

COMPUTING REFLECTANCE RATIOS FROM AN IMAGE

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Abstract—A photometric invariant called reflectance ratio is presented that can be computed from a single brightness image of a scene. The brightness variation in an image of a surface depends on several factors; the three-dimensional shape of the surface, its reflectance properties, and the illumination conditions. Since neighboring points on a smoothly curved surface have similar surface orientations, their brightness values can be used to compute the ratio of their reflectance coefficients. Based on this observation, an algorithm is developed that estimates a reflectance ratio for each region in the image with respect to its background. The algorithm is computationally efficient as it computes ratios for all image regions in just two raster scans. In the first scan, the image is segmented into regions using a sequential labeling algorithm. During labeling, the reflectance ratio between adjacent pixels is used as a measure of connectivity. In the second scan, a reflectance ratio is computed for each image region as an average of the ratios computed for all points that lie on its boundary. The region reflectance ratio is also a photometric invariant; it represents a physical property of the region and is invariant to the illumination conditions. Several experimental results are included to demonstrate the invariance of reflectance ratios to imaging and illumination parameters. A brief discussion on the application of reflectance ratios to the problems of object recognition and visual inspection is also given.

Surface reflectance	Reflectance ratio	Photometric invariant	Connectivity
Sequential labeling	Region reflectance ratio	Object recognition	Inspection

1. INTRODUCTION

The primary objective of early vision processing is to recover physical and geometrical properties of scenes from their two-dimensional images. This is a challenging task since the brightness distribution in an image depends on several factors; the illumination of the scene, the shapes of objects in the scene, and their reflectance properties. Further, these factors can vary from one scene point to the next. The recovery of scene properties is therefore an under-constrained problem. Machine vision research has focused primarily on the problem of recovering three-dimensional shape information from two-dimensional images. The shape recovery problem is typically constrained by making assumptions regarding the reflectance properties of the scene and the illumination conditions. Little effort however has been directed towards recovering and using other physical properties such as reflectance, roughness, and material.

Here, we address the problem of computing the reflectance of regions in the scene with respect to their backgrounds. The result is a physical property of each region that is invariant to the brightness and direction of illumination. This photometric invariant, referred to as the reflectance ratio, provides valuable information for machine vision applications such as object recognition and inspection. Traditionally, object recognition systems have used only geometric (shape) information to represent objects of interest and to recognize them.^(1,2) Recognizing a three-dimensional object in a two-

dimensional brightness image is more a problem of appearance matching rather than shape matching. Appearance is related not only to shape but also reflectance and illumination. It is therefore clear that recognition systems must use additional physical properties to both represent objects as well as to recognize objects in images. The reflectance ratio invariant presented in this paper is an example of a physical property that can be robustly and efficiently computed from a single image.

The problem of computing the reflectance of regions in a scene was first addressed by Land.⁽³⁾ In general, image brightness is the product of surface reflectance and illumination. Hence, it is impossible to separate the contributions of reflectance and illumination at a single image point if the point is treated in isolation. Land constructed a set of ingenious experiments to show that humans are able to perceive the reflectance of scene regions even in the presence of non-uniform and unknown illumination. He developed the retinex theory that suggests computational steps for recovering the reflectance of scene regions. Though it is not possible to determine the absolute reflectance of scene regions, the relative reflectance (or "lightness") of regions can be computed. The retinex theory is based on the assumption that the scene is subjected to smoothly varying illumination and consists of patches with constant reflectance. Under these assumptions, reflectance values change abruptly at region boundaries while illumination variations are small. As a result, it is possible to filter out the effects of illumination. Later,

Land and McCann⁽⁴⁾ proposed a one-dimensional hardware implementation for computing lightness. Subsequently, Horn⁽⁵⁾ extended these ideas to two dimensions and proposed several analog methods for implementing the lightness computation. Horn's approach was later improved upon by Blake.⁽⁶⁾

The main idea underlying Land's lightness computation is global consistency. The lightness value computed for any particular region must be consistent with those computed elsewhere in the image. However, realistic images include shadows, occlusions, and noise. Each one of these factors can cause a region boundary to go undetected or the computed lightness of a region to be erroneous. Such errors can affect the lightness values computed for other regions in the image. For this reason, Land's global method is not applicable to most real images. In this paper, we develop an alternative scheme for computing the ratio of the reflectance of a region to that of its background. The image is first segmented into regions of constant reflectance. Next, a reflectance ratio is computed for each region and its background using only points that lie close to the region's boundary. In this approach, the reflectance ratio computed for any particular region is not affected by those computed for regions elsewhere in the image. Adopting another approach, Finlayson⁽⁷⁾ recently used ratios of neighboring pixels in three color channels to compute histograms for object recognition.

In their analysis and experiments, Land and McCann⁽⁴⁾ restricted themselves to planar (two-dimensional) scenes with patches of constant reflectance. These scenes are similar in appearance to the paintings of the Dutch artist Mondrian. In contrast, our derivation of the reflectance ratio is based on the analysis of regions that lie on curved surfaces. In the case of curved surfaces, image brightness variations result from both illumination variations as well as surface normal changes. For curved surfaces, our reflectance ratio invariant is valid when a region and its background have the same distribution (scattering) function but different reflectance coefficients (albedo).

The paper is organized as follows. First, we derive the reflectance ratio for two neighboring points on a curved surface and state the conditions under which it is invariant to illumination and imaging parameters. Next, we introduce the notion of a region reflectance ratio and present an algorithm for computing region ratios in digital images. The algorithm is efficient in that it produces region ratios in just two raster scans of the image. We have conducted several experiments to test the accuracy and robustness of the algorithm. The computed ratios demonstrate remarkable invariance to illumination direction, sensor direction, and the aperture of the imaging optics. We conclude this paper with a discussion on the application of reflectance ratios to object recognition and inspection problems.

2. REFLECTANCE RATIO

The reflectance of a surface depends on its roughness and material properties. In general, incident light is

scattered by a surface in different directions and this distribution of reflected light can be described as a function of the angle of incidence, the angle of emittance, and the wavelength of the incident light. Consider an infinitesimal surface patch with normal \mathbf{n} , illuminated with monochromatic light of wavelength λ from the direction \mathbf{s} , and viewed from the direction \mathbf{v} . The reflectance of the surface patch can be expressed as

$$r(\mathbf{s}, \mathbf{v}, \mathbf{n}, \lambda). \quad (1)$$

Now consider an image of the surface patch. If the spectral distribution of the incident light is $e(\lambda)$ and the spectral response of the sensor is $s(\lambda)$, the image brightness value produced by the sensor is

$$I = \int s(\lambda)e(\lambda)r(\mathbf{s}, \mathbf{v}, \mathbf{n}, \lambda) d\lambda. \quad (2)$$

If we assume the surface patch to be illuminated by "white" light and the spectral response of the sensor to be constant within the visible-light spectrum, then $s(\lambda) = s$ and $e(\lambda) = e$. We have

$$I = sepR(\mathbf{s}, \mathbf{v}, \mathbf{n}) \quad (3)$$

where $\rho R(\mathbf{s}, \mathbf{v}, \mathbf{n})$ is the integral of $r(\mathbf{s}, \mathbf{v}, \mathbf{n}, \lambda)$ over the visible-light spectrum. We have decomposed the result into $R(\cdot)$ which represents the dependence of surface reflectance on the geometry of illumination and sensing, and ρ which may be interpreted as the fraction of the incident light that is reflected in all directions by the surface. Incident light that is not reflected by the surface is absorbed or transmitted through the surface. Two surfaces with the same distribution function $R(\cdot)$ can have different reflectance coefficients ρ .

As a result of the white-light assumption, the reflectance coefficient ρ is independent of wavelength. This enables us to represent the reflectance coefficient of the surface element with a single constant. The same can be achieved by using an alternative approach which does not require making assumptions about the spectral distribution of the incident light and the spectral response of the sensor. Consider a narrow-band filter with spectral response $f(\lambda)$ placed in front of the sensor. Image brightness is then

$$I = \int f(\lambda)s(\lambda)e(\lambda)r(\mathbf{s}, \mathbf{v}, \mathbf{n}, \lambda) d\lambda. \quad (4)$$

Since the filter is narrow-band, it essentially passes a single wavelength λ' of reflected light. Its spectral response can therefore be expressed as

$$f(\lambda) = \delta(\lambda' - \lambda). \quad (5)$$

The image brightness measured with such a filter is

$$I = s'e'r(\mathbf{s}, \mathbf{v}, \mathbf{n}, \lambda') \quad (6)$$

where $s' = s(\lambda')$ and $e' = e(\lambda')$. Once again, the reflectance function can be decomposed into a distribution function and a reflectance coefficient

$$I = s'e'\rho'R'(\mathbf{s}, \mathbf{v}, \mathbf{n}). \quad (7)$$

In this case $R'(\cdot)$ represents the distribution for a particular wavelength of incident light. On the other hand, for white-light illumination, $R(\cdot)$ represents the distribution computed as an average over the entire visible-

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light spectrum. However, the individual terms in both (3) and (7) represent similar effects. Since we have used the white-light illumination assumption in our experiments, we will use the following expression for image brightness in our discussion.

$$I = k\rho R(s, v, n). \tag{8}$$

The constant $k = s.e.$ accounts for the brightness of the light source and the response gain of the sensor. The exact functional form of $R(s, v, n)$ is determined to a great extent by the microscopic structure of the surface, generally $R(\cdot)$ includes a diffuse component and a specular component.⁽⁸⁾ Once again, the reflection coefficient ρ is the fraction of incident light that is reflected by the surface. It represents the reflective power of the surface and is sometimes referred to as surface albedo.

Consider two neighboring points on a surface (Fig. 1). For a continuous surface, the two points may be assumed to have the same surface normal vectors. Further, the two points have the same source and sensor directions. Hence, the brightness values, I_1 and I_2 , of the two points may be written as

$$I_1 = k\rho_1 R_1(s, v, n) \tag{9}$$

$$I_2 = k\rho_2 R_2(s, v, n). \tag{10}$$

The main assumption made in computing the reflectance ratio is that the two points have the same reflectance functions ($R_1 = R_2 = R$) but their reflectance coefficients ρ_1 and ρ_2 may differ. An example is that of two neighboring Lambertian points that have different albedo values because they lie in regions that have different shades or colors. Then, the image brightness values produced by the two points are

$$I_1 = k\rho_1 R(s, v, n)$$

$$I_2 = k\rho_2 R(s, v, n). \tag{11}$$

The ratio of the reflectance coefficients of the two points is

$$p = I_1/I_2 = \rho_1/\rho_2. \tag{12}$$

Note that p is independent of the reflectance function, illumination direction and brightness, and the surface normal of the two points. It is a photometric invariant that is easy to compute and does not vary with the position and orientation of the surface with respect to the sensor and the source.

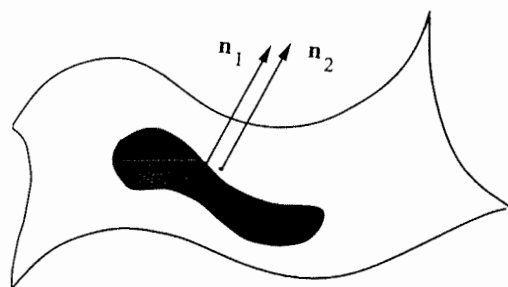


Fig. 1. Neighboring points on a surface.

We have assumed that the scene is illuminated by a single light source. Now consider the same scene illuminated by several light sources. The brightness of any point can be written as

$$I = \rho[k_1 R(s_1, v, n) + k_2 R(s_2, v, n) + \dots + k_n R(s_n, v, n)] \tag{13}$$

where s_1, s_2, \dots, s_n are the directions of the n sources that are visible to the surface point under consideration and k_1, k_2, \dots, k_n are proportional to the brightness of the n sources. Since the reflectance ratio is computed using neighboring points, it can be assumed that both points are illuminated by the same set of sources. Then, from equations (12) and (13) we see that the reflectance ratio p is unaffected by the presence of multiple light sources.

Note that by definition p is unbounded; if the second surface point is black, $I_2 = 0$, then $p = \infty$. From a computational perspective, this poses implementation problems. Hence, we use a different definition for p to make it a well-behaved function of the reflectance coefficients ρ_1 and ρ_2

$$p = (I_1 - I_2)/(I_1 + I_2) = (\rho_1 - \rho_2)/(\rho_1 + \rho_2). \tag{14}$$

Now, we have $-1 \leq p \leq 1$. We will use this definition of the reflectance ratio in the following sections.

3. REFLECTANCE RATIO OF A REGION

To this point, we have focused on two neighboring points. We now consider a surface region S that has constant reflectance coefficient ρ_1 and is surrounded by a background region with constant reflectance coefficient ρ_2 . We are interested in computing the reflectance ratio $P(S)$ of the region S with respect to its background. The brightness of the entire region cannot be assumed constant for two reasons. First, the surface may be curved and hence the surface normal can vary substantially over the region. Second, while the illumination may be assumed to be locally constant, it may vary over the region. These factors can cause brightness variations, or shading, over the region and its background as well. However, the reflectance ratio can be accurately estimated using neighboring (or nearby) points that lie on either side of the boundary between the region and the background. The reflectance ratio for a region can then be determined as an average of the ratios computed along the boundary of the region. The computed ratio is also a photometric invariant; it is independent of the shape of the surface and the illumination conditions. It is computed using a single image of the scene and provides important information regarding the physical properties of surface regions in the scene.

Before proceeding any further, it is worthwhile to compare our approach with Land's retinex theory.⁽³⁾ Our objective is similar to that of Land's, that is, to compute the reflectance of regions in a scene by computing variations in image brightness across region boundaries. Land's analysis of brightness variations

does not however include the problem of curved surfaces. The scene is assumed to be planar with matte patches of constant reflectance. In our development of the reflectance ratio we have studied the effects of surface orientation on image brightness. Our method for computing the reflectance ratio of a region is also different from that proposed by Land. The retinex theory uses global consistency to compute the reflectance of regions in the scene. In this approach, if the reflectance ratio between two regions is inaccurately estimated or if the boundary between two regions is not detected, the reflectance values computed for all other regions are inaccurate. Real images often include shadows, occlusion effects, and noise. These effects can cause a region to be merged with another, or region boundaries to be detected where none exist. Hence, Land's global consistency approach is generally not applicable to real-world scenes.

We adopt a more local approach. First, the scene is segmented into regions that are assumed to have different reflectance coefficients. Due to shadows, occlusions, and image noise, some regions may be missed and others erroneously created. However, these errors do not affect the reflectance ratios computed for other valid regions in the scene. The extension of the reflectance ratio analysis to curved surfaces and the local approach to the computation of region ratios are the two key differences between Land's lightness computation and our approach. We will see that these differences result in substantial improvements in the robustness of computed reflectance ratios.

4. COMPUTING REFLECTANCE RATIOS OF REGIONS

We present an algorithm that computes reflectance ratios for scene regions. The algorithm can be divided into two parts. First, a sequential labeling algorithm is used to segment the image into connected regions. The second phase involves the computation of a reflectance ratio for each of the segmented image regions. The algorithm is computationally efficient as reflectance ratios of all scene regions are computed in just two raster scans of the image.

4.1. Sequential labeling algorithm

Sequential labeling is a well-known technique for efficient segmentation of images.⁽⁹⁾ It has been widely

used in the context of binary images^(10,11) where it is straightforward to determine if two image pixels are "connected". Algorithms have also been proposed that use near equal brightness values to determine the similarity between pixels in gray-scale images.⁽¹²⁾ We use the reflectance ratio as a measure of similarity between two neighboring pixels. Let $p(A, B)$ denote the reflectance ratio $(\rho_A - \rho_B)/(\rho_A + \rho_B)$ of two neighboring pixels A and B. The pixels A and B are considered to be connected if $|p(A, B)| < T$, where T is a threshold value close to zero. A non-zero threshold is selected to account for brightness variations that result from image noise and surface shading effects. The connectivity between two pixels is defined as

$$c(A, B) = \begin{cases} 1 & \text{if } |p(A, B)| < T \\ 0 & \text{otherwise} \end{cases} \quad (15)$$

The sequential labeling algorithm proceeds as follows. The image is examined in a raster scan fashion (left to right and top to bottom). The label of pixel A is determined by the labels of three of its neighbors; pixel B to its left, pixel C above it, and pixel D diagonal to it.



Note that for a raster scan these three neighboring pixels have already been labeled. If pixel A is connected to either B or C (not both) then it is assigned the same label as the pixel it is connected to. Else, if A is connected to both pixels B and C and pixels B and C have equal labels, then A is assigned the same label. An interesting situation arises when A is connected to both B and C and these two pixels have different labels. In this case, we assign A the label of either B or C and record the fact that the labels of B and C are "equivalent". If none of the above cases occur and we find that A is connected to D, then we assign A the same label as D. Finally, if A is not connected to any of its neighbors, a new label is created. This algorithm can be written in pseudo code as follows.

Algorithm: Sequential Labeling

```

if (c(A,B) = 1 and c(A,C) = 1) {
  if (c(A,B) = 1 and c(A,C) = 1) then Label(A) = Label(B)
  else if (c(A,B) = 0 and c(A,C) = 1) then Label(A) = Label(C)
  else if (c(A,B) = 1 and c(A,C) = 1) {
    if (Label(B) = Label(C)) then Label(A) = Label(B)
    else {
      Label(A) = Label(B)
      Equiv(Label(B), Label(C))
    }
  }
  else if (c(A,D) = 1) then Label(A) = Label(D)
  else Label(A) = New_Label

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Here Label(.) is the label of a pixel and Equiv(.,.) records the equivalence of two labels.

Using this algorithm, the complete image can be segmented in a single raster scan. Following the raster scan, equivalences between different labels can be resolved such that all equivalent labels are represented by a single label. This information can either be stored as a table for future use or the image can be relabeled to account for the equivalences. A minor addition can be made to the sequential labeling algorithm to also obtain the areas and centroids of all the labeled regions.

4.2. Algorithm for computing reflectance ratios

Sequential labeling provides a set of image regions that correspond to surface regions. Each region is assumed to have a constant reflectance coefficient. The brightness of the region may vary due to variations in surface normal and illumination. However, a completely connected region is obtained since local brightness variations are small; neighboring pixels have nearly equal surface normal vectors and illumination conditions. The following is an example of a one-dimensional image of a region and the result of sequential labeling:

- (a) 35 37 39 41 64 77 85 87 89 89 91 92 94 96
- (b) 1 1 1 1 2 3 4 4 4 4 4 4 4 4

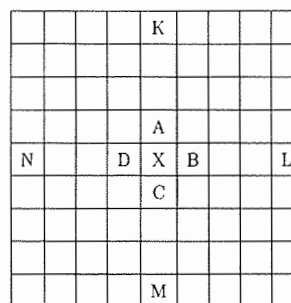
Here, label 4 corresponds to a region and label 1 represents its background. Though there are smooth brightness variations within the region and the background, the labeling is robust. This is because local brightness variations are small and reflectance ratios for connected pixels are close to zero.

In digital images, the edges between a region and its background are blurred for two reasons. First, the image has a finite resolution, causing the physical edge to lie within a pixel. The brightness value of the pixel therefore is a weighted average of the brightness values of the region and the background at the boundary.⁽⁹⁾ Second, every optical system is characterized by a blur function; due to imperfect imaging optics, each point in the scene is projected onto a small patch (not a point) of the image sensor.⁽¹³⁾ Thus, pixels on and around the edge end up with different labels from the region and the background.

One way of computing the reflectance ratio $P(S)$ of a region S is by using the average brightness of the region and the average brightness of the background. Since, brightness generally varies over both the region and the background, this will not yield an accurate reflectance ratio. Instead, we can obtain an accurate estimate of the ratio by using only points on the boundary of the region. Consider a pixel that lies in the region S but on its boundary. An estimate of the reflectance ratio can be computed using this pixel and the background pixel that is closest to it. Note that the surface normal and illumination of the region boundary pixel and its closest background pixel can be assumed to be equal. A robust estimate for the reflectance ratio of a region can be computed as an average of the ratios

computed using all its boundary pixels.

As mentioned earlier, the sequential labeling algorithm provides the area of each labeled region. Small regions that result from points that lie on scene edges can be ignored by using a threshold. We focus only on larger regions that are referred to as valid regions. The reflectance ratios for all valid regions can be computed in a single raster scan of the image. During this final raster scan, attention is given only to those pixels that lie in valid regions. If a pixel does lie in such a region, we first determine if it lies on the boundary of the region. Consider the pixel X and its four neighbors A , B , C , and D .



If X lies inside a region, it and its four neighbors have the same label. If however X lies on a region boundary, one or more of its neighbors must have different labels. Assume that the neighbor A has a different label from that of X . We examine the pixel K that lies at a distance, d , from X in the direction of A . K is used to compute a ratio estimate only if it lies in a valid region, i.e. it does not belong to an edge region. If it does lie in a valid region, it is assumed to lie on the background of the region that pixel X represents. The distance d used to find the background pixel must be large enough to avoid edge pixels with unpredictable intensities and at the same time small enough to satisfy the condition that pixels X and K have near equal normals and illumination conditions. In our implementation, d is selected by the user and is usually between two and five pixels in length. If the above conditions are satisfied, a reflectance ratio estimate is

$$q_i(\text{Label}(X)) = p(X, K) = (I_X - I_K)/(I_X + I_K). \quad (16)$$

This is the i th ratio estimate computed for the region that contains X . This process is repeated for all neighbors of X whose labels differ from that of X . During the raster scan of the image, a list of computed reflectance ratios is maintained for each valid region. The algorithm is summarized below in pseudo code.

Algorithm: Region Reflectance Ratio

```

if (Label(X) is Valid) {
  if (Label(X) != Label(A)) {
    if (Label(K) is Valid) {
      q_i((Label(X)) = p(X,K)
      i = i + 1 }
    }
  }
}
    
```

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if (Label(X) != Label(B)) {
  if (Label(L) is Valid) {
    q_i((Label(X)) = p(X,L)
    i = i + 1 }}
if (Label(X) != Label(C)) {
  if (Label(M) is Valid) {
    q_i((Label(X)) = p(X,M)
    i = i + 1 }}
if (Label(X) != Label(D)) {
  if (Label(N) is Valid) {
    q_i((Label(X)) = p(X,N)
    i = i + 1 }}

```

After all image pixels are examined, the reflectance ratio of a region S is computed as the average of the ratios in its list

$$P(S) = 1/N \sum_{i=1}^N q_i(S) \quad (17)$$

where N represents the total number of ratio estimates obtained for S .

Generally, N is not equal to the perimeter of the region for two reasons. First, each boundary pixel may produce more than one ratio estimate since it has four neighbors. Second, a boundary pixel may not produce any ratio estimates because it is surrounded by edge pixels that belong to invalid regions. A confidence measure for the ratio $P(S)$ of a region is defined as

$$\gamma(S) = N^2/A(S) \quad (18)$$

where $A(S)$ is the area of the region S . This confidence may be used as a measure of the accuracy of the reflectance ratio computed for the region. If $\gamma(S)$ is small, few ratios have contributed to the estimate and it may be unreliable.

In the above discussion, we started by selecting a region and its background. Note that a reflectance ratio may be computed for the background as well, in which case, the region and the background reverse roles; the region is the background and vice versa. We also assumed that a region and its background have constant reflectance coefficients. In practice this assumption can be relaxed; a region of constant reflectance may be surrounded by several regions with different reflectance coefficients. The reflectance ratio computed for the region is again an average of the ratios computed along its entire boundary. In this case, however, the ratio can vary with the viewing direction since the fraction of the region boundary shared with any particular background region can vary with viewing direction.

5. EXPERIMENTS

We have conducted several experiments to demonstrate the invariance of reflectance ratios to illumination and imaging parameters. Figure 2 illustrates the experimental set-up. Objects are illuminated using incandescent light sources and are imaged using a Nikon 50 mm lens and a CCD camera. The illumination and viewing directions are varied by moving the light source

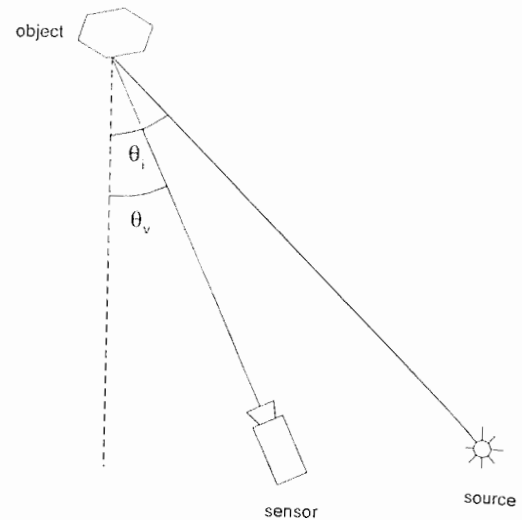


Fig. 2. Experimental set-up.

and the sensor in a plane that passes through the object. The source direction is represented by the angle θ_i and the viewing direction of the sensor by θ_v . Images are digitized using a Matrox frame-grabber and processed on a Sun Sparcstation 2. The experiments were conducted on man-made objects with letters and pictures printed on them. The printed regions have reflectance coefficients that depend on the shade or color of the paint used to print them. Generally, all regions on any given object are painted using paints of the same material but different pigments. Therefore, the reflectance functions of the different regions are similar though their reflectance coefficients differ.

Figure 3 shows an object with several regions that have different reflectance coefficients from their backgrounds. The image in Fig. 3(a) was obtained under ambient lighting conditions. Figure 3(b) shows different connected regions extracted using the sequential labeling algorithm. A reflectance ratio threshold of $T = 0.05$ (see expression (15)) was used to determine connectivity between neighboring pixels. The connected regions are displayed using different gray levels. This image shows only valid object regions, i.e. regions with areas that are neither too small nor too large. Regions with small areas generally correspond to edge regions that lie just outside a region boundary. Such regions include pixels with unreliable brightness values and their reflectance ratios are not accurate or useful. A large region could be the background of the imaged scene or the main body of an object in the scene. In either case, the reflectance ratio would depend on the configuration and reflectance of several objects contained in the scene. Hence, a valid region is large enough not to be an edge region, and small enough to be a region whose background lies on the same object.

Figure 3(c) shows the reflectance ratios of the labeled regions computed using the algorithm presented in this paper. Ratio values between -1.0 and 1.0 are offset and scaled to lie between 0 and 255 image bright-

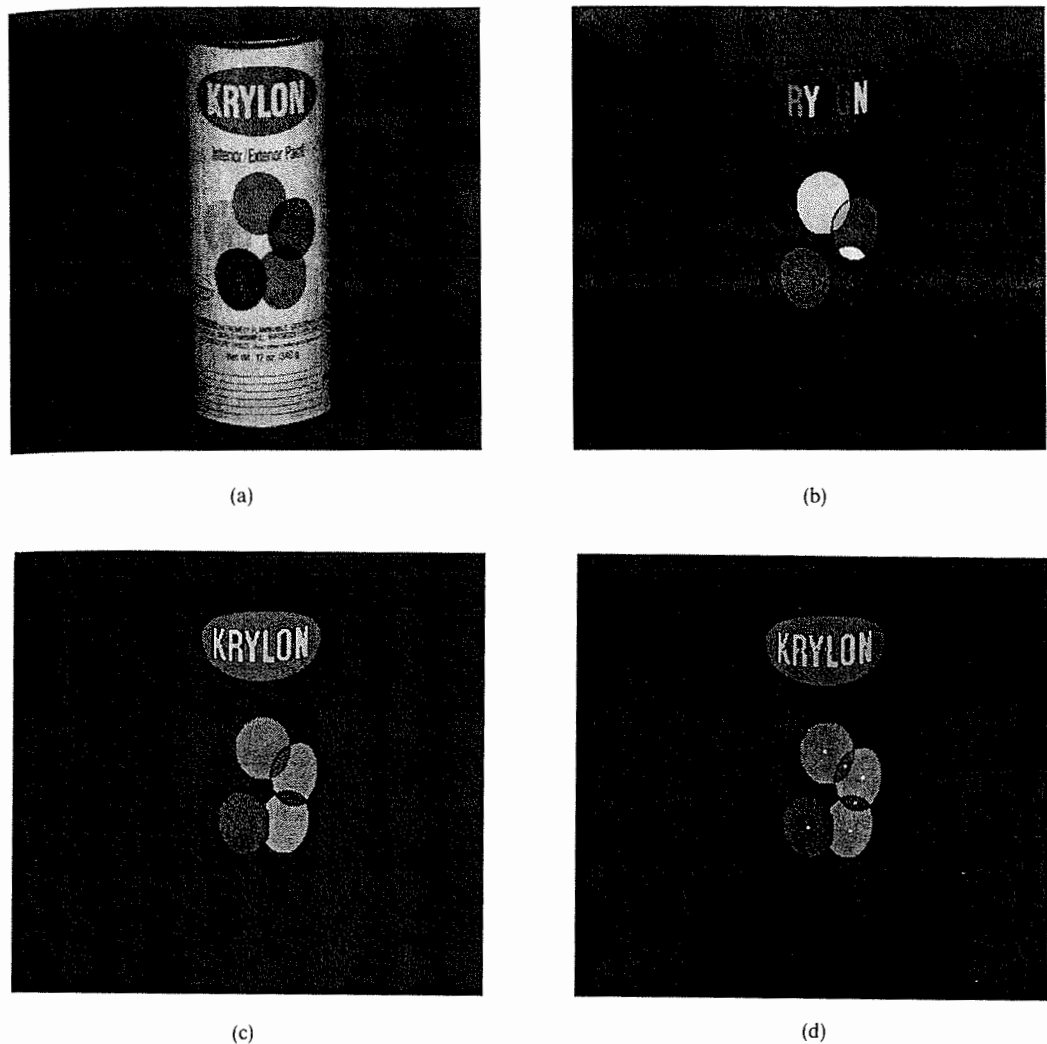


Fig. 3. Reflectance ratios and region centroids computed for a sample object: (a) brightness image; (b) labeled image; (c) reflectance ratios of object regions; (d) centroids of object regions.

ness levels. Though the image of the object includes brightness variations due to illumination and surface normal changes, the region reflectance ratios are found to be consistent with the reflectance coefficients of the object regions. Note that all letters in the word "KRYLON" have similar ratio values. In the case of the circular regions, each region is surrounded by more than one background region. Hence, the ratio of each circular region is computed as a weighted average of the ratios with respect to all the background regions. Figure 3(d) shows the centroids of the object regions. If a region is near planar, its image centroid is invariant to the viewing direction under orthographic or perspective image projections.

Figure 4 shows the invariance of reflectance ratios to the aperture size of the imaging optics. The object is illuminated from the direction $\theta_i = 0$ deg. The aperture setting was varied from 5.6 (large) to 16 (small). The reflectance ratios computed for region "K" and one of

the circular regions is plotted with respect to aperture setting. To help identify these regions, their centroids are shown in the images. The reflectance ratio for region "K" is approximately 0.29 and that for the circular region is approximately 0.05. Figure 5 shows the robustness of computed ratios to object illumination using multiple light sources. The reflectance ratios for region "K" and its oval-shaped background region are computed for source 1 in the direction $\theta_i = 40$ deg, source 2 in the direction $\theta_i = 70$ deg, and illumination by both sources, simultaneously. The sensitivity of computed ratios to source direction is illustrated in Fig. 6. The direction of a single light source is varied from $\theta_i = -70$ to 20 deg in increments of 10 deg. As seen from the figure, the ratio for region "K" demonstrates remarkable invariance to illumination direction.

The effects of varying the sensor direction are shown in Fig. 7. As the viewing direction is varied, the projec-

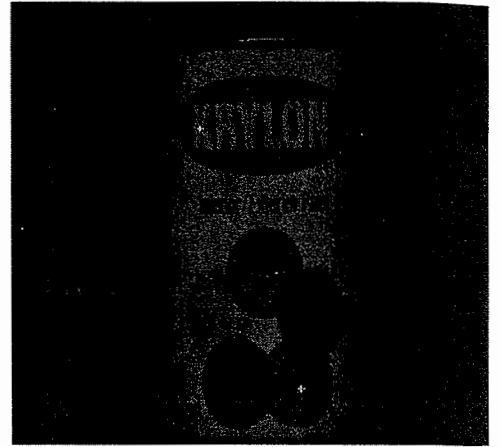
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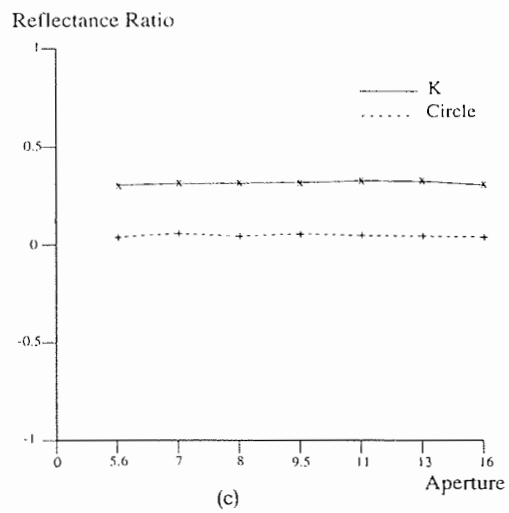
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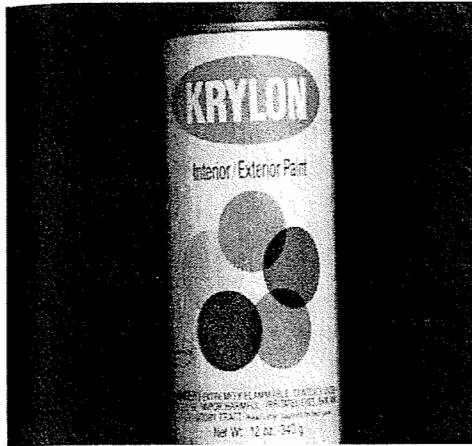
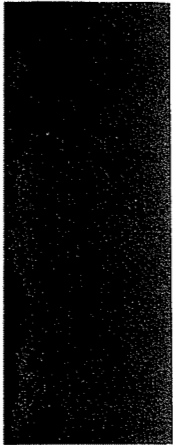


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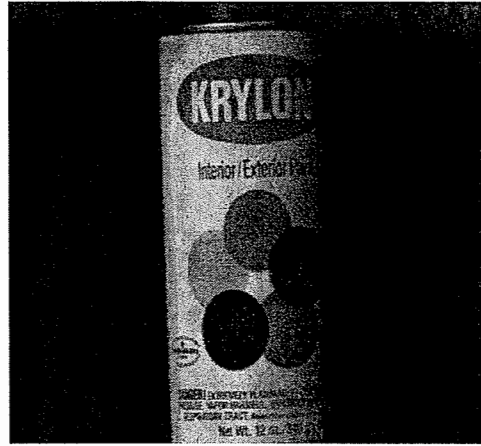


(c)

Fig. 4. Invariance of reflectance ratios of aperture size: (a) aperture setting: 5.6; (b) aperture setting: 16; (c) reflectance ratio vs. aperture setting.



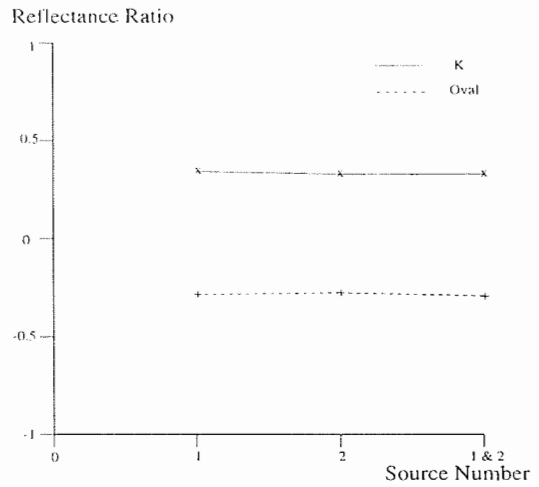
(a)



(b)



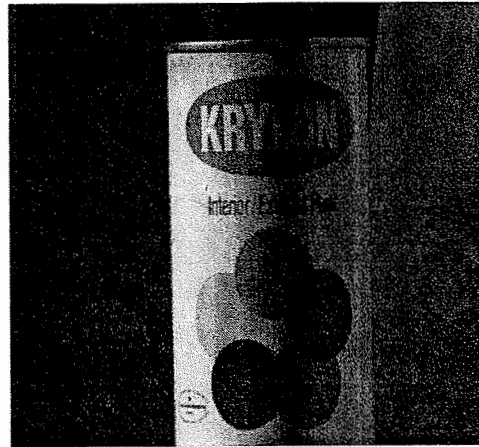
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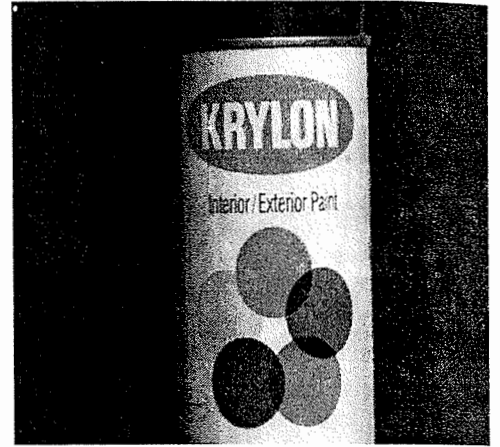
(d)

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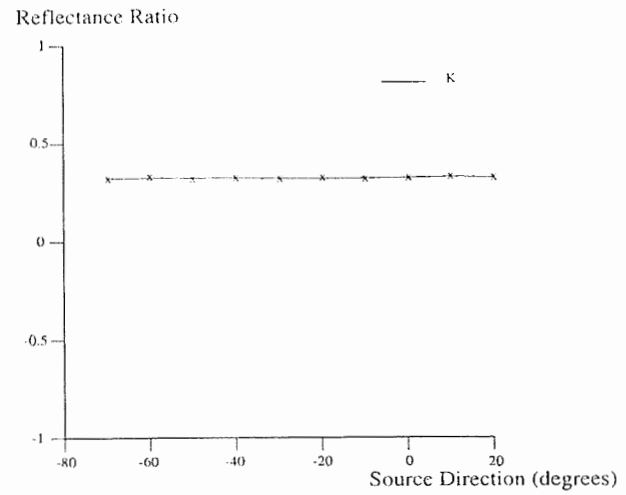
Fig. 5. Invariance of reflectance ratios to multiple light source illumination: (a) illumination by source 1; (b) illumination by source 2; (c) illumination by sources 1 and 2; (d) reflectance ratio vs. source number.



(a)



(b)

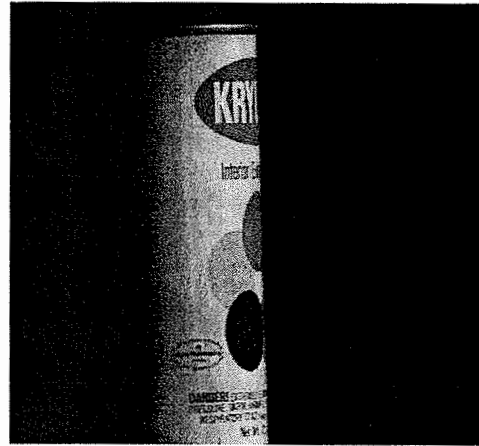


(c)

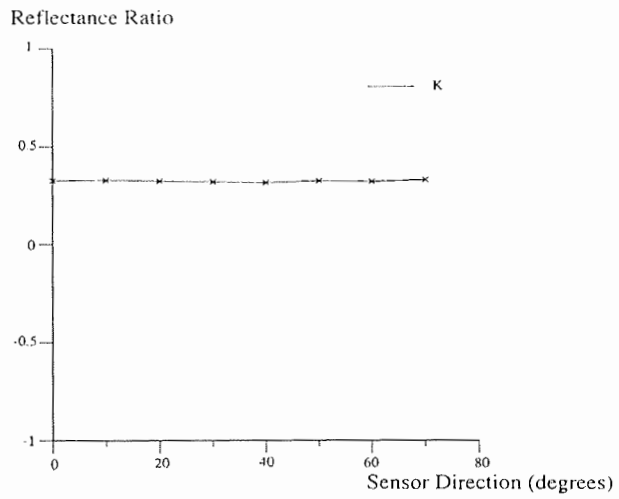
Fig. 6. Invariance of reflectance ratios to the direction of illumination: (a) source direction: -70 deg; (b) source direction: 20 deg; (c) reflectance ratio vs. source direction.



(a)



(b)



(c)

Fig. 7. Invariance of reflectance ratios to viewing direction. In general, this invariance holds only for regions that have a single background region: (a) sensor direction: 0 deg; (b) sensor direction: 70 deg; (c) reflectance ratio vs. sensor direction.

leg;



(a)



(b)



(c)

Fig. 8. Reflectance ratios computed for regions in a cluttered scene with shadows and occlusions: (a) brightness image; (b) labeled image; (c) reflectance ratios of scene regions.

ted area and shape of an object region changes. As a result, the boundary of the region also varies. Figure 7 shows the reflectance ratios of region "K" computed for different sensor directions starting from $\theta_v = -70$ to 20 deg. Though the shape and size of the region varies with the sensor direction, the ratio estimate remains nearly constant. In this case, the region is surrounded by a background region with constant reflectance. If on the other hand, a region is surrounded by several regions with different reflectance coefficients, the boundary between the region and any one of the background regions will vary with viewing directions. Hence, for regions with more than one background region, the computed ratio is, in general, not invariant to viewing direction.

The above experiments were conducted on a single object. Figure 8(a) shows an image of a scene that includes several objects. Each object has several regions of constant reflectance. The scene includes shadows and occlusions. The labeled image is shown in Fig. 8(b) and the region reflectance ratios in Fig. 8(c). Though some of the objects are curved and the illumination varies over the scene the computed ratios are consistent with the reflectance of the object regions.

6. DISCUSSION

We conclude with a brief discussion on how the computed reflectance ratios can be applied to machine vision problems. Consider the problem of recognizing three-dimensional objects in a two-dimensional image (see Fig. 8 for example). In the past, object recognition systems have relied solely on geometric models of the objects of interest. However, the complete geometry of the scene cannot generally be recovered from a single image. Hence, it is evident that recognition systems would benefit from the use of additional physical properties for object representation and identification. Reflectance, roughness, and material type are examples of physical properties that could be effectively used by a recognition system. Needless to say, just like geometry, these properties are also difficult to compute from a single brightness image. However, the invariant ratio introduced in this paper is an example of a physical property that can be computed efficiently and accurately from a single image.

The algorithm presented in this paper is currently being incorporated in a system that uses reflectance ratios to recognize objects that have surface patches with different reflectance coefficients. Many man-made objects with printed pictures or text fall in this category (Fig. 8). Scenes that include such objects produce images with many regions that can confuse object

recognition algorithms that use only geometric information. Reflectance ratios of image regions can be used to hypothesize the existence of an object in the image. Then the geometric arrangement of the computed ratios is used to hypothesize the pose of the object in the scene. Finally, the hypothesis is verified by using reflectance ratios and positions of other regions on the object.

Reflectance ratios can also be used for the visual inspection of printed characters or pictures. A typical inspection problem involves the verification of the position and clarity of printed characters. The sequential labeling algorithm provides the centroids of all the image regions. If a region is only partially visible or if it is incorrectly positioned, its centroid will capture these discrepancies. The reflectance ratio of the region can be used to determine if it has the correct reflectance or color with respect to its background. The advantage of using reflectance ratios here is that it is unaffected by the brightness and direction of the light source used to illuminate the objects. The simultaneous use of geometric and reflectance information outlined in this section is a powerful approach to solving a variety of machine vision problems.

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