A Rotation Invariant Content-Based Image Retrieval System based on Color Histogram, Texture Feature and Radon Transform Parameters

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ABSTRACT - The paper presents a system for retrieving images based on the information of color and texture features in images. In the proposed system, the user submits a query image and the system searches for similar images in the database. The similarity assessment between the query image and images in the database is done based upon the image color histogram, as well as the texture information. In this work, Gabor filtering technique is used to extract texture information. To make the image retrieval system invariant to rotation, we apply the Radon transform on texture images extracted by Gabor filters to estimate the directional information to adjust the orientation in texture features. The experimental results show that retrieving process is very efficient, even for rotated images with different and complicated texture structures.

1. INTRODUCTION

In recent years, Content-Based Image Retrieval (CBIR) has been a very active and interesting research area, with the thrust from two major research communities: database management and computer vision. Using CBIR techniques, images are indexed by their own visual content or features, such as color, shape, texture, etc. Similarity assessment can be then achieved by comparing image feature(s) between two different images [1].

In general, retrieval of images according to their perceptual low level features is inherently different and more complex than retrieval of well-structured data [2]. CBIR systems must take into account the uncertainty factor introduced by the query formulation as well as during the image analysis process, which results in an imprecise description of the image content. To this reason, despite many algorithms which have been proposed for image retrieval [3], each algorithm has its own characteristics and is suitable for indexing some particular categories of images.

In this work, in addition to color feature which is usually used as a basic feature in most CBIR systems, we focus on the use of texture information for the description of the image content. Roughly speaking, the class of texture images includes images that are spatially homogeneous and consist of repeated elements, often subject to some randomization in their location, size, color and orientation.

The most common methods for extracting texture features are based on multi-orientation filter-banks, spatial Gabor filters, and wavelet transform [4] [5].

However, these techniques are not originally rotation invariant, which is one of the most important properties of a CBIR system. This is an issue that has been pursued by various researchers. Greenspan et al. [6] and Halevy and Manjunath [7] [8] employed rotation-invariant structural features, using autocorrelation and DFT magnitudes, obtained via multiresolution Gabor filtering. A rotation-invariant image retrieval system based on steerable pyramids was proposed by Beferull-Lozano et al. [9], where at each level of a wavelet pyramid, the correlation matrices between several basic orientation subbands were chosen as the energy-based texture features. There are also some works using Fourier descriptors to make texture features invariant to rotation (e.g. [10] [11]).

In this paper, as mentioned before, retrieval is done based on the color and texture features. While we use color histogram to obtain color information from an image, Gabor filters is used for extracting texture image. To make the texture features invariant to rotation, Radon transform is applied to the texture image to estimate directional information which we use it then to adjust the orientation. The extracted information is the basis for feature matching in our proposed CBIR system. After a query image is submitted by a user, the system extracts features for the query image and compares them with the features information of different images in database to find some candidate images which are more similar to the query.

2. GABOR FILTERS FOR TEXTURE EXTRACTION

Texture analysis algorithms range from methods using random field to those which apply multiresolution filtering techniques such as wavelet transforms and Gabor filters [4] [5]. A two dimensional Gabor function $g(x, y)$ and its Fourier transform $G(u, v)$ can be written as:

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

(1)

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

(2)

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

Gabor Functions form a complete but nonorthogonal basis set. Expanding a signal using this basis provides a localized frequency description. Here, a class of self-similar functions, referred to as Gabor wavelets is considered. Let $g(x, y)$ be the mother Gabor wavelet, then this self-similar filter dictionary can be obtained by appropriate dilations and rotations of $g(x, y)$ through the generating function.
\[ g_m(x, y) = a^{-m} g(x', y'), \quad a > 1, \quad m, n = \text{integer} \]
\[ x' = a^{-m} (x \cos \theta + y \sin \theta), \quad \text{and} \]
\[ y' = a^{-m} (-x \sin \theta + y \cos \theta) \]

where \( \theta = n \pi / K \) and \( K \) is the total number of orientations.

The scale factor \( a^{-m} \) in Eq. (3) is meant to ensure that the energy is independent of \( m \).

Given an image \( f(x, y) \), its Gabor wavelet Transform is then calculated as:
\[ G_m(x, y) = \sum_s \sum_l I(s, l) g_m \left( x - s, y - l \right) \]

where \( g_m \) is as defined in Eq. (3) and ' indicates the complex conjugate. Here, to take the advantage of the nonorthogonality of the Gabor wavelets which leads to the redundant information in the filtered images, we use the parameters of Gabor Filters (in Eq. (3)) as defined by Manjunath and Ma [5]:
\[ a = \left( U_s / U_h \right)^{1/2}, \quad \sigma_s = \frac{(a - 1) U_h}{(a + 1) \sqrt{2} \ln 2}, \quad \text{and} \]
\[ \sigma_t = \tan \left( \frac{\pi}{2k} \right) \left[ U_h - 2 \ln \left( \frac{2 \sigma_s^2}{U_s} \right) \right] \left( \frac{2 \ln 2}{U_s} \right)^{1/2} \]

where \( U_s \) and \( U_h \) denote the lower and upper center frequencies of interest whose values set to be 0.05 and 0.4.

Calculating the transform coefficients \( G_m \) for \( 3 \) scales and \( K \) orientations, the texture image as well as texture feature of the image \( f(x, y) \) can be extracted.

3. RADON TRANSFORM

The Radon transform, which is related to Hough transform [12], is able to transform two-dimensional images with lines into a domain of possible line parameters, where each line in the image will give a peak positioned at the corresponding line parameters [13]. In the most popular definition for Radon transform, a line is defined as:
\[ \rho = x \cdot \cos(\theta) + y \cdot \sin(\theta) \]

where \( \theta \) is the angle and \( \rho \) is the smallest distance to the origin of the coordinate system. Based on this form, the Radon transform for a set of parameters \( (\rho, \theta) \) is the line integral through the image \( f(x, y) \), where the line is positioned corresponding to the value of \( (\rho, \theta) \) and can be calculated by applying one of the following formulas, equivalently:
\[ g(\rho, \theta) = \int \int f(x, y) \delta(\rho - x \cos \theta - y \sin \theta) dx dy \]
\[ g(\rho, \theta) = \int_0^{\frac{\pi}{2}} \int_0^\pi f(\rho \cos \theta - r \sin \theta, \rho \sin \theta + r \cos \theta) ds \]

Using the definition, an image containing for example two straight lines are transformed into the Radon transform as shown in Fig. 1. It can be indicated that two very bright spots are found in the Radon transform, and their positions shown the parameters of the lines in the original image.

![Fig. 1. An Image with two lines (a) and its Radon transform (b).](image)

Due to such a property of Radon transform, it has been used widely in image analysis algorithms. We will show in Section 4.1.1 how the Radon Transform is applied to estimate the orientation in texture images.

4. PROPOSED CBIR SYSTEM

4.1. Feature Extraction

In this work, we use two low-level features of an image to represent its content. These features are color and texture. For color feature, we apply color histogram technique to extract histogram vector for each image. However, the situation for texture feature is rather complicated. In fact to make the retrieval system invariant to rotation, we need to apply a suitable strategy for estimating the rotation for texture images, especially for isotropic (directional) textures. To do this task, having extracted a texture image using Gabor filtering technique, we apply the Radon transform to estimate its possible direction and then extract the texture feature based on the rotation information. Figure 2 illustrates how we extract the texture feature for an image.

![Fig. 2. Block diagram of the proposed system for rotation invariant texture feature extraction.](image)

4.1.1. TEXTURE IMAGE

A texture image \( I(x, y) \) can be constructed by first taking the magnitude of the sum of all transform coefficients \( G_m \) and then modifying this value as follows:
\[ I(x, y) = \left\{ \begin{array}{ll}
T(x + N/2, y + N/2), & 1 \leq x \leq N/2, 1 \leq y \leq N/2 \\
T(x + N/2, y - N/2), & 1 \leq x \leq N/2, N/2 < y \leq N \\
T(x - N/2, y + N/2), & N/2 < x \leq N, 1 \leq y \leq N \\
T(x - N/2, y - N/2), & N/2 < x \leq N, N/2 < y \leq N 
\end{array} \right. \]

where \( T(x, y) = \sum_{m=-\infty}^{\infty} G_m(x, y) \)

In above equation, for simplicity (and without loss of generality), we suppose that the image \( I \) is \( N \times N \) and \( N \) is even. Figures 3, 4, and 5 (b) show examples of the texture images extracted using Gabor filters, where Figures 3, 4, and 5 (a) are their original images, respectively.
4.1.2 TEXTURE FEATURE

A texture feature vector $f$ for $S$ scales and $K$ orientations can be constructed using the mean $\mu_{ni}$ and the standard deviation $\sigma_{ni}$ of the magnitude of the transform coefficients $C_{m,n}$ as:

$$f = [\mu_{00}, \sigma_{00}, \mu_{01}, \sigma_{01}, \ldots, \mu_{S-1,K-1}, \sigma_{S-1,K-1}]$$ (10)

Since such a feature vector is not necessarily rotation invariant by its nature, similar texture images with different directions might not be matched in the process of similarity assessment. Some works have already been done to overcome such a problem (e.g. [7] [8] [9] [14] [15] [16]), however, most of them have a very high calculation complexity. In the next section, we will explain how we use the Radon transform to estimate the direction in texture images and then apply this information to construct a rotation invariant feature vector.

4.1.3. ROTATION ESTIMATION

As mentioned in the previous section, the texture feature vector which is calculated by using Gabor filtering is not rotation invariant. To estimate the rotation for texture images, in this work, we apply the Radon transform which has been widely used in image analysis algorithms in recent years [17] [18] [19].

Considering the orientation for texture images, they can be divided into two general categories: (i) anisotropic (directional) and (ii) isotropic textures. One could be expected that while the Gabor transform (and in general, Fourier transform) of an anisotropic texture for two different orientations should be significantly different, it is insignificant in the case of isotropic textures [20] [21]. Based on this fact, if we want to make the system rotation invariant, we should estimate the direction for anisotropic texture images, and extract features for these types of images from their non-rotated versions.

As mentioned in Section 2.3, Radon transform could be used to determine line (line-trends) parameters (its length and angle) in an image. In the case of (anisotropic) texture images, Radon transform is expected to have more variations along the direction where textures have more lines, which can be considered as their main direction.

Figures 3(a) and 3(d) show a leaf image in two different orientations (with a rotation of 40 degrees difference) and Fig. 3(b) and 3(e) indicates their texture images (that are anisotropic) extracted by applying Gabor filters, respectively. Their respective Radon angular variations around their means are also illustrated in Fig. 3(c) and 3(f), respectively. As seen in this figure, two angular distributions have a peak difference of about 40 degree that is equal to the rotation angle difference.

The same story has been repeated in Fig. 4 for a food image. Since this time the textures are isotropic, there is not a significant change in their angular distributions.

As another example, Fig. 5 shows a more complicated image (a building with two trees in front of it). Although in this case, the texture images are neither completely anisotropic, nor completely isotropic, the proposed method works quite well for this example, too. As seen in Fig. 5(c) and 5(f), two angular distributions have a peak difference of about 40 degree that is equal to the rotation angle difference of their original images.

![Fig. 3. Rotation estimation for anisotropic texture images using Radon Transform. (a) Original image, (b) Texture image extracted using Gabor transform, (c) Radon angular variations for texture image (b) which has a peak at 0 degree, (d) A 40 degree rotated version of the original image, (e) Texture image of the rotated image, (f) Radon angular variations for texture image (e) which has a peak at 0 degree.](image)

![Fig. 4. No significant change in Radon angular variations for the rotated version of isotropic texture images. (a) Original image, (b) Texture image extracted using Gabor transform, (c) Radon angular variations for texture image (b) which has a peak at 0 degree, (d) A 40 degree rotated version of the original image, (e) Texture image of the rotated image, (f) Radon angular variations for texture image (e) which has still a peak at 0 degree.](image)

![Fig. 5. Rotation estimation for an image consisting of both anisotropic and isotropic texture images. (a) Original image, (b) Texture image extracted using Gabor transform, (c) Radon angular variations for texture image (b) which has a peak at 0 degree, (d) A 40 degree rotated version of the original image, (e) Texture image of the rotated image, (f) Radon angular variations for texture image (e) with the peak around 40 degree.](image)

4.1.4. ROTATION INVARIANT TEXTURE

After estimating the rotation angle $\alpha_{n}$, we extract invariant texture feature based on a rule suggested by Zheng et al. [16]. In their paper, they proved that the image rotation in spatial domain is equivalent to circular shift of feature vector elements around its dominant orientation. For example, if the original feature vector is "abcde" and "c" is the dominant direction, then the feature vector for the rotated version of the original image with the negative angle of dominant direction is "cefab". In a more detail, this step is done as follows:
(i) Consider the closest possible orientation to $\alpha_s$ as dominant orientation.

(ii) Construct a not rotation invariant feature vector $f_r$ (that is not rotation invariant) from the original transform coefficients $G_{nm}$ (which have already calculated).

(iii) Construct a rotation invariant feature vector $f$ from feature vector $f_r$ by performing circular shift on $f_r$ around the dominant orientation calculated in step (1) based on the Zheng’s rule explained above.

It is clear that in this method, if we consider more possible orientations in Gabor filtering techniques, the precision will be increased. Let us show this fact by an example. Suppose in Eq. (3), $K=4$ (i.e. 4 orientations). Then, the main lobes of the frequency spectrum of Gabor filters are separated by 45 degrees. If $\alpha_s = 30$ degrees, then we have a rotation error of 15 degrees if we consider the dominant direction as 45 degrees. Now let $K=8$ (i.e. the main lobes separated by 22.5 degrees), in this case the rotation error is reduced to 7.5 degree.

4.2. SIMILARITY ASSESSMENT

Since we use two different features in this work, we need to define two different distance functions. The color similarity measurement of a query image $I_Q$ and an image $I_D$ from the database is defined by:

$$D_c(I_Q, I_D) = 1 - \frac{\sum_{j} h_{jQ}^T h_{jD}^T}{\sum_{j} h_{jQ}^T h_{jQ}^T}$$

where $h_{jQ}$ and $h_{jD}$ are the histogram vectors of images $I_Q$ and $I_D$, respectively. The two histograms are more similar when $D_c$ approaches to zero. Here, for simplicity, we calculate the histogram for the luminance component in HIS color system instead of individual color attributes of RGB.

The texture similarity measurement of a query image $I_Q$ and an image $I_D$ from the database is defined based on the Bray-Curtis distance metrics [22]. It was shown by Kokareh et al. that the Bray-Curtis distance has the best performance for texture image retrieval among the other distance metrics [23]:

$$D_t(I_Q, I_D) = \frac{\sum_{j} |f_{jQ}^t - f_{jD}^t|}{\sum_{j} f_{jQ}^t + f_{jD}^t}$$

where $f_{jQ}^t$ and $f_{jD}^t$ are the components of texture feature vectors of images $I_Q$ and $I_D$, respectively. In above equation the numerator signifies the difference and the denominator normalize the difference. Thus $D_t$ will never exceed one, being equal to one whenever either of the attributes is zero. Again, two texture features are more similar if $D_t$ approaches to zero.

To compare the effect of color and texture features in retrieval process together, similarity assessment is done based on three different schemes: (i) color feature only, (ii) texture feature only, and (iii) a weighted average of color and texture features. While for the first and second schemes, we just considered respective similarity distance function, for the third scheme, the final distance calculated using a weighted average of both distances as:

$$D_w(I_Q, I_D) = w_c D_c(I_Q, I_D) + w_t D_t(I_Q, I_D)$$

where $w_c$ and $w_t$ are nonnegative weight values for color and texture features, respectively. To keep the distance less than or equal to one, we should have $w_c + w_t = 1$.

5. EXPERIMENTAL RESULTS

The proposed system was tested on a collection which belongs to a CBIR project at the department of computer science and engineering in university of Washington [24]. The total number of images selected from this dataset is about 800, with sizes 756×504 and 504×756. Some typical images of this collection from different categories are shown in Fig. 6. We also generated 3 rotated version images from each original image with different angles which were selected randomly between 10 to 80 degrees. We then selected a total of 3000 images as images of database, and 100 more images for querying. The query images were chosen in a way that they include images from different categories and with different rotation angles.

Fig. 6. Some typical images used for evaluation [24].

The performance of the proposed system was evaluated by using HitIn_M Assessment formula as:

$$HitIn_M(F, I_Q) = N_R / M$$

Where $F$ is the type of feature(s) used for similarity assessment (color only, texture only, and a weighted average of color and texture features), $I_Q$ is the query image, and $N_R$ is the number of relevant images in $M$ top most candidate images for the query image. The accuracy for 500 query images is then defined as:

$$Accuracy = \frac{\sum_{i=1}^{500} HitIn_M(F, I_Q)}{500}$$

To verify and show the effectiveness of our approach, we did three different experiments as follows:
(i) Using the proposed method in Section 4.1, with $S=4$ and $K=6$, the results are summarized in Table 1 for some different values of $M$, as well as different weight values for the weighted average scheme.

<p>| Table 1. Accuracy for different criterion based on the experiment (i). |
|--------------------|----------------|----------------|</p>
<table>
<thead>
<tr>
<th></th>
<th>Color</th>
<th>Texture</th>
<th>Weighted Average $w_1 = 0.75$, $w_2 = 0.25$</th>
<th>Weighted Average $w_1 = 0.5$, $w_2 = 0.3$</th>
<th>Weighted Average $w_1 = 0.25$, $w_2 = 0.75$</th>
</tr>
</thead>
<tbody>
<tr>
<td>M=50</td>
<td>0.36</td>
<td>0.34</td>
<td>0.37</td>
<td>0.30</td>
<td>0.59</td>
</tr>
<tr>
<td>M=40</td>
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<td>0.39</td>
<td>0.45</td>
<td>0.36</td>
<td>0.64</td>
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<tr>
<td>M=30</td>
<td>0.56</td>
<td>0.61</td>
<td>0.52</td>
<td>0.61</td>
<td>0.70</td>
</tr>
<tr>
<td>M=20</td>
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<td>0.63</td>
<td>0.57</td>
<td>0.65</td>
<td>0.73</td>
</tr>
<tr>
<td>M=10</td>
<td>0.67</td>
<td>0.64</td>
<td>0.61</td>
<td>0.66</td>
<td>0.75</td>
</tr>
</tbody>
</table>

(ii) Using the proposed method in Section 4.1 with the same scale value as the previous experiment (i.e. $S=4$), but with different orientation values ($K=4$, $K=6$, $K=8$, $K=10$). In this experiment, the accuracy just calculated for texture feature and $M=20$. The results are shown in Table 2.

| Table 2. Accuracy of the system based on the experiment (ii) for $M=20$. |
|--------------------|-------|-------|-------|-------|-------|
|                    | Orientations | 4     | 6     | 8     | 10    |
| Accuracy           | 0.63   | 0.66  | 0.69  | 0.71  |

(iii) In this experiment, to show the effectiveness of our approach in increasing the accuracy, we didn’t consider the rotation and just used the original texture features extracted by using Gabor filters with $S=4$ and $K=6$. The results are shown in Table 3.

| Table 3. Accuracy of the system based on the experiment (iii). |
|--------------------|-------|-------|-------|-------|-------|
|                    | M     | 50    | 40    | 30    | 20    | 10    |
| Accuracy           | 0.41  | 0.44  | 0.46  | 0.50  | 0.52  |

In the experiment (i), the best results from viewpoints of accuracy as well as retrieval time were obtained using four scales and six orientations with weighted average mechanism with weights 0.25 and 0.75 for color and texture features, respectively. From the experiment (ii), it is seen that the accuracy of the system is increased as the number of orientations for Gabor transform is increased, however for bigger orientation values, the retrieval time is increased. Finally, the experiment (iii) shows that if we don’t consider the rotation, although the retrieval time is about half of the other experiments, accuracy is very low in compare with the experiments (i) and (ii).

5. CONCLUSION

In this paper, we proposed a system for retrieving images based on color Histogram and texture features, where for extraction of the texture feature vector, we used Gabor wavelet transform. To make the image retrieval system invariant to rotation, we applied the Radon transform on texture images extracted by Gabor filters to estimate the directional information for those texture images which consists of anisotropic textures in their structure. The experimental results on images with very complicated textures show that retrieving is done very efficiently in this work even for the rotated images.

REFERENCES

[16] Zhang D.S. and Lu G., Content-Based Image Retrieval Using Gabor Texture Features, In Proc. of


