Statistical Analysis and Psychological Evaluation of Surfaces under Various Illuminations

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Abstract: Perceptions of image surface are very challenging work for computer vision. Human can amazingly expert at recognizing the reflective properties of surfaces of various materials which a robot can not do easily so far. Smoothly we can differentiate a shiny metallic sphere from the plastic sphere of similar dimensions and structure. In this paper, various image surfaces are analyzed according to various image statistics for robot vision systems. Identification of synonymous objects under various real-world illumination or other environments are very daunting task. However, this is very challenging and crucial for machine vision systems. Both statistical analyses and human evaluation by various subjects under rigorous illumination conditions, we find significant improvement in our analysis and emphasis the importance of statistical evaluation of surfaces for computer vision. Our findings clearly demonstrate that skewness has direct resemblance with the surface glossiness-level. Intensity histogram also shows crucial clue for surface analysis.

1. Introduction

Human can easily distinguish between different types of surface quality and different types of illumination on surface. Even they can distinguish reflectance of complex surface very easily. For example, distinguish an objects material, from rough or smooth, clean or dirty, liquid or solid, even soft or hard is very easy for human. The ability to recognize and characterize materials is essential to interaction with the visual world. We recognize coins as much by their metallic reflectance properties as by their shapes. Recent machine vision systems are incapable to distinguish materials accurately in different illumination or real-world environment. Many vision applications still under-challenge for material recognition. An autonomous vehicle should be able to recognize an icy patch or mud before driving. An industrial inspection system should be able to recognize a product for supply. In these circumstances, estimating the reflectance of a complex surface under different illumination from a single image is an intricate problem. Resent work in reflectance recognition has shown that certain statistics measured on images of a surface are diagnostic of reflectance. In this paper we analyzed various image surfaces according to various image statistics for machine vision system. Identification of similar objects under various real-world illumination is very daunting task. However, this is very challenging for robot vision system.

The paper is organized as follows: Section 2 presents some related works. In Section 3, we present the research method for surface analysis. Next, in Section 4, we illustrate the experimental results with our developed datasets. In Section 5, we illustrate psychological evaluation and finally, we conclude the paper in Section 6 with future work guidelines.

2. Related Work

The image of a surface originates from the coalition of the surface geometry, the surrounding illumination, and the surface optics. These components can be complicated. Such as the reflectance at each point is characterized by a four dimensional function known as bidirectional reflectance distribution function (BRDF). Many researchers like G. Warld [1] developed an "imaging gonioreflectometer" for BRDF measurement, which for each illumination direction captures radiance in all directions simultaneously. Marschner et al. [12] developed a technique for measuring BRDFs from multiple images of a curved surface like skin under controlled point source illumination. For surface analysis, a person can guess some of the reflectance properties. Vision researchers have studied the lightness constancy problem since the 19th centaury [2]. There have been two approaches to lightness constancy – the low level and high level approaches. Herring proposed that low level physiological mechanisms like adaptation and local interaction are critical for lightness constancy [4]. Hemholtz on the other hand, described lightness constancy as high-level process of unconscious inference, whereby an observer deduces the most likely explanation of a visual image by drawing upon prior experience [4]. Most work on lightness perception has focused on diffuse reflection from flat Lambertian surface patches under artificial illumination. Such conditions are uncommon in our daily visual experience; we normally encounter non-Lambertian surfaces under complex real world illumination. Recently a number of studies have focused on stimuli that incorporate some of the complexity of real world conditions.

Nishida and Shinya [5] directed psychophysical evaluation to determine the accuracy of human surface reflectance estimation. They found that observers fail to estimate the reflectance of surfaces of arbitrary shape under point source illumination. They showed that the observers' matches correlate strongly with the luminance histograms of the images.

Fleming et al. [6] showed that observers can estimate the reflectance of a surface accurately when the illumination is representative of that found in the natural world scenes. This suggests that humans implicitly use statistics of real world illumination to estimate reflectance.

Motoyoshi et al. [7, 8] demonstrates that simple image based statistics are indicative of surface reflectance. Motoyoshi et al. have shown that moment statistics of the luminance histogram and sub-band histograms of images of real world textured surfaces are correlated with the perceived reflectance and gloss of a surface. Similarly, M. Landy [3] emphasized gloss and lightness issues on surface properties.

In this work, we perform psychophysical studies to discover the accuracy of lightness identification for images of real world surfaces. Currently psychophysicists have established authentication for different types of lightness perception methodology based on image properties such as brightness distributions [13]. These methodologies do not demand a high-level understanding of the image.

3. Statistical Surface Analysis

Based on different geometry, variations in lighting condition, of various objects, having both gray-scale and color, we craft the recognition process. We have developed two datasets. One dataset is combined with six different fruits under nine different illumination levels (Fig. 1). And second dataset is combined with 40 different shapes candy surface in constant illumination condition (Fig. 5). We employ single-camera and based on this dataset, we analyze by computing mean, variance, Michelson contrast, luminance histogram and skewness of the image surfaces under various illumination conditions.

A histogram h for a gray-scale image I with intensity values in the range $I(x,y) \in [0, K-1]$ would contain exactly K entries, where for a typical 8-bit grayscale image, $K = 2^8 = 256$. Each individual histogram entry is defined as,

$$h(i) = \text{the } number \text{ of pixels in } I \text{ with the intesity value } i$$

for all $0 \le i < K$. We can redefine histogram as,

$$h(i) = card\{(x,y) \mid I(x,y) = i\} \tag{1}$$

where, $card\{\ldots\}$ denotes the number of elements ("cardinality") in a set [11]. The standard deviation (s.d.) and skewness of the intensity histogram are defined as:

$$\text{s.d.} = \sqrt{\frac{\sum (I(x,y) - m)^2}{N}} \tag{2}$$

$$\text{skewness} = \frac{\sum (I(x,y) - m)^3}{N(\text{s.d.})^3} \tag{3}$$

where, $I(x,y)$ is the luminance of pixel, m the mean luminance and N the number of pixels (256x256). Our motto is to distinguish the objects under diverse surface reflectance-levels and to comprehend the best-suit statistical analysis for identifying a visual system for an intelligent system.

In this paper, we also computed the Michelson contrast ($\partial_{m.c.}$).Michelson contrast is commonly used for patterns where both bright and dark features are equivalent and take up similar fractions of the area. It is computed after standard deviation divided by mean pixel values of that image, as follows,

$$\partial_{m.c.} = \frac{\text{s.d.}}{m} \tag{4}$$

4. Results and Analysis

4.1 Statistical Surface Analysis on Diverse Illumination Conditions

From our 'Fruits-Illumination Dataset', we used six different fruits under nine different illumination levels. Fig. 1 shows one object with nine different illumination conditions. Fig. 2 shows six different objects in same illumination condition. We examined objects or surface's mean, variance, standard deviation, skewness and Michelson contrast. We find that skewness is varying according to the illumination condition. We find that dark surface skewness is higher than light surface.

Figure 1. 'Fruits-Illumination Dataset': Object-1 with nine different illumination conditions

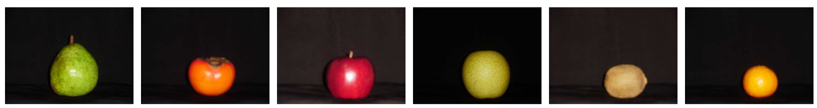


Figure 2. Six different objects in same illumination condition

In our analysis, we also find that dark surfaces tend to have higher Michelson contrast. For lighter surfaces, tend to have lower Michelson contrast, as shown in Fig. 3. For lighting condition no. 1 to no. 3 we find that Michelson contrast is same because illumination reflection varying very little. But in case of lighting condition no. 4 and no. 5 we identify distinct difference for reflectance. Later on last for lighting condition no. 6 to no. 9 vary on slightly.

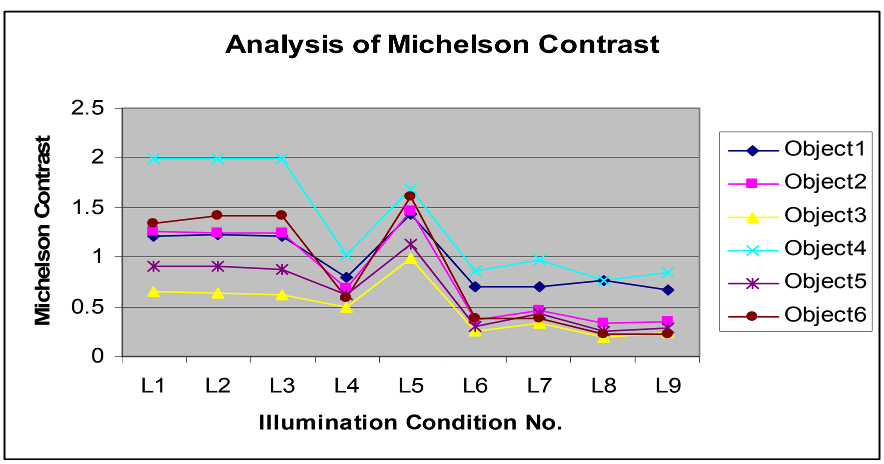


Figure 3. Analysis of Michelson Contrast for different illumination conditions for various object surfaces.

4.2 Statistics of Intensity Histogram

From our 'Candy Dataset', we used forty different shapes and size candy under constant illumination levels (Fig. 4). We photographed yellow, red, pink, orange materials. We choose this color because the red channel of and yellow or orange objects looks like light gray material and the blue channel look like dark gray materials (Fig. 5).

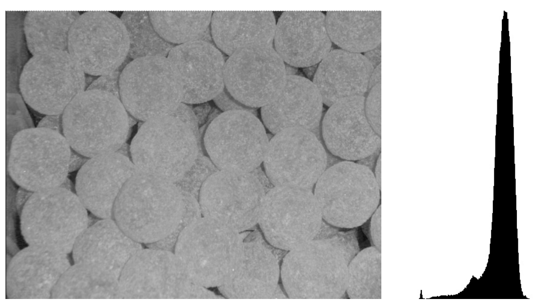
In this dataset we want to find same result with color channel image and gray scale image.

Figure 4. ‘Candy Dataset’ sample in constant illumination

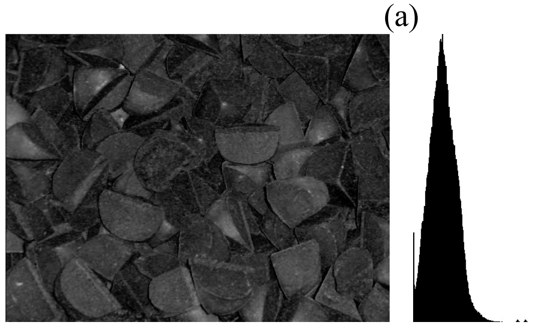
(a) original (b) B channel (c) G channel (d) R channel

Figure 5. Each color channel in different reflectance

We find that intensity histograms of light and dark surface explain methodical differences. Considering the materials and their histogram of Fig. 6, the histograms of dark surface show higher standard deviations and are usually positively skewed. We can explain it another way that surface of higher reflectance have more inter-reflection hence light bounces around filing up the shadow, leading to lower local contrast as opposed to materials with lower reflectance.



(a)



(b)

Figure 6. Histogram intensity for (a) light surface & (b) dark surface

5. Psychological Evaluation

We know that humans can distinguish materials reflectance very smoothly. Therefore it is meaningful to ask human observers to judge the reflectance of a material, by showing them a single image in monitor. We formulate two psychophysical experiments with our two different datasets. In both experiment, we find that humans are not perfectly lightness constant. Human performance is between perfect constancy and no constancy. We compared our image statistics to human judgments. We find that the statistics and humans performances were same. In this experiment, seven adult human observers participated. All observers had experience participating in psychophysical experiments.

Table 1. Psychological evaluation: Average Recognition Rate (RR) for Fruit database.

Object□s No.	**RR (%)**
F1	81.0
F2	79.4
F3	84.1
F4	77.8
F5	69.9
F6	84.1
Total rec.	*79.4*

Table 1 shows the average recognition results for each object (e.g., for Object#1, F1 – total accurate recognition was achieved 79.4%).

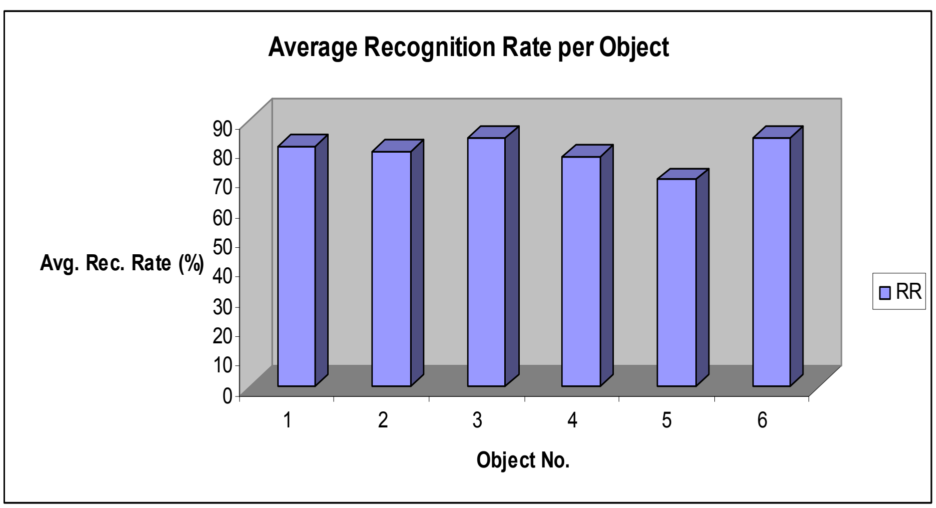


Figure 7. Average recognition rate per object for Fruit database.

Fig. 7 depicts the average recognition rates per object for the Fruit database. We notice that for Fruit#5, we overall recognition result is poor (only 69.9%). It is due to the fact that object#5 is smaller kiwi fruit, which is brown in color and hence it absorbed most of the incident light. Therefore, its overall glossiness and reflectance was lower than other fruits. That's why the human evaluation pointed it as a darker image. Apart from this case, the recognition rates for other objects are satisfactory. Though this result has comparatively lower recognition results than we have expected prior to the analysis, we feel that based on the image surface, glossiness, its reflectance and background, the evaluation will vary from subject to subject. In future, we will have to explore these issues and find more appropriate reasons after having analysis with different datasets with more subjects. We have accomplished similar experiments with our Candy dataset.

6. Conclusions

In this paper, we explore some statistical values or cues to understand image surface in various illumination conditions. Experimental results of image statistics for different image surfaces sometimes fail to determine the nature of texture of the surface or distinguish the illumination variations. These issues should be resolved in near-future. In future we can also do experiment with complex surface dataset. We are hopeful that role of image statistics of real world materials can provide robust machine vision systems so that a robot or an intelligent system can easily identify and recognize a material or object similar to the perceptions of human being. We also will find the relevancy of kurtosis [10] for visual perception. Human evaluation should be carried out robustly with more datasets and subjects under various constrained environments to demonstrate the robustness of this research.

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