Fourier Based Rotation Invariant Texture Features for Content Based Image Retrieval

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Abstract—This paper presents a statistical view of the texture retrieval problem by combining the two related steps, feature extraction and similarity measurement. Based on spectral representation of texture images under Fourier transform, rotation invariant signatures of orientation spectrum distribution are extracted. Peak Distribution Vector (PDV) obtained on the spectral signatures capture texture properties invariant to image and surface rotation. The PDV is used to measure the similarity measurement by computing sum of square distance between query and data base images. The method is applied to content based retrieval system with a database of over 1000 randomly chosen texture images from photometric texture database. Experimental results indicate that the new method significantly improves the retrieval rates compared with the Zhang’s approaches while it retains comparable levels of computational complexity.

Keywords—Peak Distribution Vector, Photometric texture database, Rotation invariant spectral signatures, Sum of square distance.

I. INTRODUCTION

Visual information in large digital databases has been escalating during the last decade. Content-based image retrieval (CBIR) has been gaining the interest of the research community. Typically, the features used in CBIR systems are low-level image features, such as color [1], shape [2], and texture [3]. As the texture feature captures different aspects of image, this work focuses on the use of texture information for image retrieval. Some of the most popular texture feature extraction methods for retrieval are based on filtering or wavelet-like approaches [4-10].

These methods effectively measure energy (possibly weighted) at the output of filter banks as extracted features for texture discrimination. An important property of a CBIR system is rotation invariance. A geometrically transformed texture is always perceived as the same texture by human observer. Loosely speaking, the class of texture images include images that are spatially homogeneous and consist of repeated elements (image texels), often subject to some randomization in their location, size, color and orientation. The Zhang’s texture extraction methods include multi-orientation filter-banks and spatial Gabor filters [11]. The basic assumption for these approaches is that the energy distribution in the frequency domain identifies a texture.

Greenspan [12], Haley and Manjunath [13], [14] employed rotation-invariant structural features, using autocorrelation and DFT magnitudes, obtained via multiresolution Gabor filtering. Recently, a rotation-invariant image retrieval system based on steerable pyramids was proposed by Beferull-Lozano [15]. In this system, the correlation matrices between several basic orientation sub-bands at each level of a wavelet pyramid are chosen as the energy-based texture features.

Kashyap and Khotanzad [16] developed a circular simultaneous autoregressive model for the extraction of rotation invariant texture features. Chen and Kundu [17] modeled the features of wavelet sub bands as a hidden Markov model (HMM). These models are trained using texture samples with different orientations that are treated as being in the same class. Mao and Jain [18] presented a multiscale rotation simultaneous autoregressive (MR-SAR) model where a multivariate rotation-invariant SAR (RISAR) model is introduced, which is based on the circular autoregressive (CAR) model.

Most rotation invariant texture analysis methods were designed for the image rotation problem. If the image texture results solely from albedo variation rather than the surface relief or if the illumination is not directional or immediately overhead, then these schemes are surface rotation invariant as well [19, 20]. However, 3D surface textures are often illuminated from one side when they are photographed in order to enhance their image texture. Such imaging acts as a directional filter of the 3D surface texture.

In many cases rotation of a textured surface produces images that differ radically from those provided by pure image rotation. These images show that rotation of a 3D surface texture does not result in a simple rotation of the image texture. Rotation of the physical texture surface under fixed illumination conditions can also cause significant changes to its appearance. This is mainly due to the directional filtering effect of imaging using side-lighting. It also causes failure of classifiers designed to cope with image rotation. The rotation of a rough surface is not equivalent to rotation of its image [19, 20]. The conventional rotation-invariant algorithms fail under these conditions.

Some rotation invariant texture analysis methods had been designed for image rotation as well as surface rotation [22 – 24] using photometric stereo method which needs three images for texture analysis. But we can’t expect three query images all the time. This becomes a limiting factor for those approaches.

This paper proposes a new method for image as well as surface rotation invariant texture feature extraction for retrieval. The rest of the paper is organized as follows: section II discusses the proposed CBIR system; section III
focuses the experimental results. Finally, section IV concludes this paper.

II. METHODOLOGY

In this section, we propose an algorithm of computing the texture signatures, evaluate its performance in capturing the texture properties and further develop it to achieve rotation invariance.

The problem associated with texture feature extraction is the task of identifying isotropic or directional textures at different orientations. Most of the rotation invariant feature methods are based on image rotation rather than physically surface rotation, where the main interest of the proposed work exists. The image directionality is a product of the illuminant tilt angle and the surface directionality. In this way a surface rotation may not be equivalent to image rotation if the illuminant is not also rotated. The directionality in the image of a directional surface is the product of both the surface and illuminant directionalities. If the surface is an isotropic one, then the surface rotation will have no significant effect on the image directionality as long as the illuminant direction is held constant. On the other hand, if the surface is a directional one, the surface rotation will alter the imaged texture beyond simple rotation. This means that a rotated directional surface is distinctly different in appearance compared to the unrotated surface. Both of these effects can be seen in Fig. 2.

We cannot expect the images in the digital libraries are in the category of only unrotated, it may be a set of image as well as surface rotated versions.

In the proposed method, rotation invariant texture features have been extracted using spectrum analysis. The spectral signature of rotated and unrotated textures is estimated. By applying Fourier Expansion, the rotation invariance has been achieved. The properties of rotated and unrotated textures are analyzed as follows:

A. Projection

The projection function can capture the regularity of textures at different orientations. To give attention to both Surface rotation and Image rotation the proposed feature extraction uses two types of projections. At first the Image I(x, y) with tilt angle α and orientation angle β is projected on to a Cartesian plane of f(x, y, z).

\[
x = M \sin \beta \cos \alpha \\
y = M \sin \beta \sin \alpha \\
z = M \cos \beta
\]  

(1)

The following shows that the projection of f(x, y, z) onto a Spherical co-ordinate plane can be evaluated by its three dimensional Fourier version.

Let f(x, y, z) be the texture image in Cartesian plane. The three dimensional Fourier transform of f(x, y, z) is

\[
F(u,v,w) = \iiint f(x,y,z) \exp \left( - j2\pi(ux + vy + wz) \right) dx dy dz
\]  

(2)

Let \( f_x, y, z \) be the rotated version of \( f(x, y, z) \). Then the relationship of these two images is formulated as follows:

\[
f_x(x, y, z) = f(x, y, z)
\]  

(3)

\[
\begin{bmatrix}
x' \\ y' \\ z'
\end{bmatrix} =
\begin{bmatrix}
R_{11} & R_{12} & R_{13} \\
R_{21} & R_{22} & R_{23} \\
R_{31} & R_{32} & R_{33}
\end{bmatrix}
\begin{bmatrix}
x \\ y \\ z
\end{bmatrix}
\]  

(4)

Where \( R \) is the orthogonal matrix.

It is known that when the original texture is rotated by an angle, the frequency spectrum is also rotated by the same angle (this is the rotation property of the Fourier transform).

The one-dimensional Fourier transform of (2) is

\[
P(u) = \int f(x, y, z)dydz \exp(-j2\piux) dx
\]  

(5)

\( P(u) \) can also be written in another form of

\[
P(u) = \int f(x, y, z) \exp(-j2\pi(ux + vy + wz)) dx dy dz
\]  

(6)

\( = F(u,0,0) \)

Equation (6) implies that the projection of \( f(x, y, z) \) onto the x-axis is \( F(u, v, w) \) evaluated along the u-axis. This is the direct result of the separability of Fourier transform. More generally, combining with the rotation property, the one dimensional Fourier transform of \( f(x, y, z) \) projected onto a plane at angles \( \theta \) and \( \Phi \) with the x-axis and y-axis is just \( F(u, v, w) \) evaluated along the plane at angles \( \theta \) and \( \Phi \) with the u and v axis as shown in the (6). That is (2) can be evaluated by \( F(u, v, w) \) alternatively. This produces a feasible way of the projection function analysis.
B. Rotation Invariant Texture Signatures

Let $F(\rho, \theta, \Phi)$ be the Fourier transform of the projection of $f(x, y, z)$ onto a plane at angles $\theta$ and $\Phi$

Where

$$\rho = \sqrt{u^2 + v^2 + w^2}$$
$$\Phi = \tan^{-1}(v/u)$$
$$\theta = \cos^{-1}(w/\sqrt{u^2 + v^2 + w^2})$$

and $F(\rho, \theta, \Phi)$ that of the Projection of $f(x, y, z)$ onto a plane at angles $\theta_0$ and $\Phi_0$.

The relationship between the rotated and unrotated image in Polar form can be represented as follows:

$$F(\rho, \theta, \Phi) = F(\rho, \theta, \Phi)$$

(7)

Since the frequency distribution (spectrum magnitude as the probability of the corresponding frequency) can give a description of texture periodicity, the central moment of (5) is calculated as follows:

$$C_1(\theta) = \sum_{\rho} (\rho - \bar{\rho}_1) F(\rho, \theta, \Phi)$$
$$C(\theta) = \sum_{\rho} (\rho - \bar{\rho}) F(\rho, \theta, \Phi)$$
$$C(\Phi) = \sum_{\rho} (\rho - \bar{\rho}) F(\rho, \theta, \Phi)$$
$$C(\Phi) = \sum_{\rho} (\rho - \bar{\rho}) F(\rho, \theta, \Phi)$$

(8)

where $\bar{\rho}$ and $\bar{\rho}_1$ are the mean value of $\rho$ and $\rho_1$. $C(\theta)$ measures the periodicity of texture regularity. Similarly $C_1(\theta)$, $C(\Phi)$ and $C(\Phi)$ is calculated as shown in the (8). Notice that the power spectrum provides a measurement of the amplitude of texture regularity. Thus we take it into account and compute the spectral signatures at angle $\theta$ and $\Phi$ as follows

$$T_1(\theta) = C_1(\theta) \sum_{\rho} F(\rho, \theta, \Phi_1)$$
$$T(\theta) = C(\theta) \sum_{\rho} F(\rho, \theta, \Phi)$$
$$T(\Phi) = C(\Phi) \sum_{\rho} F(\rho, \theta, \Phi)$$
$$T(\Phi) = C(\Phi) \sum_{\rho} F(\rho, \theta, \Phi)$$

(9)

Such that the orientation spectral signatures $T(\theta)$, $T_1(\theta)$, $T(\Phi)$ and $T(\Phi)$ are obtained. It is obvious that the texture signature is rotation dependent and it is a periodic function of $\theta$ and $\Phi$ with a period of $2\pi$. Assume $T(\theta)$ and $T(\Phi)$ is computed from $f(x, y, z)$ and $T_1(\theta)$ and $T_1(\Phi)$ is computed from $f(x, y, z)$ rotated by $\Delta \theta$ and $\Delta \Phi$ from $f(x, y, z)$. It is not difficult to see that $T(\theta) = T_1(\theta)$ if $\theta_1 = \theta + \Delta \theta$. Similarly for $T(\Phi)$. This implies that a rotation of the input image $f(x, y, z)$ by $\Delta \theta$ and $\Delta \Phi$ is equivalent to a translation of its spectral signatures by the same amount along the orientations. Since the Fourier magnitude is invariant to translation, the Fourier expansion of $T(\theta)$ and $T(\Phi)$ provides a set of rotation invariant features for the input image $f(x, y)$.

III. RESULTS AND DISCUSSION

A. Image Data Base

We have carried out our experiments on images in the Photometric Texture database, a sample of which is shown in Fig. 3.

In order to test the efficacy of the proposed features for rotation invariant texture analysis, we carry out the experiment on 20 structured texture images selected from the Photometric Texture Database as illustrated in Fig. 3. In this database, images were captured and stored individually while surfaces were rotated and illuminated in varied conditions. The database consists of four synthetic textures and thirty real textures. In terms of rotation invariant texture classification scheme, this texture database provides a set of surface rotations and image rotations along with the registered photometric stereo image data. Each texture has 40 samples under varying image rotations and surface rotations. Rotations are carried out by an increment of 30° and 45°. We consider texture samples with surface rotations of 30°, 60° and 120° and image rotations of 0°, 45°, 90°, 135°, 180°, 225°, 270° and 315° respectively.

Each texture image and its image and surface rotated versions are of size 512x512, from which subimages of size 100x100 are extracted. Thus a database of 1000 images is constructed for this experiment. A database of 24 images (1 for each texture class, 0° rotation ) is used for training and the remaining for testing.
Fourier expansion of Spectrum
Signature of unrotated Image
methods for measuring the performance of a system have been created and used by researchers. No standard performance measure is established in image retrieval. The precision-recall-graph is a common performance measure which can be summarized in one number by the area under the graph. Precision is the ratio of the number of relevant images to the number of retrieved images. Recall is the ratio of the number of relevant images to the total number of relevant images in the database. Precision and recall alone contain insufficient information we can always make recall value 1 just by retrieving all images. In a similar way precision value can be kept in a higher value by retrieving only few images or precision and recall should either be used together or the number of images should be specified. Apart from Precision and Recall, the other measures of performance evaluation are Error Rate and Retrieval Efficiency.

1) Image Retrieval Examples: Qualitative evaluation of our method was carried out by visually examining the images of retrieval results. However this can only be based on a subjective perceptual similarity, since there exist no correct ordering that is agreed upon all people [21]. Fig. 6 shows some examples of retrieval results to demonstrate the capability of the proposed method. In this figure the query image is textile (an1), the system almost perfectly retrieves all images of the same textile textures and also images of other types of textile textures. In this case, all relevant images are correctly ranked as the top matches following by images of similar textures shown in Fig. 6. Fig. 7(a), (b) and Fig. 8 shows a set of graphs illustrating this comparison in retrieval performances as functions of number of top matches considered. By the definition of retrieval efficiency, we can say it depends on precision and recall. As can be seen in the Fig 7 (a), (b), the precision and recall values of the proposed method for different number of retrievals are greater than the Zhang’s method. Thus it automatically improves the retrieval efficiency and reduces the error rate. The average values of all the performance evaluation measures for 3, 6, 9,12,15,18 and 22 retrievals are tabulated above in the Table 1.

2) Computational Complexity: The proposed retrieval system has been implemented in a MATLAB environment. The feature extraction step involves taking three dimensional fourier transform of the input image and estimating the rotation invariant spectral signatures in a three dimensional coordinate system. It was found that the computation time is higher(12 seconds for Zhang’s method, 20 seconds for proposed) than the Zhang’s approach[25] with higher retrieval rate. We can forfeit the computation time which is not much greater to achieve greater efficiency.

In terms of classification accuracy, the photometric stereo[19,20] method provides better results than the proposed approach. It is well suited for texture classification problem. But the computational complexity is very high. We need three overlapped images to construct the photometric stereo which we cannot expect from all the query and database images of a retrieval system.
In this paper we have proposed a novel rotation invariant textural feature for Image retrieval. Our approach involves extraction of rotation invariant spectral signatures for both image and surface rotations in a three dimensional co-ordinate system using three dimensional Fourier transform. Experimental results based on a large sample data set of forty real textures selected from the Photometric texture database with different orientations, show that the proposed method outperforms the other rotation invariant retrieval schemes and an overall retrieval efficiency of 87.7% was achieved. Further, it is simpler to compute; it is more robust and perceptually meaningful; the physical meaning of the feature is more clear. Therefore, the proposed signatures are useful for texture based image retrieval. In our future work, texture segmentation will be incorporated into our system to facilitate texture-based retrieval. Scale invariance will also be considered.

IV. CONCLUSION

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