Using Linear Models for the Illumination-Invariant Classification of Color Textures

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Abstract

Spatial structure in a color image can be represented using correlation functions defined withing and between sensor ba nds. Using a linar model for surface spectral reflectance wiht the same number of parameters as teh number of classes of photoreceptors, we show that illumination changes correspond to linear transformations of a surface correlation matrix. From this relationship, we derive a distance function for comparing sets of spatial correlations functions that can be used for illumination-invariant recognition. We demonstrate using a large body of experimetns that this distance function can be used for accurate texture classification in the presence of large changes in illumination spectral distribution.

Modeling Color Texture

We model multiband texture using a set of spatial correlation functions that characterize spatial interaction within and between sensor bands. This model was previously parametrized by surface location and orientation and used for geometry-invariant surface recognition.[2] In this section the model is extended by asuming a finite dimensional linear model for surface spectral reflectance. This extension will allow the computation of an illumination-invariant distance function for comparing color textures.

A color imaging system records N measurements at each location (α,β) given by

$$Ii(\alpha,\beta) = \lambda \int l(\lambda) s(\alpha,\beta,\lambda) fi(\lambda) d\lambda \quad 1 \le i \le N \tag{1}$$

where $l(\lambda)$ is the spectral power distribution of the scene illumination, $s(\alpha,\beta,\lambda)$ is the spectral reflectance of the surface, $f_i(\lambda)$ is the sensitivity of the ith sensor class, and λ denotes wavelentgth. Following the work of several authors we represent the spectral reflectance function at each location (α,β) using the approximation

$$s(\alpha,\beta,\lambda) = \sum_{1 \le j \le N} \sigma j(\alpha,\beta) Sj(\lambda) \tag{2}$$

where the $S_j(\lambda)$ are a set of fixed basis functions.

As in [2], define a set of correlation functions within and between sensor bands by

$$\underset{1 \le_i, j \le N}{R_{ij}(n,m)} = E[(I_i(\alpha,\beta) = \bar{I}_i)(I_j(\alpha+n,\beta+m) - \bar{I}_j)] \tag{3}$$

where I_i and I_j are the repective spatial means and E denotes the expected value. Define a symmetric matrix of correlation functions for the case $N = 3$ by

$$R(n,m) = \begin{bmatrix} R_{11}(n,m) R_{12}(n,m) R_{13}(n,m) \\ R_{21}(n,m) R_{22}(n,m) R_{23}(n,m) \\ R_{31}(n,m) R_{32}(n,m) R_{33}(n,m) \end{bmatrix} = A\Phi(n,m)A^{\mathrm{T}} \tag{4}$$

where A is a matrix that depends on teh illumination but not on the surface and $\Phi(n,m)$ is a matrix that depends on surface properties but is independent of illumination (1). Similar relationships hold for $N > 3$ with the corresponding increase in the dimenion of the matrices. If $R(n,m)$ is the matrix of correlation functions ofr the surface corresponding to an illumination $l(\lambda)$ and R is the matrix of correlation functions for the same surface corresponding to an illumination l, then

$$R(n,m) = M\tilde{R}(n,m)M^{\mathrm{T}} \tag{5}$$

where $M = A\,\tilde{A}^{-1}$.

Let each correlation function R_{ij} be represented over a fintie set of P values of the coordinates (n,m) so that the resulting values of $R_{ij}(n,m)$ can be stored in a P dimensional colomn vector. We arrange these column vectors into a $P \times 6$ correlation matrix C. Let C be the correlation matrix for a surface under illumination $l(\lambda)$ and let C be the corresponding matrix for the same surfafce under illumination $\tilde{l}(\lambda)$. Then from (5), we have

$$C = \tilde{C}L \tag{6}$$

where L is a 6×6 matrix. Therefore, for a change in illumination the correlaiton matrices are related by a linear transformation.

Illumination-Invariant Texture Recognition

Represent a color texture under an illumination $l(\lambda)$ by a $P \times 6$ correlation matrix C as in (6). We will characterize C by an orthonormal basis obrained by computing the singular value decomposition (SVD) given by $C = U\Sigma V^{\mathrm{T}}$ where the columns of the $P \times 6$ matrix $U = [u_1, u_2, \ldots, u_6]$ are orthonormal eigenvectors of CC^{T}, Σ is a 6×6 diagonal matrix of singular values $\sigma_1, \sigma_2, \ldots, \sigma_6$, and the columns of the 6×6 matrix $\mathrm{V} = [v_1, v_2, \ldots, v_6]$ are orthonormal eigenvectors of $C^{\mathrm{T}}C$.

Consider another Px6 correlation matrix $C'=[c'_1,c'_2,...,c'_6]$. We can determine if C' is related to C by a linear transformation as in (6) by considering how well the columns of C' can be represented using the basis vectors $(u_1,u_2,...,u_6)$ corresponding to C. The best approximation to the columns of C' using the basis $(u_1,u_2,...,u_6)$ in the sense of minimizing the square error is given by the projection $k_{ij}=u_j^T c_i'$. We define

$$D = \sum_{1 \le i \le 6} \left\| c_i' - ((u_1^T c_i')u_1 + (u_2^T c_i')u_2 + \ldots + (u_6^T c_i')u_6) \right\|^2 \tag{7}$$

which is a measure of the distance of the vectors $c'_1,c'_2,..,c'_6$ of C' from the space spanned by the basis $(u_1,u_2,...,u_6)$. Given a color texture represented by a correlation matrix $C=U\Sigma V^T$, other color textures represented by matrices C' that are related to C by an illumination change will give small values of the distance D.

Experimental Results

A database was constructed by acquiring color images of 20 textures under nearly white illumination. A set of 60 test images for classification was obtained by imaging each of the database textures under yellow, red, and green illumination. The textures were taken from various sources including sand, trees, carpets, clouds, wallpaper, patterned cloth, and wrapping paper. Figures 2-6 show several of the color textures. In each figure the database image under white illumination is shown in the upper left. The test images taken under yellow, red, and green illumination appear in the upper right, lower right, and lower left quadrants respectively.

Each of the 60 test images is characterized by an estimated correlation matrix C' and compared to each database texture using the distance function D of (7). Each test texture is classified as an instance of the database texture for which it has the smallest D. For comparison, we also consider the Euclidean distance function D' between a Px6 correlation matrix $C=[c_1,c_2,...,c_6]$ and a $P\times6$ correlation matrix $C'=[c'_1,c'_2,...,c'_6]$. Observe that D' is a measure of the difference between C and C' but does not attempt to account for illumination changes.

Using the uncorrected distance function D', only 33 of the 60 test textures are classified correctly. This indicates that the illumination changes are significant enough that a direct comparison of normalized correlation functions is not effective for classification. Using the distance function D, each of the 60 test textures is classified correctly. Figure 1 is a plot of the D value computed between test texture 19 under red illumination and each of the 20 database textures labeled t_1 to t_{20}. Note the large difference between the distance computed for the correct match t_{19} and the distances computed for the other database textures. This distribution is typical of the classification experiments.

References

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