distribution

Color constancy methods use the information provided by image pixels to perform illumination estimation. These pixels contain both spatial and color information. Recently it has been shown that spatial information does not provide any additional information in terms of illumination estimation that cannot be obtained directly from the color distribution [12].

Beside the color distribution of individual images, another source of information that can be used in illumination estimation is the distribution of possible illumination colors [25] [26] [27] [28] [29] [30] [23] [31]. For a successful chromatic adaptation, only the direction of the three-element vector $\mathbf{e}$ from Eq. (2) is important, while its amplitude is disregarded. This effectively reduces the dimension of $\mathbf{e}$ from 3 to 2 and instead of using all three RGB components to describe the illumination source, only two chromaticity components can be used. For a color described with its $RGB$ components, the $r, g$, and $b$ chromaticity components are calculated as follows:

$$r = \frac{R}{R+G+B}, \quad g = \frac{G}{R+G+B}, \quad b = \frac{B}{R+G+B}. \tag{3}$$

Only two components are needed because the third one can be calculated from the equation $r + g + b = 1$. The behaviour of real-world illuminations can be seen by using the color constancy benchmark datasets. Scenes of images in these datasets contain calibration objects used to measure the scene illumination, which is then provided as ground-truth illumination for every image i.e. for every image the value of $\mathbf{e}$ is known. While testing a method that tries to estimate $\mathbf{e}$, the calibration objects are first masked out, the method estimates the illumination $\mathbf{e}$ for the image scene, and then this estimation is compared to the ground-truth illumination. The largest publicly available color constancy dataset is the GreyBall dataset [32] with its 11346 images and ground-truth illumination $\mathbf{e}$ for each of them. If the chromaticities of the ground-truth values of $\mathbf{e}$ are calculated and displayed as shown in Fig. 2, a regularity for the $rb$ chromaticity can be observed.

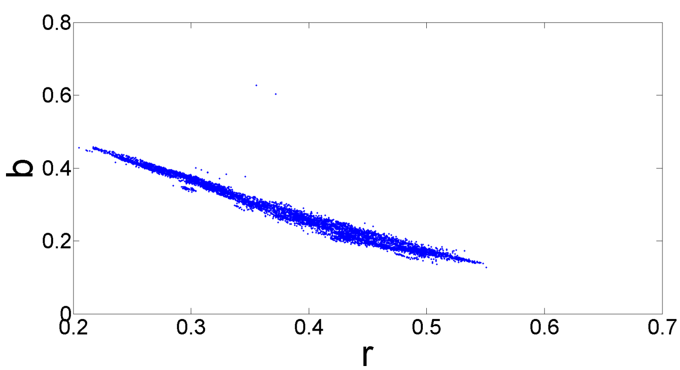


Fig. 2: Ground-truth $rb$-chromaticities for the GreyBall dataset.

The correlation between components of the $rb$ chromaticity is $-0.9904$, which is far greater than the correlation for $rg$ (0.187) and $gb$ ($-0.3211$) chromaticities. Similar correlation for the $rb$ chromaticity components can be observed for the ColorChecker dataset [20] and for all nine NUS datasets [12] all of which were created with different cameras. For them the lowest found correlation in terms of absolute value was $-0.9755$. Since each camera uses its own RGB space that is converted to a standard RGB space later after achieving color constancy, this shows that the correlation of illumination chromaticity components is independent of the used RGB space. The demonstrated regularity makes it possible to assume that in most cases it is enough to look for the illumination only along a single line instead of looking for it in the whole chromaticity plane. However, based on the used RGB space, the line parameters will differ.

## III. The proposed method

Since the $rb$-chromaticity components of the ground-truth illumination values have a high correlation, one of them can be reconstructed from the other relatively accurately thus decreasing the number of values needed to describe the illumination $\mathbf{e}$ from 2 to 1. In this way the set of possible chromaticities is represented by a single line as shown in Fig. 3. A similar illumination constraint has been proposed in [31]. By knowing the value of $r$ and slope-intercept form parameters $a_1$ and $a_0$ of the fitted line, the value of $b$ can be reconstructed as:

$$b = a_1 r + a_0. \tag{4}$$

If $r_0$ and $r_1$ are the minimum and maximum values of chromaticity component $r$ found in the ground-truth data, respectively, then the interesting part of the fitted line is the one for $r_0 \leq r \leq r_1$. Every $r$ can be described by a value $x \in [0, 1]$ calculated as:

$$x = \frac{r - r_0}{r_1 - r_0} \tag{5}$$

By knowing the values of $a_0, a_1, r_0$, and $r_1$, which can all be obtained from the learning image set, the only information that is needed to estimate the illumination of the scene of a given image is the value of $x$. The problem is how to calculate it relatively fast and accurately.

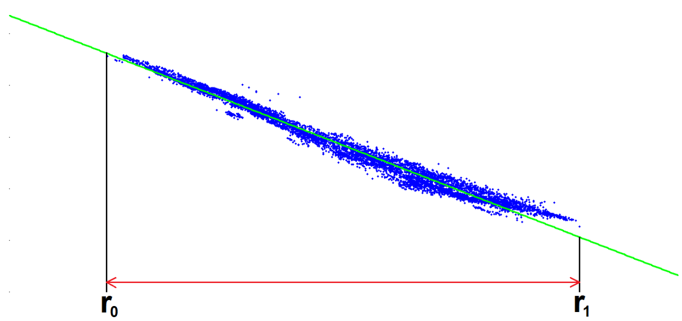


Fig. 3: A line fitted through the ground-truth illuminations in the $rb$ chromaticity space.

We propose to solve this problem by learning the relationship between the information provided by the image color distribution and the value of $x$. A good way to represent the color distribution is to use color histograms, which have already been successfully applied in the field of color constancy [33] [29] [30] [23]. The histogram $\mathbf{h} = (h_1,\ h_2, ...,\ h_{n^3})^T$ is calculated by counting the number of pixels in each of the $n \times n \times n$ equal partitions of the RGB colorspace represented by histogram bins. In order to eliminate the influence of the image size, the bin values are normalized by dividing each of them by the total number of image pixels. Higher values of $n$ give a more descriptive, but also a significantly greater histogram.

To get most of the variability in the histogram bins, the principal component analysis (PCA) [34] is performed on the learning set histograms. The obtained transformation matrix $\mathbf{M}$ is used to take only the first $k$ most significant components resulting in $\mathbf{h}' = \mathbf{M}\mathbf{h} = (h_1',\ h_2', ...,\ h_k')^T$. The relationship between elements of $\mathbf{h}'$ and the value $x$ is then found by performing multiple linear regression [35] with elements of $\mathbf{h}'$ being the predictors. By using the obtained coefficients $\mathbf{c} = (c_1,\ c_2, ...,\ c_k)^T$, the value of $x$ is predicted as follows:

$$x = \mathbf{c}^T\mathbf{h}'. \tag{6}$$

The proposed method has parameters $a_0$, $a_1$, $r_0$, $r_1$, $\mathbf{M}$, and $\mathbf{c}$. It also has two hyperparameters: $n$, resolution of the histogram, and $k$, the number of used histogram principal components. Their fixed combinations represent models. The best model i.e. the best hyperparameter combination is selected from a predefined set of combinations by conducting a grid search: each hyperparameter combination values are used in learning the method's parameters during the cross-validation on the learning set. Therefore in each cross-validation loop the learning is performed on a subset of the initial learning set, while the rest is used for testing. The model that results in the lowest generalization error after cross-validation it selected to be the best model. The described process is known as model selection [36]. After the model selection process, the final parameter learning is performed once again on the whole learning set using the hyperparameters of the best model.

The proposed method is a learning-based one and we decided to name it Color Cat (CC). The pseudocode for applying CC is given in Algorithm 1. It should be mentioned that even though the regularity of the chromaticities of different illuminations has already been exploited in several published methods and patents, e.g. in [25] [26] [28] [23], the Color Cat method exploits it in a different and novel way.

**Algorithm 1** Color Cat

1: $I = GetImage()$
2: $\mathbf{h} = I.CalculateHistogram(n)$
3: $\mathbf{h}' = \mathbf{M}\mathbf{h}$
4: $x = \mathbf{c}^T\mathbf{h}'$
5: $r = x(r_1 - r_0) + r_0$
6: $b = a_1 r + a_0$
7: $g = 1 - r - b$
8: $\mathbf{e}=(r, g, b)^T$

## IV. Experimental results

### A. Benchmark datasets

For the PCA that is performed as the part of the proposed method on the learning set images, a higher ratio of number of learning set images i.e. histograms to number of bins of an individual histogram ($n^3$) makes a more significant contribution than a mere higher number of learning set histograms [37]. Since the number of bins $n^3$ that need to be transformed grows fast, the GreyBall dataset was used for testing because it contains 11346 images, which is much more than other currently available color constancy datasets. In this way the color distribution can be represented well with more bins without causing a too low ratio of number of images to number of bins. Since the image formation described in Eq. (1) assumes a linear model and images in the GreyBall dataset are non-linear i.e. their sensor data was non-linearly processed, methods are often tested on both non-linear and linear versions of its images. The linear versions are obtained by applying an approximated inverse gamma-correction.

TABLE I: Performance of different color constancy methods on the original GreyBall dataset (lower is better).

| method | mean (°) | median (°) | trimean (°) | max (°) |
|---|---|---|---|---|
| do nothing | 8.28 | 6.70 | 7.25 | 36.84 |
| **Low-level statistics-based methods** | | | | |
| GW | 7.87 | 6.97 | 7.14 | 48.13 |
| WP | 6.80 | 5.30 | 5.77 | 38.71 |
| SoG | 6.14 | 5.33 | 5.51 | 41.22 |
| general GW | 6.14 | 5.33 | 5.51 | 41.22 |
| GE1 | 5.88 | 4.65 | 5.11 | 41.22 |
| GE2 | 6.10 | 4.85 | 5.28 | 41.70 |
| **Learning based methods** | | | | |
| PG | 7.07 | 5.81 | 6.12 | 41.94 |
| EG | 6.81 | 5.81 | 6.03 | 40.35 |
| IG | 6.93 | 5.80 | 6.05 | 41.88 |
| NIS | 5.19 | 3.93 | 4.31 | 44.49 |
| EB | 4.38 | 3.43 | 3.67 | 45.56 |
| **proposed** | **4.22** | **3.17** | **3.46** | 43.74 |

TABLE II: Performance of different color constancy methods on the linear GreyBall dataset (lower is better).

| method | mean (°) | median (°) | trimean (°) | max (°) |
|---|---|---|---|---|
| do nothing | 15.62 | 14.00 | 14.56 | 42.26 |
| **Low-level statistics-based methods** | | | | |
| GW | 13.01 | 10.96 | 11.53 | 62.99 |
| WP | 12.68 | 10.50 | 11.25 | 46.54 |
| SoG | 11.55 | 9.70 | 10.23 | 58.15 |
| general GW | 11.55 | 9.70 | 10.23 | 58.15 |
| GE1 | 10.58 | 8.84 | 9.18 | 58.40 |
| GE2 | 10.68 | 9.02 | 9.40 | 56.05 |
| **Learning based methods** | | | | |
| PG | 11.79 | 8.88 | 9.97 | 49.01 |
| EG | 12.78 | 10.88 | 11.38 | 58.30 |
| IG | 11.81 | 8.93 | 10.00 | 47.49 |
| HVLI | 9.73 | 7.71 | 8.17 | 59.99 |
| NIS | 9.87 | 7.65 | 8.29 | 56.10 |
| EB | **7.97** | **6.46** | **6.77** | 53.59 |
| **proposed** | 8.73 | 7.07 | 7.43 | 52.42 |

### B. Accuracy

The error of color constancy methods is commonly described by the angular error i.e. the angle between the ground-truth illumination and the illumination estimation. If a method is tested on a dataset, then the most important error statistics is the median of angular errors on individual images [38]. The reason to favor the median over the mean angular error is that the error distribution is often not symmetrical.

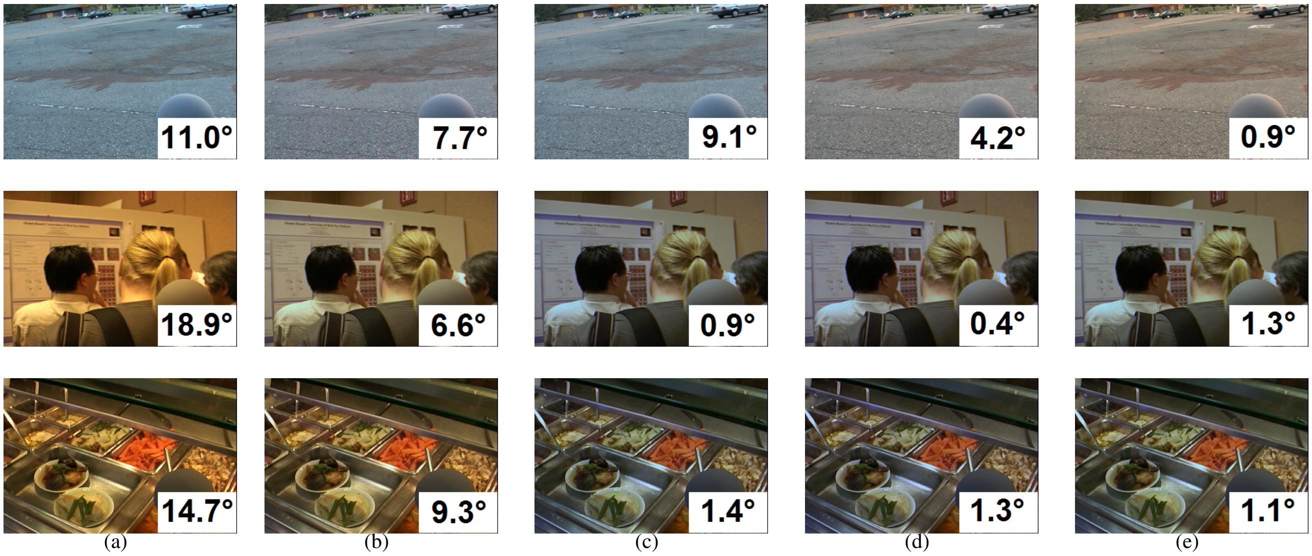


Fig. 4: Example of chromatic adaptation based on the methods' illumination estimation and respective illumination estimation errors: (a) do nothing, (b) White-patch, (c) Natural Image Statistics, (d) Exemplar-based, and (e) the proposed method.

Since the proposed method has to learn the optimal values of its parameters, a cross-validation is needed to test the method's performance and a 15-fold cross-validation was performed with the folds provided by the GreyBall dataset authors. Each of the $15$ folds contains images taken at a different location. As described before in Section III, beside learning the parameter values the proposed method has to choose the best model i.e. to select the optimal values for the hyperparameters in the process of model selection. Model selection contains its own cross-validation and because of this the whole testing process results in a nested cross-validation [36] with the inner cross-validation of the model selection being a 5-fold one.

Table I shows the errors for the GreyBall dataset and Table II for its linear version. The errors of other methods were taken from [39] and [40]. For the original GreyBall dataset the proposed method outperforms all methods and for its linear version it is outperformed only by a single method. A visual comparison of the proposed method and several other methods' performance is given in Fig. 4.

### C. Computation cost

After the learning process is over and the needed parameters values are known, the computation complexity of the illumination estimation of the proposed method is determined by the calculation of the histogram, its reduction via PCA transformation matrix multiplication, and multiplying it with the multiple linear regression coefficients to calculate $x$, which then leads to direct calculation of the illumination estimation. If $N$ is the number of image pixels, then the complexity of the proposed method expressed in Big-O notation is

$$O\left(k(n^3+1)+N\right). \tag{7}$$

In order to compare the proposed method to other methods in terms of speed, the Gray-world and the proposed method were implemented in C++ and compiled with all optimizations disabled. The Gray-world method was chosen because in a recent speed test it outperformed all other methods [12]. The testing was performed on a computer with Intel(R) Core(TM) i5-2500K CPU by using only one core. The Gray-World method has no parameters, and for the proposed method $n$ was set to $10$ and $k$ to its maximum value across different GreyBall folds. It took $5.97s$ for the Gray-world to process the first $1000$ images of the GreyBall dataset and $9.04s$ for the proposed method. By calculating the ratio of the execution time of the proposed to the execution time of the Gray-world method and comparing it to similar rations for other methods based on data provided in [12] it can be concluded that in terms of illumination estimation execution speed only three low-level statistics-based methods including Gray-world are faster than the proposed method.

## V. Conclusions and future research

A novel fast and accurate learning-based color constancy method has been proposed that exploits information available in the image and illumination color distribution to estimate the illumination. The method outperforms most of the other color constancy methods in terms of accuracy and computation cost. In future the observed illumination chromaticity regularity could be used to further improve the existing color constancy methods' accuracy.

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