A HIERARCHICAL APPROACH TO ROTATION-INVARIANT TEXTURE FEATURE EXTRACTION BASED ON RADON TRANSFORM PARAMETERS

Mahmoud R. Hejazi and Yo-Sung Ho

Gwangju Institute of Science and Technology (GIST)
1 Oryong-dong, Buk-gu, Gwangju 500-712, South Korea

ABSTRACT

In this paper, we propose an efficient hierarchical method for extracting invariant texture features using the Gabor wavelets and Radon transform parameters. The proposed method applies the Radon transform to estimate the directional information in the high-band texture image extracted by Gabor wavelets. The directional information is then used to make the texture feature invariant to rotation. To show the efficiency of our scheme, we developed a texture-based image retrieval system based on the proposed method and evaluated it on a set of images from the Brodatz album. Experimental results show that the proposed system outperforms previous rotation-invariant systems significantly.

Index Terms**—** Image analysis, image databases, image matching, Radon transforms, wavelet transforms

1. INTRODUCTION

Explosive growth of image databases demands effective and efficient tools that allow users to search and browse through such large collections. Traditional keyword based methods alone are no longer suitable for retrieving a particular image among such a huge amount of images. Instead there are more tendencies to use methods that index images by their own visual contents or features, best known as content-based image retrieval (CBIR) techniques [1].

Among the different features, texture is one of the most important ones. Its importance is due to its presence in many real world images. The majority of existing works on texture analysis assumes that all images are acquired from the same orientation. This assumption is not realistic in practical applications, where images may be taken with different rotation, scale, and so on. As a result, the performance of these methods becomes worse when this underlying assumption is no longer valid.

In this work, we address the problem of extracting efficient rotation invariant texture features and examine their capabilities in increasing the retrieval accuracy in CBIR systems. In general, this is an issue that has been pursued by many researchers. Haley and Manjunath employed rotation-invariant structural features, using autocorrelation and DFT magnitudes, obtained via multiresolution Gabor filtering [2]. However, in this method, since the classes are defined a *priori*, it is not suitable for retrieval applications, where each image forms a separate class and must be trained individually.

Some activities have been done to address these problems. Do and Veterli [3] proposed a steerable wavelet domain HMM for rotation invariant texture characterization and retrieval. A rotation-invariant image retrieval system based on steerable pyramids was proposed by Beferull-Lozano *et al.*, where at each level of a wavelet pyramid, correlation matrices between several basic orientation subbands were chosen as the energy-based texture features [4]. One drawback of steerable transforms comes from the fact that they are oversampled and result in a significant storage penalty with respect to critically sampled transforms.

Campisi *et al.* [5] model the texture as the output of a linear system driven by a binary image. Features extracted from the autocorrelation function of the binary image are used for classification of the texture. Jafari and Soltanianzadeh proposed an approach for detecting the principle direction in texture images using the Radon transform [6]. They rotate the texture image based on the estimated direction and then apply a wavelet transform to extract a rotation-invariant texture feature. However, their work is restricted with the limitations of the Radon transform for images with complicated textural structures. Another drawback returns to the image rotation, where we may lose relatively large amounts of data that in turn decrease the accuracy of the retrieval.

To overcome the abovementioned problems, in this paper, we propose a novel hierarchical approach for extracting the rotation-invariant texture features in images with any kind and amount of the textural complexity. In this method, we estimate the direction based on the textural information of an image and its rotated version using the Gabor wavelets and Radon transform parameters. Through experiments, we will see that the proposed approach significantly increase the retrieval accuracy compared to previous works.

2. MATHEMATICAL PRELIMINARIES

Since in this work we use the Gabor transform for texture analysis and the Radon transform for estimating the orientation in texture images, here, we briefly touch the related topics before starting the main discussion. The details on these topics can be found in the works of Manjunath and Ma [7] and Toft [8], respectively.

2.1. Gabor Filters for Texture Analysis

A 2-D Gabor function $g(x,y)$ and its Fourier transform is defined as

$$g(x,y)=\left(\frac{1}{2\pi\sigma_x\sigma_y}\right)\exp\left[-\frac{1}{2}\left(\frac{x^2}{\sigma_x}+\frac{y^2}{\sigma_y}\right)+j2\pi Wx\right], \qquad (1)$$

$$G(u,v)=\exp\left[-\frac{1}{2}\left(\frac{(u-W)^2}{\sigma_u}+\frac{v^2}{\sigma_v}\right)\right], \qquad (2)$$

where $\sigma_u = 1/2\pi\sigma_x$ and $\sigma_v = 1/2\pi\sigma_y$.

Considering $g(x,y)$ as the mother Gabor wavelet, a class of self-similar functions (filters), referred to as discrete Gabor wavelets can be obtained by appropriate dilations and rotations of $g(x,y)$ as

$$g_{mn}(x,y) = a^{-m} g(x',y'), \quad a>1, \text{ where}$$
$$x' = a^{-m}(x\cos\theta + y\sin\theta),\ y' = a^{-m}(-x\sin\theta + y\cos\theta), \tag{3}$$
$$\text{and } \theta = n\pi/K,\ \ m,n = \text{integer}.$$

Here, we define the parameters of the Gabor Filters as it was done by Manjunath and Ma [7]:

$$a = (U_h/U_l)^{\frac{1}{S-1}},\quad \sigma_u = \frac{(a-1)U_h}{(a+1)\sqrt{2\ln 2}},\ \text{and}$$
$$\sigma_v = \tan\left(\frac{\pi}{2k}\right)\left[U_h - 2\ln\left(\frac{2\sigma_u^2}{U_h}\right)\right]\left[2\ln 2 - \left(\frac{(2\ln 2)^2\sigma_u^2}{U_h}\right)\right], \tag{4}$$

where S and K are the number of orientations and scales, and U_l and U_h denote the lower and upper center frequencies. In this work, these values set to 4, 6, 0.05 and 0.4, respectively. Given an image $I(x,y)$, its Gabor wavelet transform is then defined as

$$G_{mn}(x,y) = \iint I(s,t) g_{mn}^{*}(x-s, y-t)\, ds\, dt\,. \tag{5}$$

Using Eq. (5), we can construct a texture feature vector f for S scales and K orientations using the means and standard deviations of the magnitudes of transform coefficients G_{mn} as

$$f = [\mu_{00}\ \sigma_{00}\ \mu_{01}\ \sigma_{01} \dots \mu_{(S-1)(K-1)}\ \sigma_{(S-1)(K-1)}]. \tag{6}$$

We also define the texture image $t_b(x,y)$ as the magnitude of the sum of the transform coefficients G_{mn} for all orientations and all or some scales (bands) as

$$t_b(x,y) = \left|\sum_{n\in b}\sum_{m=1}^{K} G_{mn}(x,y)\right|, \tag{7}$$

where the set b includes all scales by default. However, we may consider only some scales for construction of the texture images. For instance, if we let the set b include only high-band scales, a high-band texture image is then constructed.

2.2. Radon Transform for Line Detection

The Radon transform is the projection of the image intensity along a radial line oriented at a specific angle. It transforms a 2-D image with lines into a domain of possible line parameters r and θ, where r is the smallest distance from the origin and θ is its angle with the x-axis. The Radon transform of a 2-D image $f(x,y)$ is then defined as

$$R(r,\theta) = \int_{-\infty}^{+\infty}\int_{-\infty}^{+\infty} f(x,y)\delta(r - x\cos\theta - y\sin\theta)\, dx\, dy\,. \tag{8}$$

Figure 1 exhibits the Radon transform of a typical image for a reference line with parameters r and θ.

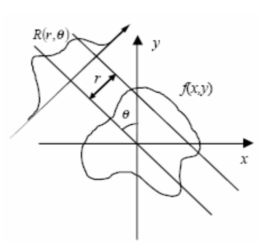

Fig. 1 The Radon transform of a typical image.

3. ROTATION-INVARIANT TEXTURE EXTRACTION

3.1. Basic Idea

Considering the orientation, the texture of an image can be divided into four different categories: (i) anisotropic with one dominant direction; (ii) multidirectional anisotropic; (iii) isotropic (non-directional); and (iv) mixed, where the dominant direction for a texture is defined as the direction with more straight lines.

We first construct the texture image using Eq. (7). However, instead of extracting the texture image for all bands, we construct the high-band texture image, that not only decrease the processing time, but also highlight the line-trends information due to its high-pass filtering property. Here, for constructing the high-band texture image, we only use the $(S\text{-}1)^{\text{th}}$ and S^{th} scales in Eq. (7).

The Radon transform of the high-band texture image is then calculated for all reference lines with θ from 0° to 179°. However, to make the method isotropic, a disk shape area from the middle of the image is selected before applying the Radon transform. We then compute the variance of the result for each reference line, and form the variance array S_R as

$$S_R(\theta) = Var_{\theta\in[0,180)}[R(r,\theta)]. \tag{9}$$

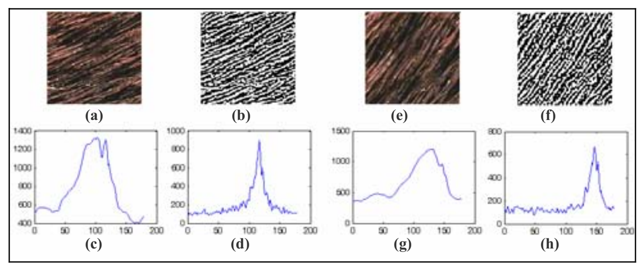

Fig. 2 Rotation estimation for a one-directional texture (fabric).

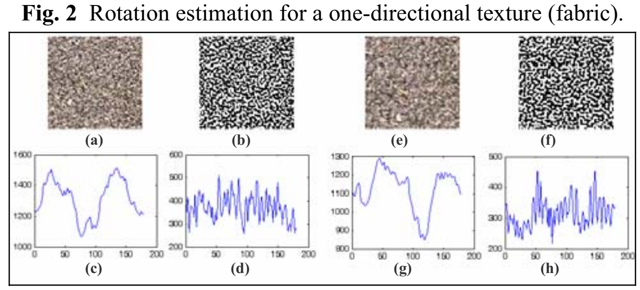

Fig. 3. Rotation estimation for an isotropic texture (fabric).

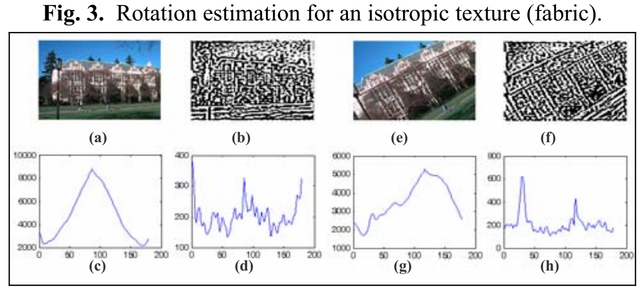

Fig.4. Rotation estimation for a mixed texture (building, trees, etc). (a) original image, (b) high-band texture image, (c) variance array of the Radon transform of the original image, (d) variance array of the Radon transform of the texture image, (e) a 30° rotated version of the image, (f) texture of the rotated image, (c) variance array of the Radon transform of the rotated image, and (h) variance array of the Radon transform of the texture of the rotated image.

In general, considering the definition of the Radon transform, we expect a smaller variation along the dominant direction and larger variations in the direction perpendicular to the dominant direction for anisotropic textures. Examples of Figs. 2-4 not only clarify the above discussion, but also show that the estimation is much more precise when we apply the Radon transform on the (high-band) texture image.

From Fig. 2, we also see that the rotation angle can be easily estimated for an anisotropic texture with one dominant direction by comparing the global maxima in the variance arrays of the texture of the original image and the texture of the rotated image. The rotation angle for a purely (or an almost purely) isotropic texture may not be detected in most cases if we only consider the global maximum (Fig. 3). For multidirectional and mixed textures, the situation is rather complicated. However, in most cases, we have some peaks whose values are close together (Fig. 4).

3.2. Hierarchical Scheme for Direction Estimation

Figure 5 shows the block diagram of the proposed hierarchical approach. The system proceeds through the hierarchy when the estimation cannot be established with certainty at each level.

In the first level, in addition to the construction of the texture feature, the high-band texture image is also extracted. We then try to find the anisotropic textures with a dominant direction, directly from the texture of the original image by comparing the values of the first and second maxima (i.e. Peak_{01} and Peak_{02} in Fig. 5) in the variance array S_{R^0}, where R^0 is the Radon transform of the texture image. If their difference is great enough, e.g. more than one third of the value of the first maximum, the dominant direction D is then perpendicular to the angle which maximizes the variance array:

$$D = \arg\max_{\theta}(S_{R^0}) - 90^\circ . \qquad \textbf{(10)}$$

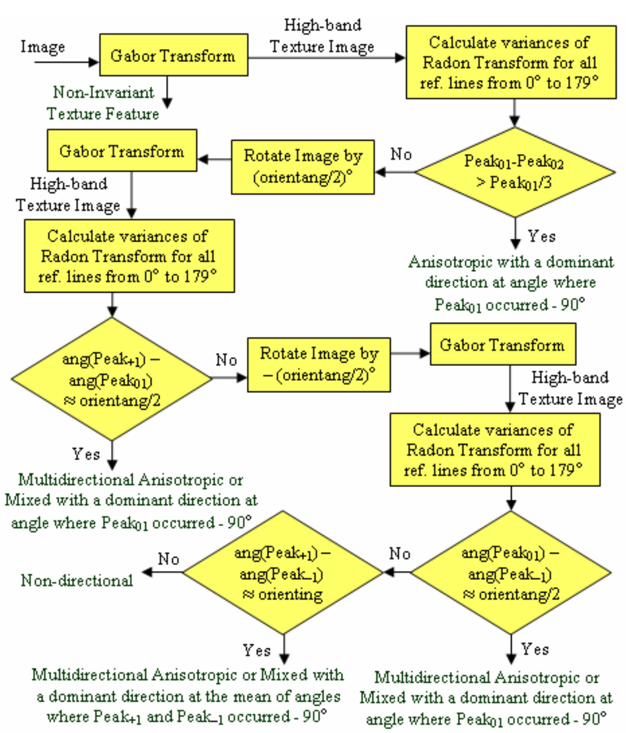

Fig. 5 The block diagram of the proposed hierarchical approach.

Experiments show that the dominant direction is estimated in about 40% cases at this level.

In the second level, we rotate the image by the half of the orientation angle of the Gabor transform (i.e. *orienting*/2 in Fig. 5 which is 15° in this work), and then extract the high-band texture image for the rotated image. Comparing the global maxima of the variance arrays S_{R^+} and S_{R^0}, if their difference is close to *orientang*/2, the dominant direction is estimated using Eq. (10). Here, R^+ is the Radon transform of the texture of the positively rotated image. Experiments show that the estimation is done in more than 75% cases at the first two levels.

In the third level of hierarchy, the situation is similar to the previous level, however this time we negatively rotate the image by *orientang*/2. Again a decision is done if the difference between the global maxima of the variance arrays S_{R^0} and S_{R^-} is close to *orientang*/2, where R^- is the Radon transform of the texture of the negatively rotated image. If the condition is satisfied, we again calculate the dominant direction using Eq. (10).

Finally in the last level of hierarchy, we compare the difference between the global maxima of variance arrays S_{R^+} and S_{R^-}. A decision is then made if the difference is close to *orientang*. However, this time the dominant direction is calculated as

$$D = 0.5 \times (D^+ + D^-) , \qquad \textbf{(11)}$$

where D^+ and D^- are the dominant directions of the positively and negatively rotated images, calculated using Eq. (10), replacing R^0 by R^+ and R^-, respectively. The remaining textures are considered as non-directional. Experiments show that only a small fraction of textures (less than 5%) remains unestimated in this method. We will show this fact later through experimental results.

3.3. Rotation-Invariant Texture-Based System

In order to show the efficiency of our hierarchical approach, we developed a rotation invariant texture-based image retrieval system using the proposed scheme. Similar to all other CBIR systems, we first index the images of the collection in an offline process. Here, the indices consist of the non-invariant texture feature and the dominant direction, extracted using the proposed method.

In an online process, we submit an image query and try to find the similar images from the collection. Let F_Q and F_{DB} are the non-invariant features of the image query and an image from the collection with dominant directions D_Q and D_{DB}, respectively. To make the feature rotation invariant, we do the following steps:

(i) The rotation difference between the dominant orientations of two images is calculated as $R_D = D_Q - D_{DB}$.
(ii) Consider the closest possible orientation of the texture feature to R_D as the dominant orientation O_{dom}.
(iii) Construct a rotation invariant feature F_Q^{inv} by performing a circular shift on F_Q around the dominant orientation O_{dom} that is based on the rule suggested by Zheng and Lu [9].
(iv) Comparing F_Q^{inv} and F_{DB} using a distance similarity metric. In this work, we use the Bray-Curtis distance which has a good achievement in texture-based image retrieval applications.
(v) Repeat the above steps for all images in the collection.
(vi) Candidate images are the images with smaller distance values.

4. EXPERIMENTAL RESULTS

We evaluated the system on a set of texture images from the Brodatz album [10], including 864 images with sizes 128×128, from 54 textural classes, consisting 8 Bark, 4 Brick, 1 Cloud, 9 Fabric, 3 Flower, 4 Food, 1 Grass, 8 Leaves, 2 Metal, 3 Sand, 1 Stone, 3 Tile, 3 Water, 2 Food, and 3 miscellaneous classes. We also generated 3 rotated versions of each image with angles 20°, 75°, and 105°, results in a total of 3456 images. Figure 6 shows some typical images from this collection and their rotated versions.

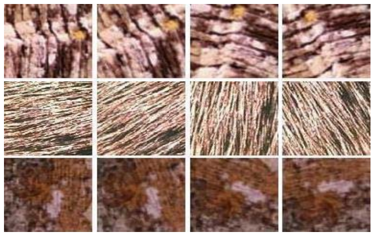

Fig. 6. Three typical images and their rotated versions.

We then performed two different experiments to evaluate the proposed scheme. In the first experiment, we measured the correct direction estimation rate for different texture categories. For this purpose, we keep 864 non-rotated images for comparison, and estimate the rotation angle for the other 2592 images using the proposed method. Here, the estimation is supposed to be correct if the following condition is satisfied:

$$\left|a_R - \left(D_0 - D_{\alpha_R}\right)\right| < 2^\circ, \qquad \textbf{(12)}$$

where a_R is the rotation angle, and D_0 and D_{a_R} are the dominant directions of the non-rotated and rotated images, respectively, calculated using the hierarchical scheme.

Results are presented in Table 1 for different textural categories. As expected, the best estimation is for anisotropic textures. The approach also has a reasonable correct detection rate for the mixed and isotropic textures which have not been considered widely in previous works. The percentage of the unestimated images for each category is also shown in Table 1. It can be seen that only about 5% of images remain unestimated in this method.

Table 1 Correct direction estimation rate for different categories.

	Anisotropic (one-direction)	Anisotropic (multi-direction)	Mixed & Isotropic
Correct Detection	95.8% (276/288)	86.3% (352/408)	79.6% (1509/1896)
Unestimated	0% (0/288)	2.7% (11/408)	6.8% (128/1896)

In the second experiment, we compared the accuracy of the approach with some representative works in this area [2], [6], [7], [9]. For this purpose, we considered 3348 images for the image database and indexed them in the offline process. Other 108 images were used for querying (2 images from each class). In the online process, we submitted the queries, and calculated the average precision and recall for the first M retrieved candidates, whose results are drawn in Fig. 7. The lowest curves in both graphs, which were drawn as references for comparison, are related to a standard (non-invariant rotation) method using Gabor filters [7].

As seen in Fig. 7, our approach outperforms previous works significantly. From Fig. 7, it is seen that the approach proposed by Haley and Manjunath [2] has the closest accuracy to ours. However in their method, as mentioned in Sec. 1, each dataset forms a different class and should be trained individually, that is not practical in actual CBIR problems.

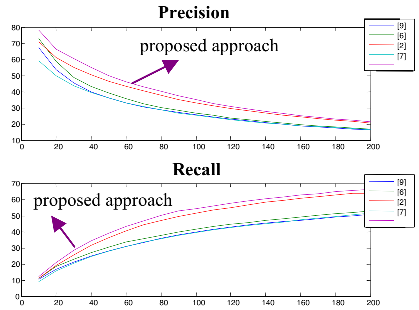

Fig. 7 Precision and recall as a function of *M.*

5. CONCLUSION

In this paper, a hierarchical scheme was proposed to estimate the directional information in images with different textural complexity. The estimation is performed based on the textural information of the image and its rotated versions using the Gabor wavelets and the Radon transform. We then utilized the proposed approach to develop a rotation-invariant texture-based image retrieval system. Experiments indicate that the retrieval accuracy has been increased significantly in this system compared to previous works.

6. ACKNOWLEDGMENT

This work was supported in part by IITA and in part by MIC through RBRC.

7. REFERENCES

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