Introduction

Determination of illumination of a scene from a single image or an image sequence is an important problem in computer vision and computer graphics. When a camera acquires an image, the sensor outputs reflect the effective illumination in the scene. Photo developers and printers must take care to correct the effects of the illumination before producing the final image. Current film developers and printers use time consuming and manually assisted algorithms for color correction. The problem arises in the new and developing technologies of Digital Cameras, which will most likely replace the current film-based cameras. In the digital cameras, the images are directly viewed on the computer monitor following acquisition. Thus, correction for illumination must be performed automatically on-line by the camera. This promotes the need for efficient algorithms for scene illumination estimation.

The approach presented here for dealing with this problem introduces the following:
1) Illumination classification is performed rather than illumination estimation.
2) Illumination evaluation is image content dependent, specifically an object based approach is used. Thus using spatial information in the image, pixels associated with an object are segmented and grouped as a subset that is considered in the illumination estimation process using the object's spectral characteristics.

2

Illumination Classification Based on Image Content

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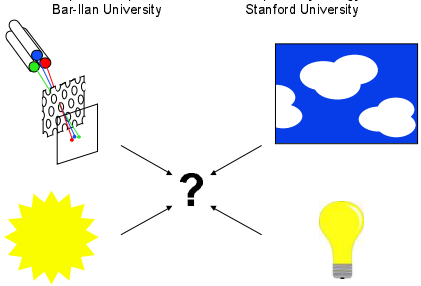


1

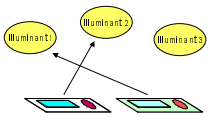
Part 1: Illumination Classification

Rather than estimating the scene illumination (determining the exact spectral distribution of the illuminating source), we perform Illumination Classification.

The problem then reduces to: Given a finite set of illuminant classes, determine which of the classes is most probable as the illuminant of a given image.

Classification is sufficient for color correction since efficient algorithms use look-up tables (rather than closed form solutions or computations) to correct color values. The look-up table to be used is determined by the estimated scene illuminant. A finite number of look-up tables are used in the process, corresponding to a finite number of illuminant classes.

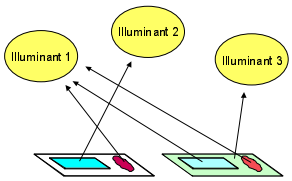
Illumination Classification rather than Illumination Estimation, simplifies the problem at hand: the exact illuminant need not be recovered. The solution space is finite and the solution becomes more robust to approximations and errors. Where illumination estimation errs, illuminant classification may still provide the correct answer.



4

Our Approach

- Perform Illumination classification rather than illumination estimation.
- Exploit spatial information in image. Namely, use Object Based Illumination Estimation.



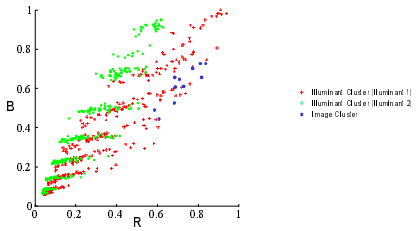
3

Image Clusters

The set of pixel values of a given image forms a cluster of 3D points in the camera sensor space. Illumination can be determined by classifying the image cluster to one of the illuminant clusters.

Intuitively the image cluster will be classified to the "closest" illuminant cluster. A metric must be used to measure the "distance" between the image cluster and each illuminant cluster.

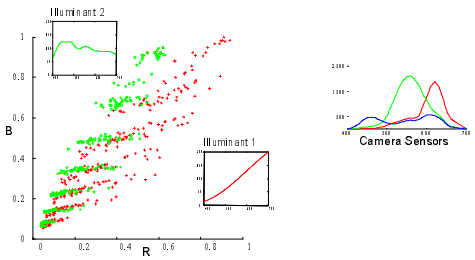
Considering several illuminant clusters, it is obvious that the greater the "distance" between the illuminant clusters, the better the illumination classification will perform.



6

Illuminant Classes

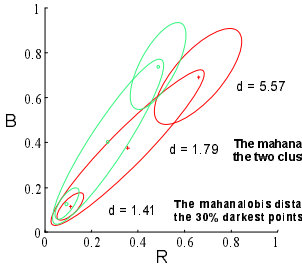
Given an illuminant, we consider the set of all surface reflectances viewed under the illuminant by a known set of camera sensors. A large set of possible sensor outputs is obtained. Given a finite number of illuminants, several sets of possible sensor outputs are obtained, one for each illuminant. Each such set forms a cluster of points in the 3D sensor output space.



Two Illuminant Clusters obtained by plotting the Munsell surfaces as viewed by the three Kodak DCS-20 camera sensors under two illuminants - tungsten bulb (CIE standard illuminant A) and typical daylight (CIE standard illuminant C). A 2D projection of the sensor space is shown (corresponding to the R and B camera sensors).

Distances Between Illuminant Classes

The set of Munsell surfaces form two clusters of 3D points for two different illuminants (CIE-A and CIE-C). The mahanalobis distance is computed between subsets of the cluster points:



The mahanalobis distance between the 30% brightest points.

The mahanalobis distance between the two clusters.

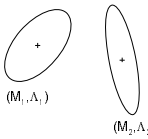
The mahanalobis distance between the 30% darkest points.

The means are represented as '+' and '.' for the two clusters. The ground truth ellipsoids shown as ellipse with width and length proportional to the covariance matrix.

8

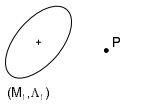
Distance Metric Between Clusters

The distance metric used in this work is the Mahanalobis Distance which is defined between two Gaussian distributed clusters (given by mean vector M and covariance matrix Λ) as:



$$(M_1 - M_2)^t (\Lambda_1 + \Lambda_2)^{-1} (M_1 - M_2)$$

This metric can also measure the distance between a single point P and a cluster:

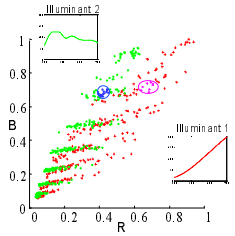


$$(P - M_1)^t \Lambda_1^{-1} (P - M_1)$$

7

Apriori knowledge on the surface reflectance can be exploited for improving Illumination Classification.

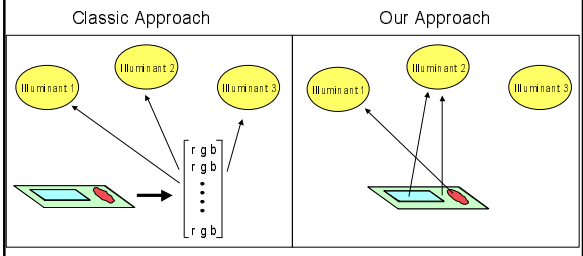
Previous approaches assume the sensor outputs may originate from any one of the points in the illumination clusters. Apriori knowledge on the surface reflectances constrains the associated sensor outputs to originate from a subset of cluster points marked with an ellipse for each Illumination Cluster.



If the distance between these subsets of cluster points is greater than the distance between the Illumination Clusters themselves, then classifying using apriori knowledge provides better classification.

10

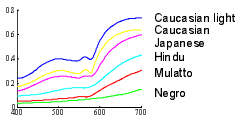
Part 2: Spatially Dependent Illumination Classification



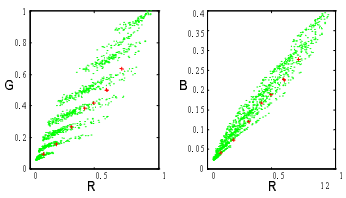
9

Skin Tone Based Illumination Classification

Skin Spectral Reflectances (Wyszecki & Stiles)



Distribution of all surface reflectances vs skin surface reflectances as viewed under CIE illuminant A (tungsten).



12

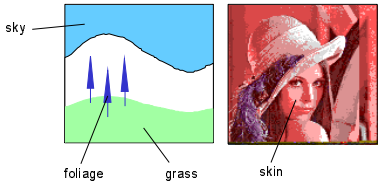
Object Based Illumination Classification

In order to provide apriori spectral information on the surface reflectance associated with the pixel values, we assume an Object Based approach.

Thus using spatial information in the image, pixels associated with an object are segmented and used in the illumination estimation process while exploiting the object's spectral characteristics.

Computer Vision techniques can be used to find objects in an image. The Object Based Illumination Classification technique can be applied to the pixels associated with the object.

In this work we exploit the spectral reflectance characteristics of Human Skin, to improve illumination Classification performance. Face detection tools can be used to extract face pixels associated with skin surfaces.

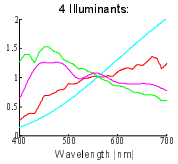


11

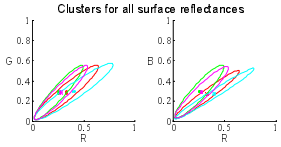
Experimental Results - Simulation

Four illuminants were chosen. For each illuminant, the Illumination Cluster associated with all surface reflectances (Munsell surface reflectances) was created. For each illuminant, the Illumination Cluster associated with the skin surface reflectances was created.

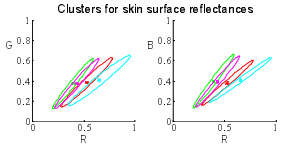
4 Illuminants:



Clusters for all surface reflectances

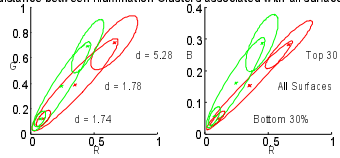


Clusters for skin surface reflectances

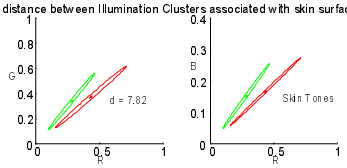


Compare Cluster Distances for different representations

The distance between Illumination Clusters associated with all surface reflectances:



The distance between Illumination Clusters associated with skin surfaces:

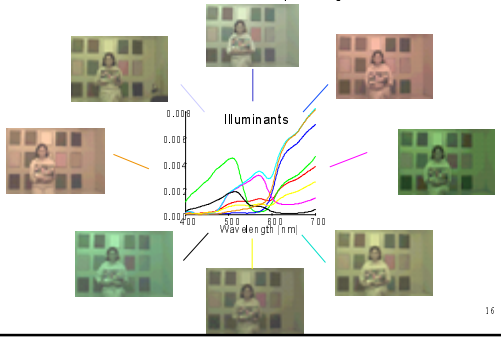


13

The inter-cluster distance is greater between the Illumination Clusters associated with the skin surfaces.

Experimental Results - Real Images

A set of 12 calibrated images containing a human face was obtained under 8 different illuminants. The illuminants of the scene were measured for each acquired image.



16

The simulation was performed as follows:

An image containing a human face which was acquired under white illumination. One of the four illuminants was chosen, zero mean gaussian noise was added to the illuminant and a new image was created containing the same scene as the original but viewed under the new illuminant.
The pixel values of the new image were used to determine the scene Illuminant by classifying according to the four original illuminant clusters using all image pixels and using only the skin pixels which were extracted manually. The process was repeated 40 times (10 times for each illuminant).

Image under White Illumination

Image under CIE-A Illumination

Simulation Results: Classification according to All image pixels:
No of Hits : 26 (65%)

Classification according to skin pixels:
No of Hits : 37 (92.5%)

15

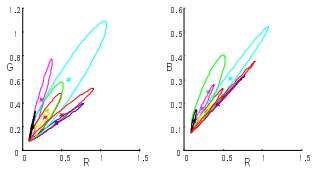
Classification Results - Real images

Illuminantion Classification was applied to the 12 images using all the pixels in the image and using the skin pixels (which were manually extracted).

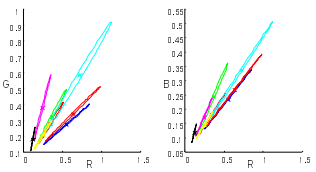
True Illuminant Class	Classification using All Reflectances	Classification using Skin Reflectances
1	6	1
2	2	2
3	3	3
3	2	3
4	2	4
5	6	5
6	1	1
6	6	6
7	7	7
8	8	8
8	8	8
8	8	8
No Errors:	5	1

18

The 8 illuminant clusters associated with all Munsell surface reflectances:



The 8 illuminant clusters associated with the skin surface reflectances:



17

Conclusion

A new approach to Illumination Estimation has been suggested. First, Illumination Classification rather than Illumination Estimation is adopted. Classification simplifies the problem at hand since the exact illuminant need not be recovered. The solution space is finite and the solution becomes more robust to approximations and errors. Additionally, by following the Classification notation, we can find optimal camera sensors for the Illumination Estimation problem.

We further propose that Illumination Classification should be image content dependent. Specifically, an Object Based Illumination Classification approach is proposed. Using spatial information in the image, pixels associated with an object are segmented and grouped as a subset that is considered in the illumination estimation process using the object's spectral characteristics.

Simulation and real image experimentation showed the advantages of the Object Based Illumination Classification approach.

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19