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Exemplar Based Illumination Estimation

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***Abstract* — Illumination estimation is the ability to estimate the color of light source. The color of light source may influence the appearance of object in the scene. Human has the normal tendency to identify the actual color of object in spite of variations in the color of the light source. But, it is not easy for computer vision systems to find the actual color of objects in the scenes. In this paper exemplar based illumination estimation is extended. The exemplar based method focuses on the surfaces in the image and estimates illumination by learning the models for each training surface in the training image. Then nearest neighbor model for each surface of the test image are searched and its illumination is estimated based on comparing the statistics of pixel that belong to nearest neighbor surface model and the target surface model.**

***Key Words* — Color, Illumination Estimation, Exemplar Based Learning, Computer Vision.**

I. Introduction

Color is important in many applications such as human computer interaction, color feature extraction and color appearance models. The color of light source significantly affects the color of object in the scene. As a result, the image of the same object, taken by the same camera but under different illumination, may vary in its measured color values.

Fig.1 shows images captured under different light conditions. This color variation may introduce undesirable effects in digital images. Human has the ability to identify the actual color of object despite variations in the color of the light source. However, it is not easy for computer vision systems to identify the actual color of objects in the images. The goal of color constancy is to estimate the actual color of object in an acquired scene disregarding its illuminant.

The color of objects in the scene consists of the actual color of surface, the color of illuminant and the camera characteristic. Hence it is essential to remove the color of illuminant, to recover the actual surface color. Image color for a Lambertian surface [9] at location can be modeled as,

$$f(x) = \int_{\omega} e(\lambda)\rho k(\lambda) s(x,\lambda) d\lambda, \qquad (1)$$

Where, $e(\lambda)$ is the color of the light source, $s(x,\lambda)$ is the surface reflectance and $\rho k(\lambda)$ is the camera sensitivity function ($k \in \{R,G,B\}$). ω *is* the visible spectrum, x is the spatial coordinates and λ is the wavelength of the light.

To recover the actual surface color, it is required to remove the color of the illuminant. As, removing the color of illuminant is an easier task, estimation of illumination is the aim of the color constancy. The process of color constancy consists of two main steps: In the first step, the color of the illuminant is estimated which is the main part and the second step consists of removing the effect of the estimated illumination which is called as color correction. Basically, the term illumination estimation may refer to estimating the geometry or direction of light [1]-[2], estimating the full spectral power distribution of light [3] or estimating the color of light. The project focuses on the color of the light and therefore, here illumination estimation refers to estimation of color of light. The project does not recover the actual color of surface objects and therefore it does not include the standard two color constancy steps i.e. illumination estimation and color correction. In computer vision, color constancy is important for applications such as image retrieval, object detection and color reproduction. Therefore various algorithms for estimating illumination have been proposed by researchers [4].

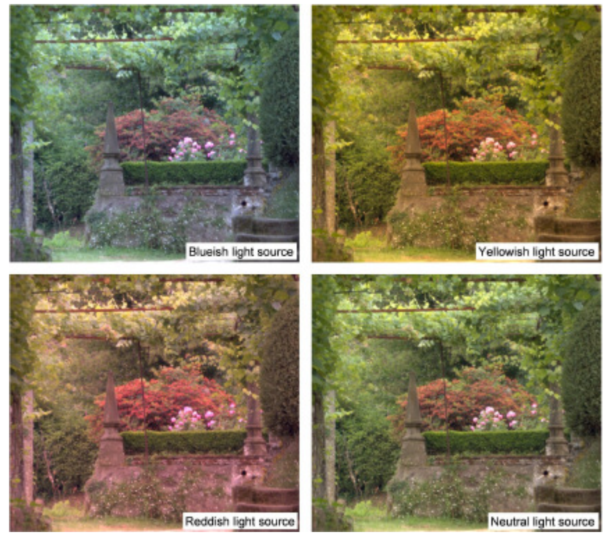


Fig. 1. Images Captured Under Various Sources

The paper is organized as follows. Section II contains the literature review of various illumination estimation methods. The implementation details are given in section III. In section IV algorithm is explained. Section V contains the results and discussion. The paper is concluded in section VI.

II. Literature Survey

Illumination estimation methods can be classified into following groups: (1) Static Methods, (2) Physics Based Method (3) Learning Based Methods and (4) Gamut Based Methods. The static methods, estimate the illuminant for each image based on its statistical or physical properties. These methods can be applied to any image without the need of training. The physics-based methods estimate the illuminant using physical models of image formation. Whereas learning based methods estimate the illuminant using a model which is learned on training images. Hence, it is necessary to train a model before the estimating the illuminant. Gamut based methods compares a canonical gamut and image gamut to estimate the illuminant.

The first color constancy method is Retinex, developed by Land [5] and it is based on the assumption that an abrupt change in chromaticity is caused by a change in reflectance model. This implies that the illuminant smoothly varies across the image and does not change between adjacent or nearby locations. Various implementations have been proposed using this theory. The white patch algorithm is also based on the retinex theory. Its assumption is that, white patch is present somewhere in the image, which reflects maximally and achromatically. Thus, the color of illuminant can be recovered from the brightest pixel. In practice, the maximum response of each color channel is taken into consideration separately, potentially from different pixels. However, all these methods assumes that the illuminant transition is smooth, which is not the case. Hence, Retinex theory was a first step towards color constancy.

Grey World algorithms are based on the well-known Grey-World assumption [6], i.e. the average reflectance in image under a neutral light source is achromatic. Hence it is determined that, the deviation from achromaticity in the average color of scene is due to the effects of the illuminant. Thus, by computing the average color in the image, the color of the light source is estimated. On the other hand, instead of calculating the average color of pixels, it has been shown that, computing the average color of all segments of image may increase the performance of the Grey-World algorithm [7]-[8]. This is a very simple algorithm to find the color of light source of a scene. As, the grey world algorithm is sensitive to large uniformly colored surfaces, many methods worked on identifying the grey surfaces in the image i.e. they tried to find the surface under a colored light source that would appear grey if rendered under a white light source.

Forsyth et.al. [9] introduced the gamut mapping algorithm. This algorithm is based on the assumption that, one can observe only a limited number of colors for a given light source in real world images. As a result, any variations in the image colors are caused by variation in the color of light source. The limited set of colors under a given illuminant is represented as a canonical gamut C which is computed under a given light source by observing many surfaces. Bayesian method is other learning-based approach to illumination estimation problem [10, 11]. In this method the variability of reflectance of illuminant is given as independent random variables. Here the illuminant prior could be uniform over a subset of illuminants. The comparative analysis of the illumination estimation methods is presented in table **I.**

Table I: Comparative Analysis of the Methods

Color Constancy Technique	**Advantages**	**Disadvantages**
Statistical Color Constancy	* Simple to implement * Fast execution * Accurate for adequate parameters	* Opaque parameter selection * Inaccurate for inferior parameters * Limited success on real images
Physics Based Color Constancy	* No training phase * Few parameters * Fast execution	* Mediocre performance * Difficult to implement
Learning Based Color Constancy	* They are simple to implement * Tunable for specific data set * Potentially high accuracy * Incorporates semantic	* Requires training data * Slow execution * Difficult to implement
Gamut Based Color Constancy	* Straight-forward computation * Good performance * Potentially high accuracy	* Requires training data * Difficult to implement * Proper preprocessing is required

There are number of algorithms present for the estimation of illumination but we will be using exemplar based method for illumination estimation. The exemplar based method focuses on surfaces in the image and deals with the illumination estimation problem by learning the model of each surface in the training images. The nearest neighbor models for each surface of test image are searched and its illumination is estimated based on comparing the statistics of pixels that belong to nearest neighbor surface model and the target surface model. The estimated illuminants over surfaces are combined to generate unique estimate.

The exemplar based method of illumination estimation includes following steps:

(1) Find surfaces in an image.

(2) Find a similar surface in the training dataset for each image surfaces.

(3) Estimate the illumination for each surface by comparing the statistics of pixels that belong to similar surfaces with the target surface.

(4) Combine these estimated illuminants into a unique estimate.

III. Implementation Details

The exemplar based method belongs to learning-based method of illumination estimation. Learning based methods extract color, texture or shape features from sets of training images, and estimate the illuminant color for each image using several statistical illumination estimation algorithms. The exemplar based method classify or estimate test examples based on examples already seen which is similar to a concept of learning in humans. Therefore, the exemplar based method is considered as learning-based method. Fig 2 shows block diagram of exemplar based illumination estimation.

1) **Convolve Images With Filter Bank: -** The MR8 filter bank [12] is used to extract texture feature. Images are convolved with filter bank, to generate filter responses. The MR8 filter bank consists of 38 filters (i.e. 2 isotropic filters plus 6 orientations at 3 scales for 2 oriented filters,). The filter bank contains filters at multiple orientations however it records only the maximum response across all orientations. Images are convolved with filter bank, to generate filter responses. The performance of MR8 filter bank is good in texture classification applications and also its implementation is fast

2) **Construct Filter Response Vectors: -** A response vector of each pixel is formed by storing the response from each filter. The size of filter response vector is 8, because it records only the maximum response across all orientations.

3) **Clustering Responses to Create Texton Dictionary: -** The resulting filter response vectors are divided into clusters using k-means clustering algorithm. The response vectors corresponding to the cluster centers are considered as the textons. The histogram of frequency of textons in the dictionary is a common description for texture detection.

4) **Split Training Images into Segments: -** Mean shift segmentation [13] is used to find surfaces for training as well as test images. Surfaces are the segmented regions of images.

5) **Label Filter Response with Dictionary:** - The response of filter bank are labeled with nearest neighbor texton in texton dictionary.

6) **Extraction of Color Feature: -** For color features, the 3 channel histogram is added to surface model. Then the histogram is stretched to make surface model invariant to variation in illumination color. Thus, to make color constant surface model each channel is divided by its maximum value before computing the histogram. In algorithm, MaxRGB function makes the input pixel color constant. As a research, simple preprocessing is applied to basic MaxRGB. As a preprocessing step median filter is applied to each surface of an image before computing MaxRGB. Applying median filtering before computing MaxRGB is expected to improve results. Fig 3 shows the MaxRGB Processing.

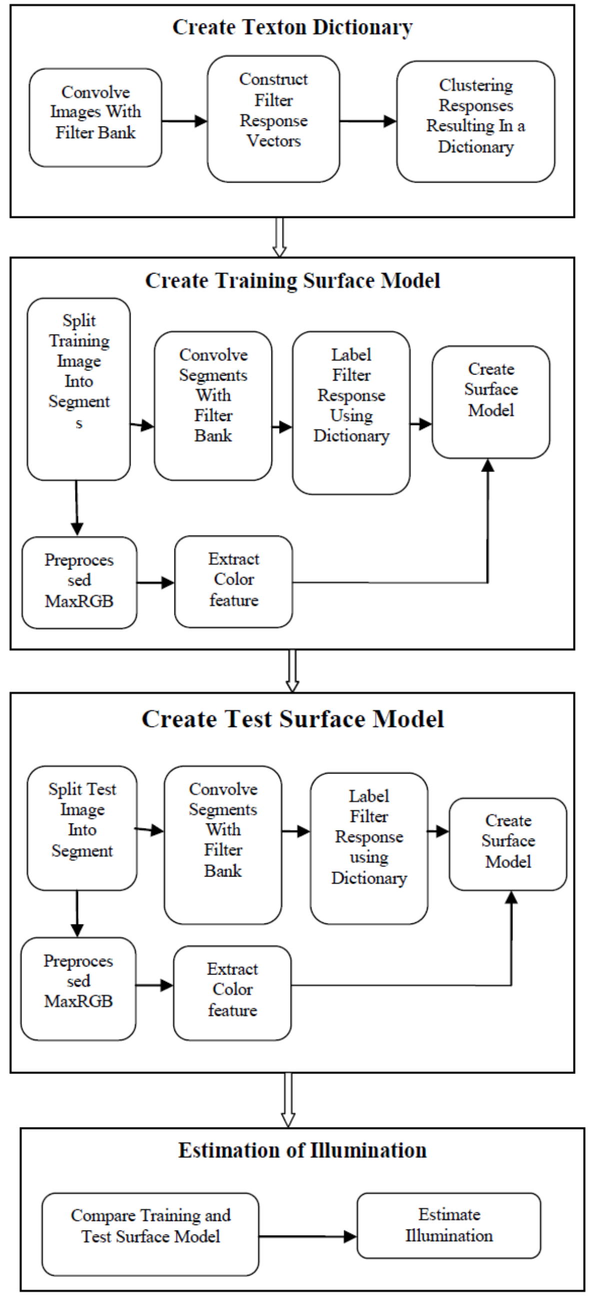


Fig. 2. Exemplar Based Illumination Estimation

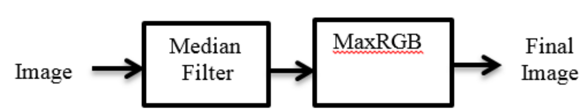


Fig. 3. MaxRGB Processing

7) **Create Surface Model: -** Each surface model include four normalized histograms (1 texture histogram, 3 color constant normalized histogram) stored in a single vector. Also it contains information about the actual illumination.

8) **Compare Training and Test Surface Models: -** The surface model of test image is compared with the

models matching to training surfaces by nearest neighbor classifier. M nearest neighbor surface models are selected from training surfaces.

9) **Estimation of illumination:-** From the test surface model and its nearest neighbor models among training models, the test surface's colors are transferred to its corresponding training surface colors linearly by 3 X 3 matrix. This matrix which transforms test surface to training surface can be written as:

$$D = M_{test}^{-1} D_H M_{train} \qquad (2)$$

Where M is the color constant diagonal transformation of surface color from the preprocessed Max-RGB method. D_H is the transformation of the test surface's histograms to training surfaces' histograms. D_H is approximately the identity matrix. Finally, as the illumination color of training surface 'e_{train}' is known, the estimation for test surface illumination color is:

$$e_{test} = De_{train} = M_{test}^{-1} D_H M_{train} e_{train} \qquad (3)$$

Given a test image, there are n large enough surfaces and M nearest neighbor surfaces from training data, and M illumination estimates by equation (3) corresponding to each. The final estimate is the median or the mean of all of these estimates.

IV. Algorithm

1: Input: Image dataset I

2: Output: Estimated illuminant

3: Create Texton Dictionary

- features ← convolve images with MR8 filter bank
- textons ← k- means clustering of filter responses

4: Finding surfaces

- surfaces← mean shift segmentation of training image

5: Create surface models for training images

- **for all** S in surfaces **do**
- features ← convolve S with MR8 filter bank
- label ← NN(features,textons)
- texture hist <-normalized histogram of labels
- Scc ← Preprocessed_MaxRGB(S)
- color hist ← normalized histogram of each color channel in Scc
- trainmodelS ← (texture hist, color hist)
- **end for**

6: Create surface model for test images

- Repeat step 5 for test surface

7: **for all** i in KNN(testmodelS,trainmodels) **do**

8: estimatesSi ← equation(3)

9: **end for**

10: **end for**

11: **return** estimates

V. Dataset And Discussion

In this project, the GreyBall dataset of Ciurea and Funt [14], is used which contains many low quality real-world images. The dataset contains 11346 images extracted from 15 video clips recorded under a variety of imaging conditions (city, mall, indoor, desert, forest, road etc.). The ground truth is picked up by attaching a grey sphere to the camera. The scene illuminant of each image is measured in terms of mean of RGB values of the pixels on the sphere. However the images have the resolution of only 360 × 240 pixels. The quality of images is not good because of the movement of the camera while recording clips. This dataset is widely used to evaluate color constancy methods because of the variation of imaging conditions in this dataset.

To evaluate the performance of algorithm, error of estimation is to be calculated. Angular error and Euclidean error are two measures used to calculate the error of estimation. In this project we will use angular error for measurement of estimation error. Angular error is the angle between actual illuminant e and estimated illuminant e_{est}.

$$err_{angle}(e, e_{est}) = acos\left((e \cdot e_{est}) / (\|e\| \|e_{est}\|) \right) \qquad (4)$$

Error of estimation is to be calculated for each image. Then the overall performance of the algorithm can be the mean of errors. As the mean is sensitive to outliers, median is suggested in the literature. Median indicates the performance of methods for half of the images.

VI. Results

We have created the texton dictionary. For creating the texton dictionary images are convolved with MR8 filter bank. This filter bank consists of 38 filters. The filters are implemented at multiple orientations and scales to achieve rotation invariance. Only the maximal response among the different orientations, at each scale is kept. The final response at each position is feature vector of length 8. The response vectors are shown in fig 4.

These response vectors are clustered using k- means clustering and texton dictionary is created. The histogram of texton in a dictionary is shown in fig 5.

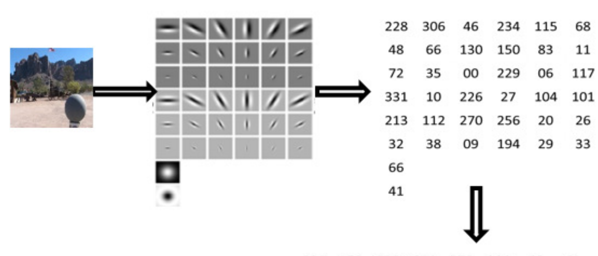


Fig 4. MR8 Filter Bank and Response Vector

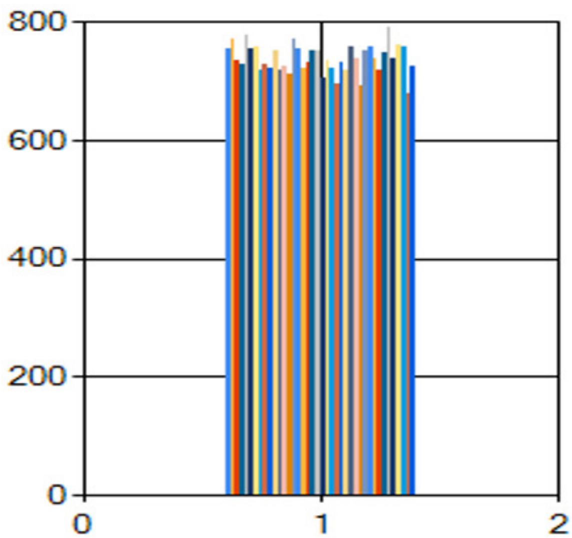
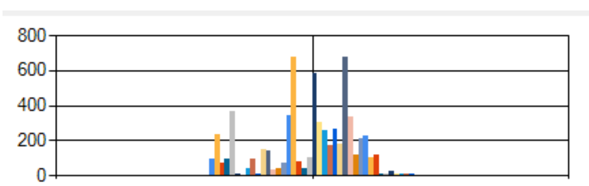
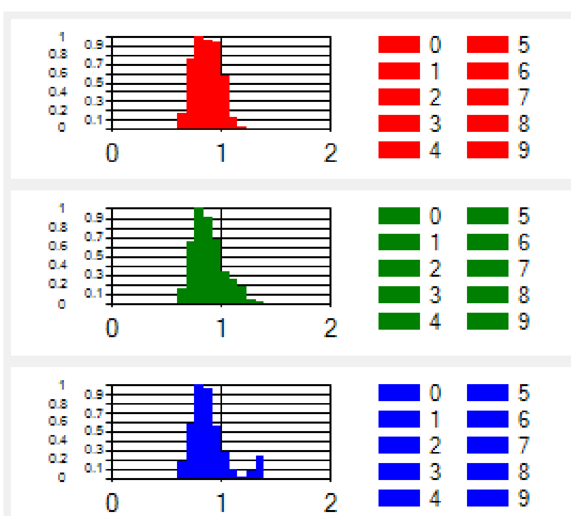


Fig. 5. Texton Histogram

Mean shift segmentation is used to find surfaces for training as well as test images. The surface models of training and test images are created for estimating the illumination. These surface models are compared and illumination is estimated. Surface model consists of one texture histogram and 3 color channel histogram. Surface models are shown in fig 6.



(a)



(b)

Fig. 6. Surface Model (a) Texture Histogram (b) 3- Channel Color Histogram

Figure 7 shows an input image, its estimated surface illumination. The surface illumination is estimated by applying median filter before MaxRGB algorithm.

(a)

(b)

Fig. 7. (a) An Input Image (b) Estimated Surface Illuminant

Conclusion

The exemplar based illumination estimation is a new method of estimating illumination. In exemplar based approach, both texture features and color features are used to find the nearest neighbor surfaces from training data and then illuminant is estimated for each surface. In the final step, these estimates are combined into unique illuminant for the whole image. We extend exemplar based method by using preprocessed MaxRGB function. A median filter is added as preprocessing step to the basic MaxRGB methods which may improve the results

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