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ILLUMINATION-EUCLIDEAN INVARIANT RECOGNITION OF COLOR TEXTURE USING CORRELATION AND COVARIANCE FUNCTIONS

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Abstract A complete set of Zernike moment correlation functions is used to capture spatial structure of a color texture. The set of moment correlation functions is grouped into moment correlation matrices to be used in illumination invariant recognition of color texture. For any change in the illumination, the moment correlation matrices are related by a linear transformation. Comparisons between suggested color covariance functions with circular and non-circular correlations have been carried out using about 600 textured images in different illuminations and rotations conditions. Our suggested method can promise in high computation efficiency as well as recognition accuracy.

Key words color texture, texture recognition, color correlations, Zernike moments, Euclidian invariants.

采用自相关和协方差函数在光照—欧氏变化条件下识别彩色纹理

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摘要 采用完整的Zernike矩自相关函数集合提取彩色纹理的空间结构信息.该函数集合生成基于自相关矩的矩阵,并在此基础上获得彩色纹理的光照不变因子.对于不同的光照变化,所获矩阵间存在着线性变化关系.600幅不同光照和旋转条件下的彩色纹理图像将先前提出的彩色协方差函数与循环和非循环自相关函数进行比较,该方法在计算效率和识别准确率方面表现出优越性.

关键词 彩色纹理,纹理识别,彩色自相关函数,Zernike矩,欧氏变换不变因子.

Introduction

Early image recognition algorithms were based on computing (geometric) invariant features for gray-level intensity images. The goal was to detect an object or classify a textured image from an image database. Despite of the increase in dimensionality, the use of colors is unavoidable in recent recognition applications. In fact, using color images may give a better recognition performance than gray-level images due to the capability of capturing local and global image features within and between color bands. Moreover, it is not possible to perform illumination invariant recognition without using color properties of an image.

Many techniques had been suggested to investigate the use of multi - bands of a color image to achieve geometry, illumination, or illumination-geometry invariant recognition. First, the work of Swain and Ballard [1] in which they showed that color distributions can be used directly for recognition without even paying attention to the spatial structure of the image. Their method, however, fails if the illumination spectral is changed or the spatial structure of the image is high (it is possible for regions with significantly different spatial

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structure to have similar color distributions). A Color Indexing color constancy algorithm [2] was developed to remove the dependency of color distributions on illumination changes. The algorithm performs well for an object recognition task but with less success when the image is highly structured as in textures. The other group of color image recognition algorithms deals with computing spatial structure based features, some of the methods are Gabor filters [3], color distributions of spatially filtered images [4], Markov random field models [5,6], and spatial covariance functions [7]. Moment invariants [8] of color covariance functions within and between bands of a color image had been used to recognize three-dimensional textures. The same color covariance functions had been used successfully in a series of illumination recognition experiments of 2-D color texture [9~11]. Jain [10] used color covariance functions to recognize multispectral satellite images. In [11], Zernike moment invariants were computed for color covariance functions, the derived Zernike moment invariants, however, were not complete. In this paper a complete set of Zernike moment correlation and covariance matrices is derived. Different color correlations are introduced, circular and non-circular. Experimental results using about 600 different illumination-rotation images are used to compare the proposed model to previously suggested color covariance functions.

1 SPATIAL INTERACTION WITHIN AND BETWEEN COLOR BANDS

To be able to recognize the texture of a color image, the interaction within and between its bands is considered in this paper. The spatial covariance family functions forms one of the most reliable schemes used to model the color texture. In this paper we will discuss four different measures of these covariance functions.

1.1 Spatial Covariance Functions

Over the image region defining the texture, each band $I_i(\alpha,\beta)$ is assumed wide-sense stationary and each pair of bands is assumed jointly wide-sense stationary. The set of covariance functions within and between sensor bands $(1\leqslant i,j\leqslant N)$ is defined as

$$C_{ij}(x,y) = E\{[I_i(\alpha,\beta) - \bar{I}_i][\bar{I}_j(\alpha + x,\beta + y) - \bar{I}_j]\} \quad (1)$$

Where $\bar{I}_i$ and $\bar{I}_j$ denote spatial means and E denotes the expected value. For the trichromatic case $N=3$ we observe the following properties:

The definition given in (1) will lead to nine covariance functions that include three autocovariance functions and six crosscovariance functions. All the nine spatial covariance functions have the following property $C_{ij}(x,y) = C_{ji}(-x,-y)$ in which only the autocovariance functions are symmetric about the origin. Therefore, we can make use of this symmetry to reduce computations.

The crosscovariance functions are not symmetric; however, only three should be computed i. e. (C_{12}, C_{13}, C_{23}), the other three (C_{21}, C_{31}, C_{32}) can be obtained using $C_{ij}(x,y) = C_{ji}(-x,-y)$. It was shown in [7] that it is useful to use only the basic six covariance functions.

Considering two surfaces S and S' oriented arbitrarily in space where $C_{ij}(x)$ and $C'_{ij}(x)$ are the corresponding covariance functions and $\{\vec{x} = [x\ y]^T\}$. From [7], those covariance functions are related by a linear coordinate transform $\boldsymbol{M}$ as $C'_{ij}(x) = C_{ij}(\boldsymbol{M}x)$.

Values of spatial covariance functions may be negative, zero, or positive.

If the illumination between the corresponding textures changes, then the relation between their corresponding covariance functions changes. Suppose a textured surface observed at two different orientations in space under different illumination conditions, also suppose that the covariance functions are arranged into a column vector $C_i(\boldsymbol{x})$, then we group the covariance functions into a covariance matrix as $C(\boldsymbol{x}) = [\mathrm{C}_1(\boldsymbol{x})\ \mathrm{C}_2(\boldsymbol{x})\cdots\mathrm{C}_6(\boldsymbol{x})]$. Following [11], let $C_i(\boldsymbol{x})$ be the covariance matrix of the surface corresponding to the illumination $l(\lambda)$ and $\tilde{C}'(\boldsymbol{x})$ be the covariance matrix for the same surface after an orientation change described by M and under illumination $\tilde{l}(\boldsymbol{\lambda})$, *then* $\mathrm{C}(\boldsymbol{Mx}) = \tilde{\mathrm{C}}'(\boldsymbol{x})\mathrm{E}$. *Where* E *is a* 6×6 *matrix with elements that depend on* $\mathrm{l}(\boldsymbol{\lambda})$ and $\tilde{l}(\boldsymbol{\lambda})$. Therefore, for a change in illumination and orientation, the covariance matrices are related by a linear transformation E and a linear coordinate transformation $\boldsymbol{M}$.

The above covariance functions had been used successfully in the recognition of color texture. In all previous works, however, they considered that all crosscovariance functions are symmetric (the fact they were enforced to be symmetric). One reason is the high degree of pixel-to-pixel correlation between different bands belonging to the same image, which leads to a very small symmetric error.

1.2 Spatial Correlation Functions

Here we assume again that over the image region defining the texture, each band $I_i(\alpha,\beta)$ is wide-sense stationary and each pair of bands is assumed jointly wide-sense stationary. We define a set of correlation functions within and between sensor bands ($1 \leqslant i, j \leqslant N$) as

$$R_{ij}(x,y) = E[I_i(\alpha,\beta) I_j(\alpha + x,\beta + y)] \quad (2)$$

where E denotes the expected value. For the trichromatic case $N = 3$, correlation functions will have the same properties as those given for covariance functions except that correlation functions will always have positive values. Positive values of correlation functions are necessary when used with moments since moments should be computed for nonnegative bounded functions. In the previous work of Kondepudy and Healey[7], they used the absolute value of color covariance functions to eliminate the negative values. This may in turn destroy the color covariance functions and the transform between the original image and its corresponding test image may be non linear or cannot be predicted.

1.3 Circular Correlation and Circular Covariance Functions

It is important to define a third group of correlation functions that capture some circular symmetric properties when the texture region is averaged within and between sensor bands. One way to do this is by averaging or estimating color correlations (or covariances) inside a circular region. We define circular correlations within and between sensor bands as:

$$\widehat{R}_{ij} = \begin{cases} E[I_i(\alpha,\beta) I_j(\alpha + x,\beta + y)] & \alpha^2 + \beta^2 \leqslant \Re \\ 0 & \text{elsewhere} \end{cases} \quad (3)$$

where $\Re$ is the radius of the region to compute the expectation value at. Similarly, circular covariance functions are defined by:

$$\widehat{C}_{ij} = \begin{cases} E[I_i(\alpha,\beta) - \bar{I}_i][\bar{I}_j(\alpha + x,\beta + y) - \bar{I}_i] & \alpha^2 + \beta^2 \leqslant \Re \\ 0 & \text{elsewhere} \end{cases} \quad (4)$$

Circular color correlations and color covariances should give better results due to the ability to capture the same amount of information as an image is rotated by an angle. Experimental results discussed later will show which of the four proposed covariances schemes outperform the others. Figure 1 shows cloth image photographed with five different illuminations.

It is our task to show that images shown in Fig. 1, and another 25 cloth images (for each illumination) at different rotation angles belong to the same original class. The spatial correlation and spatial covariance functions draws a surface that is to be recognized (instead of the original multispectral image). That surface may take the shape of a pyramid like shape or a cone like shape and may be deformed according to the combination of geometry and illumination changes. For this recognition process and how much those shapes are changing, we shall use the method of moment invariants (specifically Zernike moments).

2 ZERNIKE MOMENTS OF CORRELATION AND COVARIANCE FUNCTIONS

Zernike moments[12] may be used to produce one of the most reliable feature set used to achieve invariant pattern recognition[13-15]. It is our purpose to compute Zernike moments of covariance functions and correlation functions to obtain invariant features that will be used to recognize the color texture. The complex Zernike moments of $f(x,y)$ are defined as:

$$Z_{nl} = \frac{(n+1)}{\pi}\iint \mathrm{d}x\mathrm{d}y f(x,y)[V_{nl}(r,\theta)]^* = (Z_{n,-l})^* \quad (5)$$

where the integration is taken inside the unit disk $x^2 + y^2 \leqslant 1$, $n = 0,1,2,\cdots,\infty$ is the order and l is the repetition which takes on positive and negative integer values subject to the conditions $n - |l|$ is even, and |

Fig. 1　The image of cloth under five different illuminations
图 1　5 种不同光照下的布纹理图像

$l| < n$. Note that, $V_{nl}(r,\theta)$ are the complex Zernike polynomials given as $V_{nl} = R_{nl}(r)exp(il\theta)$ see [12] for their complete definitions. Zernike moments where l takes negative values can be obtained by making use of the complex conjugate property, which is $Z_{nl} = Z^*_{n,-l}$. In this work, Zernike moments will be used to generate invariants of color correlation and color covariance functions. These invariants are of great importance since they reduce the redundant feature of correlations and covariances. For one specific autocorrelation or crosscorrelation function that correspond one set of (i, j) value, Zernike moments is computed as

$$Z^{ij}_{nl} = \frac{(n+1)}{\pi}\sum\sum_{x^2+y^2\leqslant 1} R_{ij}(x,y)[V_{nl}(r,\theta)]^* \quad (6)$$

and for obtaining Zernike moments of color covariances just use $C_{ij}(x,y)$ instead of $R_{ij}(x,y)$ in the above equation.

2.1 Construction of Zernike Moment Correlation Invariants

It can be shown that the relation between the Zernike moment invariant matrices of the corresponding textures takes the following form, see [17] for derivation,

$$\varphi = \boldsymbol{GH}. \quad (7)$$

where φ is the Zernike moment invariant matrix of the first texture, $\boldsymbol{G}$ is the Zernike moment invariant matrix of the second texture, $\boldsymbol{H}$ is the matrix that depends totally on illumination changes. The matrix elements are given by

$$\varphi_{uk} = Re\{Z^k_{n_1l_1}(Z^k_{n_2l_2})^*\}. \quad (8)$$

where

$$g_{um} = \begin{cases} Re\{Z'^m_{n_1l_1}(Z'^m_{n_2l_2})^*\} & 1\leqslant m\leqslant 6 \\ Re\{Z'^{i_m}_{n_1l_1}(Z'^{j_m}_{n_2l_2})^* + Z'^{j_m}_{n_1l_1}(Z'^{i_m}_{n_2l_2})^*\} & 7\leqslant m\leqslant 21 \end{cases} \quad (9)$$

And

$$h_{mk} = \begin{cases} e^2_{mk} & 1\leqslant m\leqslant 6 \\ e_{i_mk}\ e_{j_mk} & 7\leqslant m\leqslant 21 \end{cases}. \quad (10)$$

where the i_m and j_m number set is given by (i_m, j_m) = {(1,2),(1,3),(1,4),(1,5),(1,6),(2,3),(2,4),
(2,5),(2,6),(3,4),(3,5),(3,6),(4,5),(4,6),(5,6)}
for all $m = 7,8,\cdots,21$ respectively, i. e. (i_7,j_7) = (1,2),$\cdots(i_{21},j_{21})$ = (5,6).

Lets assume using a total of w invariants for which $u = 1,2\cdots,w$ and in our discussed case $k = 1,2,\cdots,6$, the matrices are obvious, $\boldsymbol{\varphi}$ is a $w\times 6$ sized matrix which is the moment invariant matrix (it is translation-rotation invariant), $\boldsymbol{G}$ is a $w\times 21$ sized matrix, and $\boldsymbol{H}$ is a 21×6 sized matrix with elements that depend only on $l(\lambda)$ and $\tilde{l}(\lambda)$ which represent the effect of illumination. For texture recognition, $\boldsymbol{G}$ is represented using an orthonormal bases obtained by a singular value decomposition method as follows

$$\boldsymbol{G} = \boldsymbol{U}\Sigma\boldsymbol{V}^T. \quad (11)$$

where $\boldsymbol{U}$ is a $w\times 21$ sized matrix, $U = [u_1, u_2, \cdots, u_{21}]$ having columns that are orthonormal eigenvectors of GG^T, Σ is a 21×21 diagonal matrix of singular values $\lambda_1,\lambda_2,\cdots,\lambda_{21}$, and $\boldsymbol{V}$ is a 21×21 matrix having columns that are orthonormal eigenvectors of $\boldsymbol{G}^T\boldsymbol{G}$. For recognition purpose, the following distance function can be used:

$$D = \sum_{i=1}^{6} \| \varphi - [(u_1^T\varphi_i)u_1 + (u_2^T\varphi_i)u_2 + \cdots + (u_{21}^T\varphi_i)u_{21}] \|^2. \quad (12)$$

where $\varphi_1,\varphi_2,\cdots,\varphi_6$ are the column vectors of $\boldsymbol{\varphi}$. The above distance function characterizes how well the column vectors of $\boldsymbol{\varphi}$ can be approximated as a linear combination of the columns of $\boldsymbol{U}$. Thus, the smallest value of $\boldsymbol{D}$ for matrices $\boldsymbol{\varphi}$ and $\boldsymbol{G}$ will correspond to textures related by some combination of rotation and illumination changes. In our work, the matrix $\boldsymbol{\varphi}$ is used to store the feature of the original database under white illumination. The matrix $\boldsymbol{G}$ is used for the texture under recognition (investigation), i. e. , the texture that had undergone ullumination and geometry changes. To clarify the generation of the matrix $\boldsymbol{G}$ we will give a brief description; first, generate the six color correlation functions using (2), compute Zernike moments for each of the correlation functions using (6), and generate the elements of the $\boldsymbol{G}$ matrix using the definition given in (9) and by following the rules of generating a complete set of invariants given in [12] and [16].

3 EXPERIMENTAL RESULTS

In this section we intend to test the color covariance model and the developed color correlation model in a texture recognition task. The image database is consisted of 20 textured images as shown in Fig. 2, which contains some homogenous and inhomogeneous textures. For each image class in the database, we generated five image samples under white, red, green, blue, and yellow illuminations using HANSA color filters and the images are photographed with a Sony CCD camera. For each of the five images that have different illuminations, we generated five other rotated images at the rotation angles 30°, 60°, 90°, 120° and 150° with respect to the original non rotated image.

Thus for each class, we have a total of thirty images photographed at different illuminations and rotations. The whole image database is consisted of 600 images, a total of 20 classes with 30 images per class. For each image in the database, color covariance and color correlation functions are estimated with averages over a finite image region of size 60 × 60 pixels and for a finite image lag $C_{ij}(x,y)$ and/or $R_{ij}(x,y)$ is estimated for $|x| < 16$ and $|y| < 16$. It had been suggested to normalize color covariance functions against intensity changes by dividing by $C_{rr}(0,0)$. We will include this normalization scheme in our tests, $R_{rr}(0,0)$ will be used for normalizing correlation functions. The test is divided into two stages, the training phase for feature extraction of the original image class and the testing phase that includes feature extraction of the image under investigation that has illumination and geometry changes with respect to the original image class.

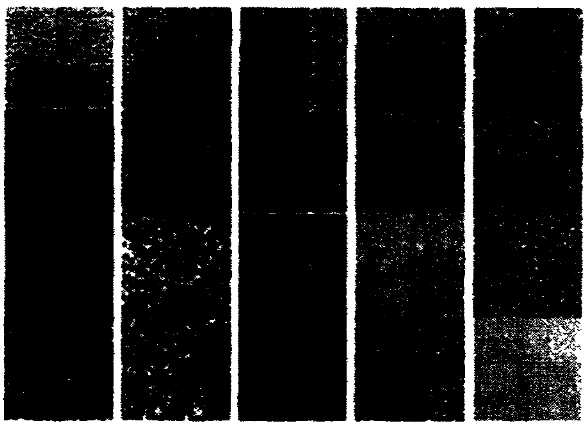

Fig. 2　The original image database used in our experiments
图 2　实验所用的原始图像库

In the training phase and after computing color covariances and/or color correlations, For comparison purpose, Zernike moment invariant matrices are computed for each image up to the 6_{th}, 8_{th}, 10_{th}, and 12_{th} orders. The training process is performed to each of the 20 color textured images photographed under white illumination and non rotated image, and all the 20 Zernike moment invariant matrices are stored to be used offline. In the testing phase, the unknown textures are extracted from the rest of the 580 images under different illuminations and rotations. The distance function defined in (23) is used as a similarity measure. The recognition performance is measured as the number of correct matches over the total number of images. See Fig. 3 for comparison purpose.

The circular correlation functions proposed in this work give the highest recognition performance 97%. On the other hand, the recognition perfomance value of using the covariance functions proposed by Kondepudy and Healey [7] is 85% and circular covariance functions gives 87%. As we increase the order of Zernike moments, the recognition performance increases for all models.

4 CONCLUSIONS

The spatial correlation functions introduced in this paper is very useful in representing and modeling color texture. Compared to a previous color covariance functions the recognition performance is higher. We also

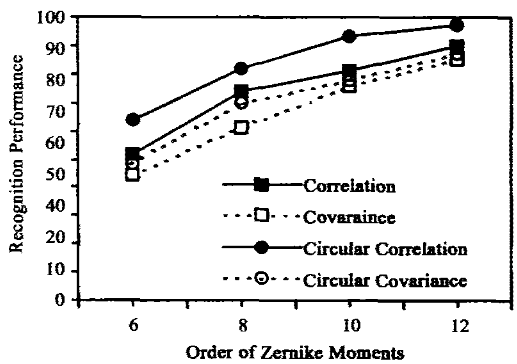

Fig. 3　Performance comparison of using Zernike moment correlation matrices and Zernike moment covariance matrices for the Illumination-rotation invariant recognition of color texture
图 3　采用 Zernike 矩相关矩阵与 Zernike 矩协方差矩阵关于彩色纹理的光照旋转不变识别的性能比较

derived a complete set of Zernike moment invariant correlation and covariance matrices to make correlation functions invariant to rotation changes of textures. The recognition performance is increased as the moment order is increased. The work also investigates four texture modeling functions, ordinary covariance, circular covariance, ordinary correlation, and circular correlation. Using Zernike moments the dimensionality of correlation feature is reduced and it may be useful to use other kinds of moments for the recognition of texture since the derived invariants posses a general form.

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