PAPER

A New Approach to Rotation Invariant Texture Analysis Based on Radon Transform

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SUMMARY In this paper, we propose a new approach to rotation invariant texture analysis. This method uses the Radon transform with some considerations in direction estimation of textural images. Furthermore, it utilizes the information obtained from the number of peaks in the variance array of the Radon transform as a realty feature. The textural features are then generated after rotation of texture along principle direction. Also, to eliminating the introduced error due to rotation of texture, a simple technique is presented. Experimental results on a set of images from the Brodatz album show a good performance achieved by the proposed method in comparison with some recent texture analysis methods.

key words: rotation-invariant texture analysis, discrete Radon transform, direction estimation, multiresolution analysis

1. Introduction

Texture features play a very important role in describing the content of images. There are a number of areas using texture analysis such as medical imaging, content based image retrieval, classification, remote sensing, document segmentation, industrial inspection and so on [1]–[6].

Texture analysis has been widely studied, and different approaches have been taken. Ideally, texture analysis should be invariant to translation and rotation. However, most of the proposed techniques assume that texture has the same orientation. In practical applications, it is very difficult or impossible to ensure that the captured texture images have the same rotation with each other. Hence, many researchers are concentrating on rotation invariant texture analysis and various methods have been proposed.

Wavelet transform is traditionally used for texture analysis. Methods using discrete wavelet transform (DWT) can be found in the literature. However, these methods are sensitive to rotation of the texture and their performance becomes worse when rotation invariant features are needed. This is because textures have different frequency components along different orientations, while ordinary wavelet transform has a limited orientation selective capability. Many attempts have been made to overcome this disadvantage. Charalampidis and Kaspairs [7] and Do and Vetterli [8] calculated the wavelet transform at different directions with exploiting the steerability to extract rotation invariant features. At the same time, image transforms, such as log-polar transform [9] and Radon transform [10], were applied at the pre-

processing stage to convert image rotation into circular shifting of the transformed data. Subsequently shift-invariant wavelet transform was applied to extract rotation invariant features.

Different from the above methods, some of the researchers concentrated on estimation of the principle direction of the texture image to apply wavelet transform or other efficient feature extraction techniques along this direction to achieve rotation invariance. There are techniques in the literature to estimate the orientation of the image, including methods based on image gradients, angular distribution of signal power in the Fourier domain, and signal autocorrelation structure [11]–[13]. Jafari and Soltanian-Zadeh [10] used the Radon transform to estimate the principal direction of the texture image and then applied wavelet transform along this direction to achieve rotation invariance. Hejazi and Ho [14] proposed a modified version of discrete Radon transform for direction estimation for suppression of introduced error due to the different number of pixels on a line for different directions and/or coordinates for a direction.

In this paper we present another method to overcome these problems. Furthermore we use the number of peaks (NOP) of the variance array of Radon transform in each direction as a realty feature to improve the accuracy of classification and retrieval systems. Also to overcome the introduced error by rotation of texture along its principle direction, we propose a simple technique that replaces the feature vectors in training dataset with efficient coordinate vectors. The proposed scheme has been extensively tested by using 60 classes of distinct natural textures selected from the Brodatz album [15].

The rest of this paper is organized as follows. In Sect. 2, we explain the introduced error by conventional Radon transform for direction estimation in images and then illustrate the proposed method to solve these problems. In Sect. 3, the concept of texture analysis based on wavelet and Gabor transforms are explained. The proposed scheme for texture analysis is presented in Sect. 4. Section 5 describes experimental results and conclusions are presented in Sect. 6.

2. Texture Orientation Estimation

The Radon transform of a two dimensional function $f(x, y)$, denoted as $R(r, \theta)$, is defined as its linear integral along a line. For this purpose, it projects an image matrix along specified directions. The integration along a particular line

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defined by a normal distance r from the origin and normal θ angle will generate the corresponding Radon transform point $R(r, \theta)$. Mathematically, it is written as

$$R(r, \theta)[f(x, y)] = \int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} f(x, y) \delta(r - x \cos \theta - y \sin \theta) dx dy \quad (1)$$

where $-\infty < r < +\infty$, $0 < \theta < \pi$. Substantially, Radon transform projects the image to the other parameter space.

It is obvious that the Radon transform provides directional information of the images and can be used to detect linear trends in images. If the principle direction of an image is defined as the direction along which there are more straight lines, the Radon transform can be utilized for this purpose, because the variance of the projection at this direction is maximum.

After determining of the principle direction, the image is orientated along this direction and analyzing of the texture is begun. However, using of the conventional Radon transform has two problems that affect on the accuracy of principle angle detection. First, for different directions, the numbers of reference lines are not equal. It is easy to see that in a square image, for $\theta = 0$, the number of reference line is minima, and for $\theta = 45$, it is maximum (Fig. 1). Second, the number of pixels on each reference line is not equal. As a result, the method is dependent to direction and also is nonhomogenous due to these problems.

Jafari and Soltanian-Zadeh used a disk area of the texture image for calculating the Radon transform to maintain the uniformly of the Radon transform for different orientations [10]. Hejazi and Ho recognized both problems and proposed a modified version of Radon transform to solve them [14]. We present a developed and also simple method to distinguish the principle angle using Radon transform. For this purpose, as showed in Fig. 2, we use a rotation rectangular region that its corners are on the border of disk area utilized in [10]. Such area causes that the number of pixels on each reference line be equal, too. The coordinates of the pixels in the rotation rectangle are obtained as follows:

Fig. 1 Reference lines for calculating of the Radon transform: (a) for $\theta = 0$ and (b) for $\theta = 45$.

$$\begin{pmatrix} x_m^\theta \\ y_n^\theta \end{pmatrix} = \begin{pmatrix} \cos \theta & \sin \theta \\ -\sin \theta & \cos \theta \end{pmatrix} \begin{pmatrix} x_m \\ y_n \end{pmatrix} \quad (2)$$

where x_m and y_n are the corresponded coordinates in the main image and θ is the rotation angle. Then, the Radon transform for an $A \times B$ rectangle is calculated by:

$$R(x_b, \theta) = \sum_{a=-A/2}^{A/2} f(x_b^\theta, y_a^\theta) \quad (3)$$

for $b = -\frac{B}{2}, -\frac{B}{2} + 1, \dots, \frac{B}{2}$. The value of $f(x_b^\theta, y_a^\theta)$ is simply calculated by nearest-neighbor interpolation.

It is easy to proof that for using the maximum space of the texture, the rectangle must be a square. Suppose that the radius of the circle be R . Then:

$$(B/2)^2 + R^2 = (A/2)^2 \quad (4)$$

Therefore:

$$S = AB = 2A(R^2 + A^2/4)^{1/2} \quad (5)$$

where S is the area of the rectangle. It is maximized if $A = B = \sqrt{2}R$.

As we will see, this method improves correct detection rate of the principle anglers. Figure 3 shows the effect of using rotation square region instead of a disk area on the

Fig. 2 The rotated square region for calculating of the Radon transform for two angles.

Fig. 3 Effect of selected area at the Radon transform result: (a) and (c) the circular and square region of a texture, (b) and (d) the Radon transform of (a) and (c), respectively.

Fig. 4 Effect of the rotation on variance array for a one-directional texture (a) original image, (b) and (c) variance array of the original image, applying the Radon transform and the Proposed method, respectively, (d) a 30° rotated version of the image, (e) and (f) variance array of the rotated image, applying the Radon transform and the Proposed method, respectively.

Fig. 5 Effect of the rotation on variance array for a multidirectional texture (a) original image, (b) and (c) variance array of the original image, applying the Radon transform and the Proposed method, respectively, (d) a 30° rotated version of the image, (e) and (f) variance array of the rotated image, applying the Radon transform and the Proposed method, respectively.

result of the Radon transform.

In general, based on the stated definition of principle angle, textures can be classified into four categories consist of: one directional anisotropic, multidirectional anisotropic, isotropic and mixed [14]. Figures 4–7 show the variance arrays of Radon transform at each projection angle for four images with different kinds of textures and their 30 degrees rotation versions: D105, D20, D24 and D66, respectively. For comparison, the variance arrays for the ordinary Radon transform as well as the proposed method have been shown. It is easy to see that for the proposed method, the rotation of the given image would result in a shift in variance array equal to the corresponded rotation without significant changes.

On the other hand, it should also be noted that the number of local maximums of the variance array contains useful

Fig. 6 Effect of the rotation on variance array for an isotropic texture (a) original image, (b) and (c) variance array of the original image, applying the Radon transform and the Proposed method, respectively, (d) a 30° rotated version of the image, (e) and (f) variance array of the rotated image, applying the Radon transform and the Proposed method, respectively.

Fig. 7 Effect of the rotation on variance array for a mixed texture (a) original image, (b) and (c) variance array of the original image, applying the Radon transform and the Proposed method, respectively, (d) a 30° rotated version of the image, (e) and (f) variance array of the rotated image, applying the Radon transform and the Proposed method, respectively.

information about the texture characteristics and can be utilized to distinguish the texture category. As we will see, the information got from the peaks number of the variance of the Radon transform as a realty feature improves the performance of the texture analyzer.

3. Feature Generation

In this section, we explain the fundamental of feature generation methods that we have used for evaluation of the proposed approach.

3.1 Gabor Filters

Gabor Filters have been widely used for the feature extraction in textural images. A two dimensional Gabor filter consist of a sinusoidal wave modulated by a Gaussian envelope. It performs a localized and orientated frequency analysis of a two dimensional signal. A 2-D Gabor function $g(x,y)$ is

defined as

$$g(x, y) = \frac{1}{2\pi\sigma_x\sigma_y} \exp \left[-\frac{1}{2} \left(\frac{x^2}{\sigma_x^2} + \frac{y^2}{\sigma_y^2} \right) + 2\pi j W x \right] \quad (6)$$

where $\sigma_u = 1/2\pi\sigma_x$ and $\sigma_v = 1/2\pi\sigma_y$ are the standard deviations of the Gaussian envelope, respectively, in the directions of the wave and orthogonal to it. The frequency response of this filter is

$$G(u, v) = \exp \left\{ -\frac{1}{2} \left[\frac{(u - W)^2}{\sigma_u^2} + \frac{v^2}{\sigma_v^2} \right] \right\} \quad (7)$$

Then, the Gabor wavelets can be obtained by these generation functions:

$$\begin{aligned} g_{mn}(x, y) &= a^{-m} g(u', v'), \quad a > 1, \quad \theta = n\pi/K \\ x' &= a^{-m}(x \cos \theta + y \sin \theta) \\ y' &= a^{-m}(-x \sin \theta + y \cos \theta) \end{aligned} \quad (8)$$

where $n = 0, 1, \dots, K-1$ and $m = 0, 1, \dots, S-1$. K and S are the number of scales and orientations. Then, for a given image $I(x, y)$, the Gabor transform is defined as:

$$W_{mn}(x, y) = \int I(x, y) g_{mn}^*(x - x_1, y - y_1) dx_1 dy_1 \quad (9)$$

The design of a filter bank consists in the selection of a proper set of values for the filter parameters. The possible combinations of the various parameters determine how the filter bank analyzes the spatial and frequency domain. During the last years various authors proposed and discussed different filter banks for various applications. In simulations, we use the parameters of Gabor Filters that were defined by Manjunath and Ma in [16]:

$$\begin{aligned} a &= \left(\frac{U_h}{U_l} \right)^{\frac{1}{M-1}}, \quad U_l = \frac{U_h}{a^{M-1}} = w \\ \sigma_u &= \frac{(a-1)w}{(a+1)\sqrt{2\ln 2}}, \quad \sigma_v = \tan\left(\frac{\pi}{2K}\right) \sqrt{\frac{w^2}{2\ln 2} - \sigma_u^2} \end{aligned} \quad (10)$$

where U_l and U_h are the lower and upper center frequencies. U_l , U_h , S and K are set to 0.05, 0.4, 6 and 4, respectively.

For constructing the feature vector, the mean μ_{mn} and standard deviation σ_{mn} of the magnitude of transform coefficient for S scale and K orientation are calculated:

$$\begin{aligned} \mu_{mn} &= \frac{1}{P \times Q} \sum_y \sum_x |W_{mn}| \\ \sigma_{mn} &= \frac{1}{P \times Q} \sqrt{\sum_y \sum_x (|W_{mn}| - \mu_{mn})^2} \end{aligned} \quad (11)$$

Using these features, the feature vector is constructed as

$$f = [\mu_{00}, \sigma_{00}, \dots, \mu_{mn}, \sigma_{mn}, \dots, \mu_{S-1K-1}, \sigma_{S-1K-1}] \quad (12)$$

Fig. 8 The 1-D dual-tree complex wavelet transform.

3.2 Dual-Tree Complex Wavelet Transform

Wavelet transform is traditionally used for texture analysis. Real digital wavelet has poor directional selectivity and is shift variant. Complex wavelet transform (CWT) solves these problems by introducing limited redundancy into the transform. But, perfect reconstruction becomes difficult for complex wavelet decomposition beyond level 1, when the input to each level becomes complex. Dual-Tree complex wavelet transform (DT-CWT), on the other hand, by exploiting of two parallel fully decimated trees with real filter coefficients, allows perfect reconstruction while still providing the other advantages of complex wavelet [17].

The DT-CWT decomposes an image in terms of a complex shifted and dilated mother wavelet $\psi(x)$ and scaling function $\phi(x)$:

$$f(x, y) = \sum_{k \in \mathbb{Z}^2} s_{j_0,k} \phi_{j_0,k}(x, y) + \sum_{b \in \theta} \sum_{j \geq j_0} \sum_{k \in \mathbb{Z}^2} c_{j,k}^\theta \psi_{j,k}^\theta(x, y) \quad (13)$$

where $s_{j_0,k}$ is scaling coefficient and $c_{j,k}$ is complex wavelet coefficient. Although DT-CWT is nonseparable, it can be implemented using two filter banks in parallel operating on the same data, as illustrated in Fig. 8 for a one dimensional input. Consequently, the dual tree does not appear to be a complex transform at all. However, when the outputs from the two trees are interpreted as the real and imaginary parts of complex coefficients, the transform effectively becomes complex. Six wavelet subbands of the DT-CWT are strongly oriented in $\{+15^\circ, +45^\circ, +75^\circ, -15^\circ, -45^\circ, -75^\circ\}$ direction and captures image information in that direction. The details of this transform can be studied in [18].

Then, the energy and standard deviation are separately calculated on each subband to construct the feature vector:

$$E_k = \frac{1}{M \times N} \sum_{i=1}^M \sum_{j=1}^N |W_k(i, j)| \quad (14)$$

$$\sigma_k = \left[\frac{1}{M \times N} \sum_{i=1}^M \sum_{j=1}^N (|W_k(i, j)| - \mu_k)^2 \right]^{\frac{1}{2}} \quad (15)$$

where $W_k(i, j)$ is the k th wavelet-decomposition subband, $M \times N$ is the size of wavelet-decomposed subband, and μ_k is the mean value of the k th subband. Resulting feature vector from n number of total subbands is as follows

$$f = [E_1, \sigma_1, E_2, \sigma_2, \dots, E_n, \sigma_n] \quad (16)$$

4. Proposed Method

In this section we explain the proposed scheme for rotation invariant texture analysis. Figure 9 shows the block diagram of the proposed method. At first, the Radon transform is calculated for angles between 0 degrees and 179 degrees in a rotated square region as explained before. Then, the variance array of the Radon transform is calculated. The principle direction, namely θ , is defined as a direction which the variance of the projection is maximum. Afterwards, the image is rotated by $-\theta$ to adjust the orientation of the image. Textural features are then generated using Gabor filters or DT-CWT.

To eliminate the effect of the introduced error due to

Fig. 9 Block diagram of the proposed method.

rotation of texture, feature vectors in training dataset are replaced with coordinated efficient vectors. For this purpose, each image in training dataset is rotated by different angles from 0 degrees to 179 degrees with 0.5 degrees steps and then backs to original position. Then features are generated for all of them and the corresponded feature vector is the mean of these feature vectors. This cause that the effect of any introduced error due to rotation of texture is reflected at the training dataset, too.

As we mentioned earlier, we also use the number of peaks (NOP) at the variance array as a really feature. It must be noted that small noise-type peaks decrease the precision of the system. Hence, to avoid this problem, variance array is passed through a smoothing process including of a standard smoothing function as [14].

In order to improve the performance of the system, another stage can be utilized for feature extraction that has been shown dashed in Fig. 9. We will show the results of the proposed method with and without using of this block. Feature extraction transforms a data space into a feature space and creates a smaller set of features from linear or nonlinear combinations of the original features. Such transformation is practically designed in a way that a reduced number of effective features represent the data set while retaining most of intrinsic information content of the data. A possible solution for feature extraction is via multi layer perceptron (MLP). The employed network has d input equal to initial features, and Q output nodes and a single hidden layer with m nodes and linear or nonlinear activations, where Q is the number of classes. During the training phase, the desired outputs are matched to the class number of labeled input, so the corresponded output is high and the others are low. Such a network maps the input d -dimensional space onto the output m -dimensional subspace. Figure 10 illustrates the architecture of an MLP neural network. The outputs of hidden layer are the compressed data and are called the nonlinear discriminant components.

We investigate our scheme for rotation invariant texture analysis in both tasks consists of classification and retrieval. The final block performs this role. In the retrieval, the relevance between the query image and any target image in database proportion to a similarity measure is calculated and

Fig. 10 Architecture of an MLP neural network.

the images at database are ranked based on maximum similarity. Before finding the distance between two images, it is necessary to normalize the individual feature components. We have used the normalized Euclidean distance metric as a similarity measure [18], which is given by:

$$NED(\bar{f}^x, \bar{f}^y) = \sum_m d_m(\bar{f}^x, \bar{f}^y) \quad (17)$$

where

$$d_m(\bar{f}^x, \bar{f}^y) = \left| \frac{f_m^x - f_m^y}{\sigma(f_m)} \right| \quad (18)$$

where $\sigma(f_m)$ is the standard deviation of the respective features over the entire database and is used to normalize the individual feature components. In classification step, we use this similarity measure for comparison of texture features, too. The classifier is a k -nearest neighbors (k -NN) with $k = 1$, that has been used in [14] and [10] for this database.

5. Experimental Results

To evaluate the performance of the proposed method, we used a dataset consist of 60 texture images of size 512×512 from Brodatz album in our experiments that has been already used in [10] and [14]. This dataset contains 8 one-directional textures D16, D49, D50, D51, D68, D76, D77, and D105; 13 isotropic textures D4, D5, D9, D23, D24, D27, D28, D48, D66, D74, D75, D98, and D110; and 17 mixed textures (including semi-isotropic textures) D8, D10, D11, D19, D25, D37, D46, D57, D81, D83, D84, D85, D86, D87, D92, D101, and D111. The remaining images are multidirectional textures. These texture images are displayed in Fig. 11.

Each image from database was divided into four 256×256 nonoverlapping regions and one 128×128 subimage from the middle of each region was extracted to create a

Fig. 11 The 60 typical textures from the Brodatz album. From left to right: First row: D1, D4, D5, D6, D8, D9, D10, D11, D15, D16. Second row: D17, D18, D19, D20, D21, D22, D23, D24, D25, D26. Third row: D27, D28, D34, D37, D46, D47, D48, D49, D50, D51. Fourth row: D52, D53, D55, D56, D57, D64, D65, D66, D68, D74. Fifth row: D75, D76, D77, D78, D81, D82, D83, D84, D85, D86. Sixth row: D87, D92, D93, D94, D98, D101, D103, D105, D110, D111.

training set of 240 images. Then, each 256×256 region was rotated at angles 10 degrees to 160 degrees with step size 10 degrees and from each rotated image, one 128×128 subimage was selected. These rotated subimages create a total number of 3840 images for the testing set.

5.1 Direction Estimation

At first, we evaluated the effectiveness of the proposed method in determining of the principle direction in a texture. For this purpose, we used 240 non-rotated images as the references for comparison. The principle angles for other 3840 images were estimated based on the proposed approach. Following [14], direction estimation is announced correct if the following condition is satisfied:

$$|\alpha_R - (D_0 - D_{\alpha R})| \leq deviation \quad (19)$$

where α_R is the rotation angle, and D_0 and $D_{\alpha R}$ are the principle direction of the non-rotated and rotated images, respectively.

Tables 1–4 summarize the results of the proposed approach in correct detection rate for different textural categories and for different values of deviation in Eq. (19). For comparison, in these tables the consequence results of the ordinary Radon transform as well as the proposed method

Table 1 Correct detection rate for textures with one-directional structures.

Deviation	Ordinary Radon Transform	Presented Method in [14]	Proposed Method
1°	71.5%	94.5%	96.7%
3°	75.4%	98.6%	96.9%
5°	77.1%	99.0%	99.8%

Table 2 Correct detection rate for textures with multidirectional structures.

Deviation	Ordinary Radon Transform	Presented Method in [14]	Proposed Method
1°	55.0%	86.8%	90.7%
3°	64.9%	89.9%	90.8%
5°	74.5%	91.3%	90.8%

Table 3 Correct detection rate for textures with mixed structures.

Deviation	Ordinary Radon Transform	Presented Method in [14]	Proposed Method
1°	51.5%	66.9%	82.2%
3°	58.7%	74.6%	86.3%
5°	66.7%	80.1%	87.9%

Table 4 Correct detection rate for textures with isotropic structures.

Deviation	Ordinary Radon Transform	Presented Method in [14]	Proposed Method
1°	41.3%	55.4%	70.4%
3°	50.7%	65.0%	73.9%
5°	56.4%	71.4%	74.8%

Fig. 12 Correct classification rate versus chosen threshold.

in [14] have been shown. It is obvious that the proposed approach improves the correct detection rate in all of the four categories. This improvement is due to the suitable choice of the pixels for calculating the Radon transform as described in Sect. 2. It causes that the number of reference lines in different directions, and also the number of pixels on each reference line be equal. Therefore the proposed method is independent to direction and also is homogenous.

5.2 Texture Classification

In this experiment, we implemented the proposed algorithm for texture classification and compared it with the proposed methods in [10] and [14]. To have a fair comparison, we did a similar experiment and classified the 3840 test images using 240 non-rotated images as training set. We examined our scheme using both Gabor and DT-CWT features, separately. DT-CWT features were calculated by up to third decomposition and Gabor features were computed using the explained scheme for 6 orientation (i.e., $K = 6$) and 4 scale (i.e., $S = 4$). Then the lengths of feature vectors were 40 and 48 for DT-CWT and Gabor, respectively. As we mentioned earlier, the feature vectors in training data set were replaced with their equivalent vectors. Moreover, the best threshold value for calculating the peak numbers in variance array was determined. Figure 12 shows the correct classification rate versus threshold values for calculation of the peak numbers using both Gabor and DT-CWT features. The corresponded curves have been labeled by Gabor-I and DT-CWT-I. In this figure, threshold equal to zero means that the NOP has

Table 5 Results of texture classification for images of Fig. 11.

Method	Features	Overall Accuracy
A	Wavelet	96.7%
B	Gabor	96.8%
C	DT-CWT	99.7%
	Gabor	99.9%
D	DT-CWT	99.5%
	Gabor	99.8%

not been used as a realty feature. To show the effect of the proposed technique for eliminating the introduced error due to rotation of texture, the correct classification rate without utilizing this technique has been showed in this figure, too. These curves have been labeled by Gabor-II and DT-CWT-II. This figure indicates that if threshold is chosen 0.6, the best results are yield. In the rest of this paper, we use this threshold for calculating the peak numbers of the variance array.

The results of the classification using proposed scheme as well as the proposed techniques in [10] and [14] have been summarized in Table 5. These methods have been named Method C, A and B, respectively. For comparison, the results of the classification without using the numbers of variance peaks are also presented in this table (Method D).

The results clearly show the effect of the each proposed stage for improving the accuracy of the texture analyzer. Since authors in [10] and [14] have shown that their schemes are better than other methods, we can conclude that our proposed scheme is very effective. Furthermore, it is seen that the increasing of the correct classification rate is considerable.

Since processing time for generating of the DT-CWT compare to generating of Gabor features is 1/6 [18], and since the difference between correct classification rate based on these features is negligible, it can be concluded that where processing time is an important factor, using DT-CWT features is more effective. It must be noted that due to excellent results, we didn't utilize the additional feature extraction stage in our classification system.

5.3 Texture Retrieval

The same as other retrieval methods such as [18], we evaluated the performance of the retrieval system in terms of the average rate of retrieving relevant images as a function of the number of top retrieved images. Figure 13 shows a graph illustrating the results of the retrieval according to the number of top matches considered both with and without using of the NOP in variance array. It is clear that using NOP as a realty feature improves the retrieval efficiency.

In the last experiment we evaluated the effect of the additional feature extraction stage in retrieval performance. For this purpose, at the feature extraction stage, 20 features from each feature vector were extracted using an MLP neural network as described in previous section to feed them in retrieval stage. Hence, the number of nodes in the hidden

Fig. 13 Average retrieval rate according to number of top images.

Fig. 14 Average retrieval rate according to number of top images after and before feature extraction (FE) for DT-CWT features.

Fig. 15 Average retrieval rate according to number of top images after and before feature extraction (FE) for Gabor features.

layer is equal to 20. The neural network was trained using training dataset with back propagation algorithm. The number of input nodes is equal to the number of initial features (40 and 48 for DT-CWT and Gabor features, respectively), and the number of output nodes is equal to the number of classes (60). Figures 14 and 15 show the effect of

the supervised feature extraction from initial features for DT-CWT and Gabor features (including NOP feature) in retrieval efficiency, respectively. The improvement of the retrieval results is the logical consequence of nonlinear supervised combination of initial features.

It is obvious that retrieval time, at the similarity measurement stage, is depended on feature vector dimensions. From this point of view, this scheme has a good performance due to implementation of neural network for feature extraction that reduces the number of features to 20.

6. Conclusion

We have introduced a new scheme for rotation invariant texture analysis. In this scheme, at first the principle direction of texture is determined using Radon transform for a rotated square region. We showed that this region improves the correct detection rate for both isotropic and anisotropic textures. Furthermore using the peak numbers of the variance of the Radon transform as a feature and replacing features at the labeled set of textures by their equivalent features, increased the performance of the texture analyzer.

Experimental results showed the improvement of the performance in the proposed method for both retrieval and classification of textural images.

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