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변형된 지역 Gabor Feature를 이용한 VQ 기반의 영상 검색

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Image Retrieval using VQ based Local Modified Gabor Feature

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Abstract - This paper proposes a new method of retrieving images from large image databases. The method is based on VQ(Vector Quantization) of local texture information at interest points automatically detected in an image. The texture features are extracted by Gabor wavelet filter bank, and rearranged for rotation. These features are classified by VQ and then construct a pattern histogram. Retrievals are performed by just comparing pattern histograms between images. Experimental results have shown the robustness of the proposed method to image rotation, small scale change, noise addition and brightness change and also shown the possibility of the retrieval by a partial image.

1. Introduction

Recently, many materials are being digitalized and made into multimedia data by the rapid development of multimedia technology, and through the spread of scanner and digital camera and by the development of the large capacity of storage equipment, numerous multimedia databases and image libraries are being constructed. The medium that plays an important role in these multimedia data is an image data and it is a difficult and bothersome problem to search a desired image in these image databases by manual work. So the efficient and automatic image retrieval by image contents such as shape, color or texture is emerging as an important research area with application to these databases[1].

This paper proposes a new retrieval method using texture information. Many existing approaches use the global features of an image, but the approach described here uses local information calculated at automatically detected interest points. The use of interest points, which correspond to the corners, has advantages over features such as edges or regions, particularly robustness to partial visibility and high informational content[2]. They are described in section 2.

Local texture features used in this paper are extracted at interest points by Gabor filter bank and rearranged to be rotationally invariant. This procedure is described in section 3.

Finally, the feature vectors are classified by VQ and form a histogram of constructed codebook index, which is described in section 4. Image retrievals are performed by comparing histograms between database images and query image. The experimental results are described in section 5.

2. Interest Point

Interest points are usually defined as points where the signal varies multiple-dimensionally, and correspond to the corners, T-Junctions, and also the points where texture changes rapidly. So these detectors are based on local derivatives[2,3].

Of the existing corner detectors, the Harris detector[3] has been known as the most efficient method considering repeatability and information content. Harris detector constructs the matrix related to the autocorrelation function in order to determine locations where the signal changes in two directions and then extracts the interest points by means of the eigenvalues of this matrix which become the principal curvatures of autocorrelation function.

The change, E, of the image intensity, I, for the small shifts (x, y) can be written as

$$E(x,y) = Ax^2 + 2Cxy + By^2 = (x,y)M(x,y)^T \quad (1)$$

$$M = \begin{bmatrix} A & C \\ C & B \end{bmatrix}$$

where, $A = X^2 \otimes W$, $B = Y^2 \otimes W$, $C = (XY) \otimes W$

$$W_{u,v} = \exp\{-(u^2+v^2)/2\sigma^2\}$$

$$X = I \otimes (-1,0,1) \approx \partial I/\partial x$$

$$Y = I \otimes (-1,0,1)^T \approx \partial I/\partial y$$

u, v : *window region*

Let α, β be the eigenvalues of M and they will be proportional to the principal curvatures of the local autocorrelation function, so about the regions of an image, there are three cases to be considered. If both of these two eigenvalues are small, the windowed region is of approximately same pixel value, and if one is large and the other is small, the windowed region corresponds to the edge component. And if both of them are large, this indicates corner point.

3. Feature Extraction

In this paper, we used Gabor filter bank to extract the texture feature vectors, which coincides well with a biological ground that optic cortex of human being has the receptive fields to direction and frequency.

3.1 Gabor functions and Wavelets

A two dimensional Gabor function $g(x,y)$ and its Fourier transform $G(u,v)$ can be written as

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

$$G(u,v)=\exp\{-\frac{1}{2}(\frac{(u-W)^2}{\sigma_u^2}+\frac{v^2}{\sigma_v^2})\} \quad (3)$$

where, $\sigma_u=\frac{1}{2\pi\sigma_x}$ and $\sigma_v=\frac{1}{2\pi\sigma_y}$. Expanding a signal using this basis provides a localized frequency description. A class of self-similar functions is referred to as Gabor wavelets and if $g(x,y)$ is the mother Gabor wavelet, then this self-similar filters can be obtained by appropriate dilations and rotations of $g(x,y)$. Gabor filter bank is generated by following equations.

$$g_{mn}(x,y)=a^{-m}g(x',y') \quad (4)$$

where, $x'=x\cos n\theta+y\sin n\theta$,

$y'=-x\sin n\theta+y\cos n\theta$, and $a=\left(\frac{U_h}{U_l}\right)^{\frac{1}{S-1}}$.

m and n indicate scale and orientation respectively, where, $m=0,1,\cdots,S-1$ and $n=0,1,\cdots,K-1$, with S being the total number of scales and K the total number of orientations in the filter bank. U_h and U_l each indicates the maximum and the minimum center frequency of the bands included in the filter bank. The $S\times K$ numbers of filters are constructed by this method.

As mentioned before, Gabor filter bank has been used for image retrieval by Manjunath[4]. In his method, the mean and the standard deviation of the signals filtered by each filter are used as a texture feature vector. Namely, he extracted the global texture patterns of database images and query images. Unlike this method, we use the local texture information in this paper. At first, interest points are detected by the method referred in section 2 and then local texture information is extracted at interest points and used as a feature vector.

We constructed Gabor filter bank of 3×12 filters which extracts a feature vector composed of 36 elements.

3.2 Rotation Problem

The texture feature calculated by Gabor filter bank has some problems to be applied to the retrieval of rotated images directly. If an image rotates, the elements of the feature vectors of an image are shifted to the next directional element position in circular order. The rotated image will be regarded as different from original image by this element shift. Fig. 1 shows the example of rotation.

So we perform the following procedure for the rotationally invariant features. At first, we set the region for calculating Gabor feature vector

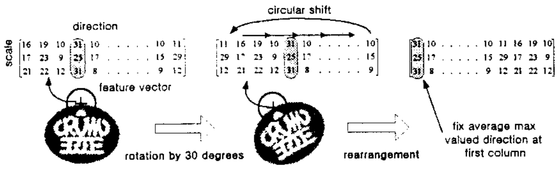

Fig. 1. The change by image rotation and the compensation

at a point circular. If the rectangular region is used, the pixels included in this region will be changed when an image rotates except multiples of 90 degrees. These changed pixels cause some changes in the feature vector. But the change of pixels will not occur in the circular region. And then we rearrange the texture feature vectors calculated for this circular region with the direction column of max averaged value in scale at the first and with the circular order maintained. The purpose of this procedure is to fix the start direction column in circular order regardless of the image rotation. This method makes the feature vectors of rotated image similar to those of original image, that is, regards two images as the same.

To all interest points, this rearranging procedure of texture feature vectors is applied.

4. Histogram by VQ

In this paper, we propose that the patterns calculated at interest points be classified by VQ and then the histogram of those patterns be constructed. Retrieval can be performed by comparing the histograms each other.

VQ is performed using LBG algorithm to the feature vectors calculated on the interest points of all the images in the database to describe the texture information of an image. After forming a codebook which efficiently describes all the feature vectors, feature vectors on all the interest points of an image are represented by the index of the codebook and form a histogram of the codebook index. All images are represented by the histograms describing texture information, and then texture based image retrieval is performed by comparing the histograms between query image and database images. To compare the histograms, we use histogram intersection method used by Swain in color based image retrieval[5]. That is, if the feature vectors of two images I_i, I_q are represented by the N-level codebook, texture information of two images can be described by the histogram $H_i[k]$, $H_q[k]$, $k=0,1,\ldots,N-1$, and comparison of these two images can be performed by the equation (5).

$$HI(H_i,H_q)=\frac{\sum_{k=0}^{N-1}\min(H_i[k],H_q[k])}{\sum_{k=0}^{N-1}H_q[k]} \quad (5)$$

5. Experiments and Results

5.1 Experiments

Image retrieval is tested for a database containing 1100 gray-valued trademark images of 128×128 pixels. 20 query images composed in situations like image rotation, scale change, brightness change, and noise addition, are used. And the codebook size was set to 100 in VQ procedure.

As a criterion of evaluating performance, we used the average retrieval rank of the desired image like equation (6) and compared the performance of the proposed method with those of the existing methods such as Zernike moments(ZM)[6], differential invariants(DI)[2] and Jain's one using gradient[7].

$$average\ retrieval\ rank = \frac{1}{M}\sum_{i=1}^{M} rank(i) \qquad (6)$$

$$\%rank = \frac{average\ retrieval\ rank}{N} \times 100$$

where, M and N each is the total number of queries and database images.

5.2 Results

For the one query image, the results of the proposed retrieval method are shown in Fig. 2.

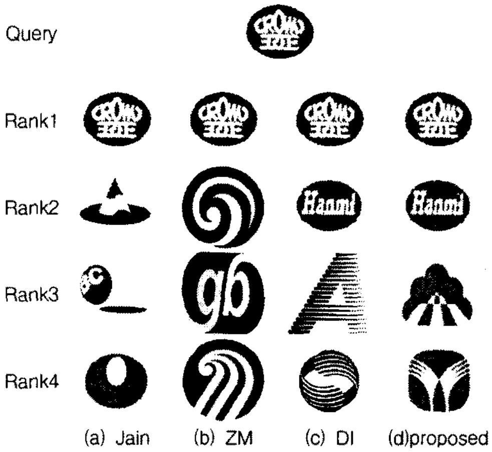

Fig. 2. Results of image retrieval

5.2.1 Retrieval of changed images

We performed image retrieval for queries in the situations of noise addition, brightness change, rotation, and scale change. For the noisy queries, 5%, 10% and 15% pixels of the query images are contaminated by white Gaussian noise. And for the brightness test, the pixels of query images are changed by +10 and -10. For the queries for image rotation, images are rotated by 5, 10, 15, and 45 degrees. Finally, for scale change, the queries are changed by 0.9 and 1.1 times. The results are shown in Table 1.

The results showed that the proposed method is more efficient than existing methods in some situations, particularly robust to the rotation and scale change. And the tests for the noise addition and brightness change also showed the efficient results which have little difference from other methods.

Table. 1. Results of image retrieval

		Jain	ZM	DI	Proposed
Noise	5%	2.1(0.19%)	1.3(0.12%)	3.6(0.32%)	2.16(0.20%)
	10%	2.6(0.23%)	10.6(0.95%)	4.3(0.39%)	5.68(0.52%)
	15%	4.2(0.38%)	41.4(3.73%)	13.0(1.17%)	10.74(0.98%)
Bright-ness	+10	9.0(0.88%)	1.0(0.09%)	7.1(0.64%)	1.05(0.10%)
	-10	1.0(0.09%)	1.0(0.09%)	4.7(0.36%)	1.05(0.10%)
Rotation	5°	Not applicable	3.26(0.30%)	9.3(0.85%)	2.32(0.21%)
	10°		6.11(0.56%)	4.26(0.39%)	2.84(0.26%)
	15°		5.67(0.52%)	7.95(0.72%)	4.84(0.44%)
	45°		13.3(1.20%)	41.8(3.77%)	4.63(0.42%)
Scale	0.9	24.7(2.23%)	22.8(2.01%)	54.2(4.89%)	5.6(0.51%)
	1.1	13.7(1.23%)	20.4(1.84%)	57.6(5.19%)	1.69(0.15%)

5.2.2 Retrieval of partial visibility

We performed the retrieval for the parts of an image. The retrieval result is shown in Fig. 3.

Fig. 3. Retrieval result for a partial image

The result indicates that in the retrieval of the partial image, the elements of histogram bin are reduced but the global shape of histogram is maintained and only a few points are necessary to recognize an image.

6. Conclusion

In this paper, we proposed a new image retrieval method robust to rotation using VQ based local texture information. Retrieval results showed that this method retrieved the desired image better than other methods in the case of noise addition, scale change, rotation and brightness change in the query image. Also this proposed method showed the possibility of retrieval for a partial image.

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