Illumination-Invariant Recognition of Local Color Distributions using Linear Models for Spectral Reflectance

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Abstract

Local color pixel distributions provide information that is useful for object recognition but are dependent on the scene illumination. We develop a method that assigns color descriptors to an object that depend on the distribution of spectral reflectance across the object and not on the illumination. For a trichromatic system, the method assumes a three-dimensional linear model for surface spectral reflectance. We present examples demonstrating the system's ability to recognize model objects in cluttered scenes independent of scene illumination.

Introduction

In this paper, we describe a method for recognizing three dimensional objects. The features used for recognition are invariants computed from local color pixel distributions. Using a finite dimensional linear model for spectral reflectance, we show that these features are invariant to object position and orientation and the configuration, intensity, and spectral content of the scene illumination. These features are easily computed from a color image and provide a large amount of discriminatory power. Hypothesized object matches are verified by illumination correction and spatial structure comparison. We have demonstrated this approach with a set of experiments using a database of models.

Color Invariants of Surface Regions

We refer to the image of a small planar surface patch P as an interest region. We assume P has matte reflectance characteristics and is illuminated, in general, by t different spectral distributions $l_1(\lambda), l_2(\lambda), \ldots, l_t(\lambda)$ from respective directions described by the unit vectors $n_1, n_2, \ldots, n_t$. Consider any subset R of P having a fixed spectral reflectance $s(\lambda)$. For each point in the image of R, a color imaging system records m measurements given by

$$P_k = \int_\lambda \left(\sum_{i=1}^{t} (n \cdot n_i) l_i(\lambda) \right) s(\lambda) f_k(\lambda) d\lambda \tag{1}$$

where n is the unit normal to the surface patch, λ denotes wavelength, and $f_k(\lambda)$ is the spectral response function of the kth sensor class.

We approximate $s(\lambda)$ with a linear model such that

$$s(\lambda) = \sum_{j=1}^{m} \sigma_j S_j(\lambda) \tag{2}$$

where $S_j(\lambda)$ are a set of m fixed spectral reflectance basis functions. Several studies have shown that models of this form can be used for the accurate approximation of spectral reflectance functions for $m \geq 3$.

Consider two images of P under different illumination and geometric conditions. We have shown[2] that the color histograms H and H' for the image interest region corresponding to P for the two images will be related by

$$rH'(M\rho) = H(\rho) \tag{3}$$

Therefore, a change of illumination and surface geometry in the scene corresponds to a scaling and affine coordinate transformation of the image color distribution for the interest region corresponding to P.

We define invariants as numbers computed from a color pixel distribution of an interest region that do not depend on any of the following: the illumination environment, the surface orientation n, or the surface distance. Invariants will depend on the distribution of the spectral reflectance vector $\sigma = (\sigma_1, \sigma_2, \ldots, \sigma_m)^T$ across P which is intrinsic to the surface. We have derived a method for the computation of invariants with these properties[1].

To illustrate the properties of the invariants, we present an example using surface regions taken from a dolphin on the surface of a block and from a boat on the surface of another block. The blocks are imaged under white, yellow, green, and red illumination and the enclosed regions in the images indicate the surface patches used for computing invariants. Figure 1 is a series of images of the dolphin block surface under the four illuminants with the same surface patch outlined for consideration in each image. Figure 2 is an image of the boat block surface under the various illuminants. Figure 3 is a 3-dimensional plot of the invariants from the 6-dimensional invariant space for each of the circled regions as well as others obtained for the same patches for different imaging configurations. The + symbols in figure 3 correspond to invariants computed from the regions in the dolphin images and the o symbols correspond to invariants computed from the regions in the boat images. The invariants computed for the two surface regions form separated compact clusters illustrating the discriminatory power and invariance to illumination spectral content and surface position and orientation.

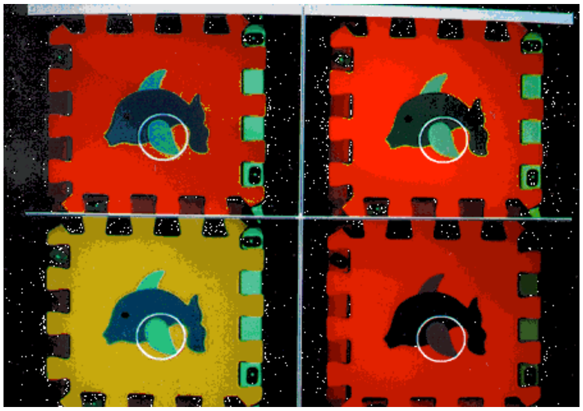

Figure 1. Dolphin under various illuminants

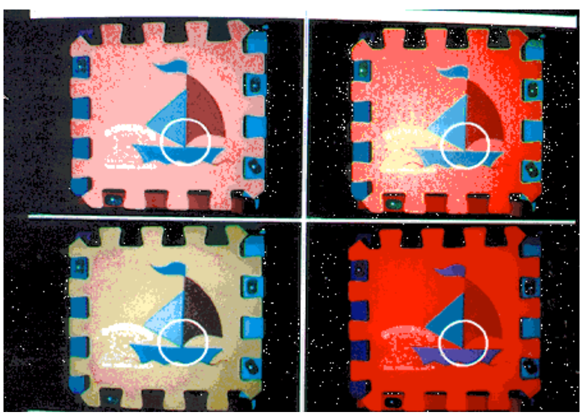

Figure 2. Boat under various illuminants

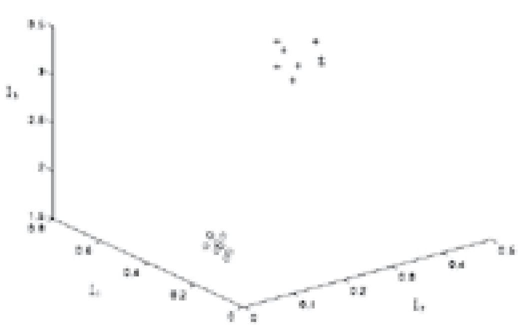

Figure 3. Invariants for Dolphin and Boat

Illumination-Invariant Recognition and Illumination Correction

When a potential match of an image region and a model surface region is identified using the invariants, the image region is transformed to its appearance under a canonical illuminant to allow direct comparison with the hypothesized model in the database. After this step, spatial properties of the image region are compared to the model for hypothesis verification and pose estimation.

Consider a model image region and an observed image region of the same surface patch under different illumination conditions. Before comparing the spatial properties of the two regions we must determine the image transformation that compensates for the relative illumination difference. Let $H(\rho)$ be the color pixel distribution for the model image region and let $H'(\rho)$ be the color pixel distribution for the observed image region. From 3, if the two regions are related by an illumination change then the normalized distributions are related by $H(\rho)=H'(M\rho)$. We have shown[2] how to use moment matrices to estimate the matrix M that specifies the relative illumination difference. Thus, applying M to each measured pixel vector ρ in the observed image region will transform the normalized observed image region color pixel distribution to equal the normalized model color pixel distribution $H(\rho)$. The image rotation angle can then be estimated by comparing the principal axes computed from spatial moment matrices in the different color bands.

Figure 4. Matches: Red illumination

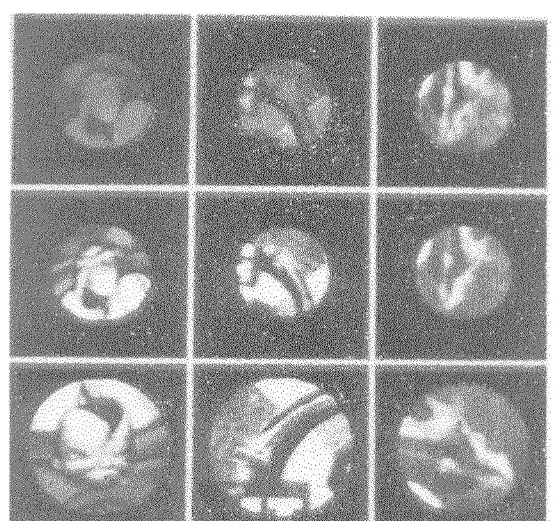

Figure 5. Illumination correction

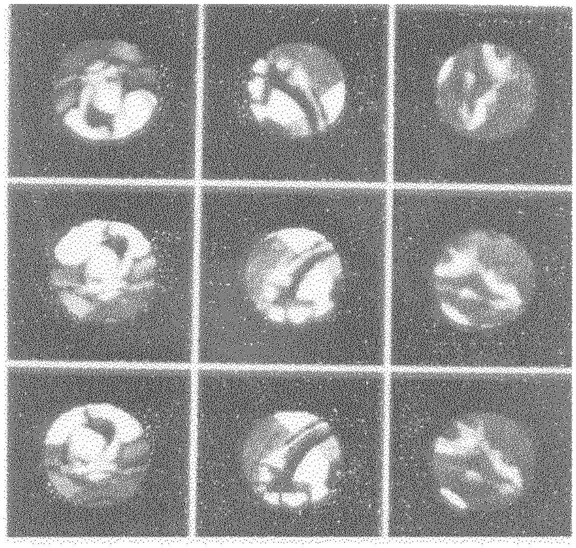

Figure 6. Rotation correction

Experimental Results

We have implemented an experimental object recognition system using the algorithm described in this paper. The system has been tested on a database that includes over twenty objects including books, toy blocks, cereal boxes, and compact disc sleeves. Figure 4 is an image of a scene containing three model objects (face, ring, dragon) under red illumination with several clutter objects. Three matches are hypothesized and circled in figure 4. Each hypothesized match corresponds to an actual match. Figure 5 shows the results of illumination correction for these three regions. For each column in figure 5, the top region is the matched region in the image followed by the region after illumination correction. For comparison, the last region in each column is the matching model image region generated from the database as it appears under the canonical white illumination at its actual scale. Figure 6 shows the results of spatial alignment for the four regions. The top region in each column of figure 6 is the illumination corrected region. Below this region is the region following rotation for spatial alignment with the matching model image region. The last region in each column is the model image region in the database following correction to the size of the matching image region. On a set of several scenes[2] each of the model objects present was correctly identified independent of distance, orientation, and the illumination environment. The system processed over 750,000 regions in these images without generating a false hypothesis.

References

1. G. Healey and D. Slater. "Global color constancy: recognition of objects by use of illumination-invariant properties of color distributions". *Journal of the Optical Society of America A*, Vol. **11**, No. 11, November 1994, 3003-3010.
2. D. Slater and G. Healey. "Combining Color and Geometric Information for the Illumination-Invariant Recognition of 3-D Objects". University of California, Irvine, Electrical and Computer Engineering Technical Report 94-12-01, 1994. Also, *IEEE Transactions on Pattern Analysis and Machine Intelligence* in press.