

Exemplar-Based Colour Constancy

Hamid Reza Vaezi Joze

hrv1@sfu.ca

Mark S. Drew

mark@sfu.ca

Simon Fraser University

Vancouver, BC, Canada

Exemplar-based learning or, equally, nearest neighbour methods have recently gained interest from researchers in a variety of computer science domains because of the prevalence of large amounts of accessible data and storage capacity. In computer vision, these types of technique have been successful in several problems such as scene recognition, shape matching, image parsing, character recognition and object detection. Applying the concept of exemplar-based learning to the well-known problem of illumination estimation seems odd at first glance since, in the first place, similar nearest neighbour images are not usually affected by precisely similar illuminants and, in the second place, gathering a dataset consisting of all possible real-world images, including indoor and outdoor scenes and for all possible illuminant colours and intensities, is indeed impossible. In this paper we instead focus on *surfaces* in the image and address the colour constancy problem by unsupervised learning of an appropriate model for each training surface in training images. We find nearest neighbour models for each surface in a test image and estimate its illumination based on comparing the statistics of pixels belonging to nearest neighbour surfaces and the target surface. The final illumination estimation results from combining these estimated illuminants over surfaces to generate a unique estimate.

The main distinctions between this work and other learning bases colour constancy methods that use spatial information by local feature descriptors such as [3, 4] is that they use this information to determined the best or combination of best possible illumination estimation algorithms while we use selected instances for illumination estimation.

We find surfaces for both training and test images by mean-shift segmentation. Since the pixels in the margin of segmented areas affect texture information, we remove margin pixels of segments by dilating segment edges as well as small segments.

In order to define a model for each surface we use both texture features and colour features. For the purpose of texture features, the MR8 filter bank [5] on three channels is selected for use because of its good performance in texture classification applications. We use the normalized histogram of frequency of appearance in that particular surface for each colour channel as our colour features. In order to make our model weakly invariant to variation in illuminant colour, We apply Max-RGB method for each surface.

Given a test surface model and its nearest neighbour surface model based on chi squared distance from training models, we can transfer the test surface's colour to its corresponding training surface's colours linearly by a 3×3 diagonal matrix.

$$e_{test} = D e_{train} = \mathcal{M}_{test}^{-1} D_H \mathcal{M}_{train} e_{train} \quad (1)$$

where \mathcal{M} is the weakly colour constant diagonal transformation of surface colour from the Max-RGB method and D_H is the transformation of test surface's histograms to training surface's histograms.

Algorithm 1 Illumination Estimation by Exemplar-Based method

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1: surfaces  $\leftarrow$  mean-shift segmentat of the test image
2: for all  $S$  in surfaces do
3:   features  $\leftarrow$  convolve  $S$  with MR8 filter
4:   label  $\leftarrow$  NN(features, textons)
5:   texture hist  $\leftarrow$  normalized histogram of labels
6:    $S_{cc} \leftarrow$  MaxRGB( $S$ )
7:   colour hist  $\leftarrow$  normalized histogram of each colour channel in  $S_{cc}$  (10 bins)
8:   model $_S \leftarrow$  texture hist. , colour hist.
9:   for all  $i$  in KNN(model $_S$ , model $_{S_{train}}$ ) do
10:    estimate $_{S_i} \leftarrow$  eq. (1)
11:  end for
12: end for
13: return median(estimate $s$ )

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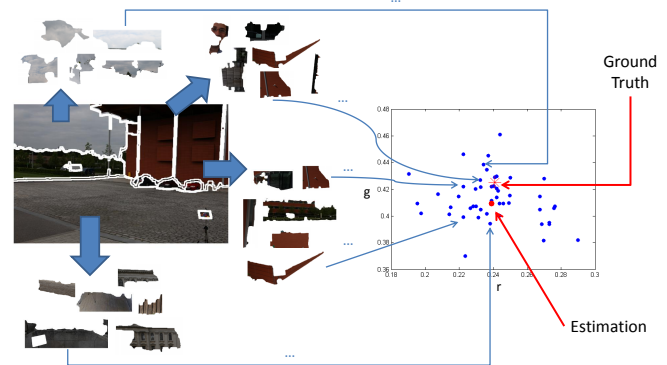


Figure 1: The procedure of estimating illuminant for a test image using exemplar-based color constancy. A test image and its nearest neighbour surface models from training images on left and estimated illuminants according to each model in rg chromaticity space on right.

Dataset Methods	Color Checker		GrayBall	
	Median	Mean	Median	Mean
White-Patch	5.7°	7.4°	5.3°	6.8°
Grey-World	6.3°	6.4°	7.0°	7.9°
Grey-Edge	4.5°	5.3°	4.7°	5.9°
Gamut Mapping pixel	2.5°	4.1°	5.8°	7.1°
Bottom-up+Top-down [4]	2.5°	3.5°	-	-
Natural Image Statistics [3]	2.5°	4.1°	3.9°	5.2°
Exemplar-Based	2.3°	3.1°	3.3°	4.4°

Table 1: Angular errors for two well-known color constancy datasets in term of mean and median for several algorithms.

Given a test image, we will have n large enough surfaces and M nearest neighbour surfaces from training data, or equally M illumination estimates by eq. (1) corresponding to each. The final estimate can be the median or the mean on the three channels separately after removing outliers of all of these nM estimates in rg chromaticity space.

We applied our proposed method to two standard colour constancy datasets of real images of indoor and outdoor scenes: the re-processed version of the Gehler colour constancy dataset [2], denoted the Color Checker dataset which include 568 images and the GrayBall dataset of Ciurea and Funt [1] which contains 11346 images. Table 1 indicates the accuracy of the proposed methods for these datasets, in terms of the mean and median of angular errors, for several colour constancy algorithms applied to this dataset.

To our knowledge, for these two standard datasets, widely used for testing colour constancy, Exemplar-Based Colour Constancy does best in terms of both mean and median angular error compared to any reported colour constancy methods, even those using a combination of algorithms such as Natural Image Statistics [3].

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