Content-based Image Retrieval Using Gabor Texture Features

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Abstract: Gabor wavelet proves to be very useful texture analysis and is widely adopted in the literature. In this paper we present a image retrieval method based on Gabor filter. Texture features are found by calculating the mean and variation of the Gabor filtered image. Rotation normalization is realized by a circular shift of the feature elements so that all images have the same dominant direction. The image indexing and retrieval are conducted on textured images and natural images. Experimental results are shown and discussed.

1. Introduction

This paper describes an image retrieval technique based on Gabor texture feature. Texture is an important feature of natural images. A variety of techniques have been developed for measuring texture similarity. Most techniques rely on comparing values of what are known as second-order statistics calculated from query and stored images [1]. These methods calculate measures of image texture such as the degree of contrast, coarseness, directionality and regularity [2, 3]; or periodicity, directionality and randomness [4]. Alternative methods of texture analysis for image retrieval include the use of Gabor filters [5] and fractals [6].

Gabor filter (or Gabor wavelet) is widely adopted to extract texture features from the images for image retrieval [5, 7, 8, 9, 10, 11], and has been shown to be very efficient. Manjunath and Ma [5] have shown that image retrieval using Gabor features outperforms that using pyramid-structured wavelet transform (PWT) features, tree-structured wavelet transform (TWT) features and multiresolution simultaneous autoregressive model (MR-SAR) features.

Basically, Gabor filters are a group of wavelets, with each wavelet capturing energy at a specific frequency and a specific direction. Expanding a signal using this basis provides a localized frequency description, therefore capturing local features/energy of the signal. Texture features can then be extracted from this group of energy distributions. The scale (frequency) and orientation tunable property of Gabor filter makes it especially useful for texture analysis. Experimental evidence on human and mammalian vision supports the notion of spatial-frequency (multi-scale) analysis that maximizes the simultaneous localization of energy in both spatial and frequency domains [12].

Currently, most techniques make an explicit or implicit assumption that all the images are captured under the same orientations. In many practical applications such as image retrieval, object recognition etc, such an assumption is unrealistic. Some other techniques carry out rotation normalization, but they are computationally demanding [10]. In this paper we propose a rotation normalization method that achieve rotation invariance by a circular shift of the feature elements so that all images have the same dominant direction. We demonstrate our retrieval results both for texture images and for natural images.

The rest of the paper is organized as follows. Section 2 describes fundamentals of 2-D Gabor filters (wavelets). Section 3 discusses texture representation and retrieval based on the output of Gabor filters. In Section 4, we present experimental results of image retrieval based on Gabor texture features. Section 5 concludes the paper with a discussion.

2. Gabor filter (wavelet)

For a given image $I(x, y)$ with size $P\times Q$, its discrete Gabor wavelet transform is given by a convolution:

$$G_{mn}(x, y) = \sum_s \sum_t I(x-s, y-t)\psi^*_{mn}(s,t)$$

where, s and t are the filter mask size variables, and ψ^*_{mn} is the complex conjugate of ψ_{mn} which is a class of self-similar functions generated from dilation and rotation of the following mother wavelet:

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

where W is called the modulation frequency. The self-similar Gabor wavelets are obtained through the generating function:

$$\psi_{mn}(x, y) = a^{-m}\psi(\tilde{x}, \tilde{y})$$

where m and n specify the *scale* and *orientation* of the wavelet respectively, with $m = 0, 1, \ldots M\text{-}1$, $n = 0, 1, \ldots, N\text{-}1$, and

$$\tilde{x} = a^{-m}(x\cos\theta + y\sin\theta)$$

$$\tilde{y} = a^{-m}(-x\sin\theta + y\cos\theta)$$

where $a > 1$ and $\theta = n\pi/N$.

The variables in the above equations are defined as follows:

$$a = (U_h/U_l)^{\frac{1}{M-1}},$$

$$W_{m,n} = a^m U_l$$

$$\sigma_{x,m,n} = \frac{(a+1)\sqrt{2\ln 2}}{2\pi a^m(a-1)U_l},$$

$$\sigma_{y,m,n} = \frac{1}{2\pi\tan(\frac{\pi}{2N})\sqrt{\frac{U_h^2}{2\ln 2}-(\frac{1}{2\pi\sigma_{x,m,n}})^2}}$$

In our implementation, we used the following constants as commonly used in the literature:

U_l= 0.05, U_h=0.4,
s and t range form 0 to 60, i.e, filter mask size is 60x60.

3. Texture representation and retrieval

In this section, we describe texture representation based on Gabor transform, texture similarity calculation and rotation normalization.

3.1 Texture representation

After applying Gabor filters on the image with different orientation at different scale, we obtain an array of magnitudes:

$$E(m, n) = \sum_x \sum_y | G_{mn}(x, y) |,$$

$m = 0, 1, \ldots, M\text{-}1$; $n = 0, 1, \ldots, N\text{-}1$

These magnitudes represent the energy content at different scale and orientation of the image.

The main purpose of texture-based retrieval is to find images or regions with similar texture. It is assumed that we are interested in images or regions that have homogenous texture, therefore the following mean μ_{mn} and standard deviation σ_{mn} of the magnitude of the transformed coefficients are used to represent the homogenous texture feature of the region:

$$\mu_{mn} = \frac{E(m,n)}{P \times Q}$$

$$\sigma_{mn} = \frac{\sqrt{\sum_x \sum_y (| G_{mn}(x, y) | - \mu_{mn})^2}}{P \times Q}$$

A feature vector **f** (texture representation) is created using μ_{mn} and σ_{mn} as the feature components [5, 10]. Five scales and 6 orientations are used in common implementation and the feature vector is given by:

$\mathbf{f} = (\mu_{00}, \sigma_{00}, \mu_{01}, \sigma_{01}, \ldots, \mu_{45}, \sigma_{45})$.

Figure 3.1 shows the energy map of the mean feature elements μ_{mn} for a straw texture image.

3.2 Rotation invariant similarity measurement

The texture similarity measurement of a query image Q and a target image T in the database is defined by:

$$D(Q, T) = \sum_m \sum_n d_{mn}(Q, T)$$

where

$$d_{mn} = \sqrt{(\mu_{mn}^Q - \mu_{mn}^T)^2 + (\sigma_{mn}^Q - \sigma_{mn}^T)^2}$$

Since this similarity measurement is not rotation invariant, similar texture images with different direction may be missed out from the retrieval or get a low rank. For example, images in Fig.1(a) and Fig.1(c) are the same image with different orientation but will have very big distance if the above measurement is applied directly. In [5], rotation invariance was not considered. In [10], feature elements are shifted in all the directions to find the best match between query image and target images. It needs expensive calculation. In this paper we proposed a simple circular shift on the feature map to solve the rotation variant problem associate with Gabor texture features. Specifically, we calculate total energy for each orientation. The orientation with the highest total energy is called the dominant orientation/direction. We then move the feature elements in the dominant direction to be the first elements in ***f***. The other elements are circularly shifted accordingly. For example, if the original feature vector is "*abcdef*" and "*c*" is at the dominant direction, then the normalized feature vector will be "*cdefab*". This normalization method is based on the assumption that to compare similarity between two images/textures they should be rotated so that their dominant directions are the same.

We now need to prove that image rotation in spatial domain is equivalent to circular shift of feature vector elements. Assume the original image is $I(x, y)$ with dominant orientation at $i\pi/N$. $I'(x, y)$ is the rotate version of $I(x, y)$ so that its dominant orientation is at 0. If at a particular scale m, the energy distribution of $I(x, y)$ is

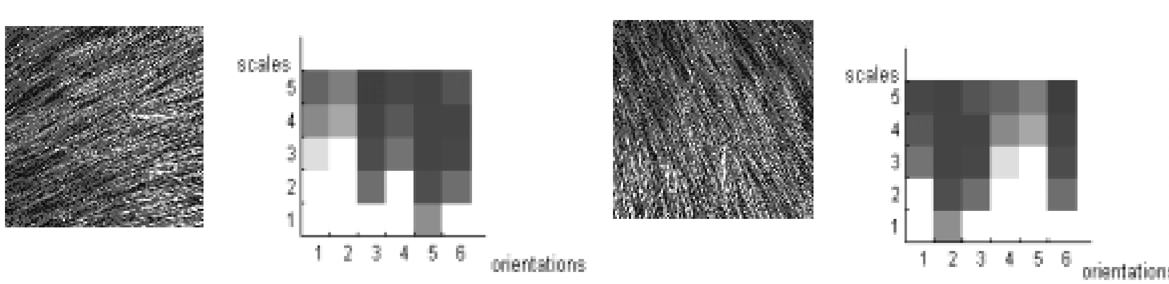
$$(E_{m,0}, E_{m,1}, \ldots E_{m,i}, \ldots E_{m,N-1})$$

then the energy distribution of $I'(x, y)$ is

$$(E'_{m,-i}, E'_{m,1-i}, \ldots E'_{m,0}, \ldots E'_{m,N-1-i}).$$

where $E_{m,0} = E'_{m,-i}$, $E_{m,1} = E'_{m,1-i}$, and so forth. Because $E'_{m,n} = E'_{m,n+N}$ (an image has the same energy distribution after rotating 180°.), we have $E'_{m,-i+N} = E'_{m,-i}$, $E'_{m,1-i+N} = E'_{m,1-i}$, etc. (Negative orientations are added by N). We then have the following energy distribution of $I'(x, y)$:

$$(E'_{m,-i+N}, E'_{m,1-i+N}, \ldots E'_{m,0}, \ldots E'_{m,N-1-i}).$$



(a) (b) (c) (d)

Figure 1. (a) a straw image, (b) energy map of (a), (c) rotated image of (a), (d) energy map of (c)

Reorder the above distribution according to orientation values, we have

$$(E'_{m,0}, E'_{m,1}, \ldots E'_{m,N-1-i}, E'_{m,N-i}, E'_{m,N-i+1} \ldots E'_{m,N-1})$$

which is the circular rotation of the original feature vector. This proves that rotation in the spatial domain is equivalent to circular shift of Gabor feature elements.

Figure 1 shows two texture images and their feature maps, the second image is a rotation of 90° of the first image. It is shown in the feature maps that image (a) has a dominant direction feature in orientation 2 (60°), while in image (b), this dominant direction feature has moved to orientation 5 (150°) and features in other directions are circularly shifted accordingly.

Compared with rotation invariant methods in [10, 11], our algorithm is simple and intuitive.

4. Experiment results

We have conducted retrieval tests both on texture images and natural images. Figure 2 shows our preliminary results on image retrieval using Gabor texture features. In all the four retrieval results shown, the top left image is the query image and the other images are retrieved images from the image database. The first 25 retrieved images are shown for illustration. The retrieved images are ranked in decreasing order based on the similarity of their Gabor texture features to those of the query image.

Figure 2(a) shows a retrieval result from texture image database which composed of 1,000 different kind of texture images collected from [13]. All the 15 similar textures in the database are retrieved in the first 18 images and there is only one irrelevant image in the first 25 retrieved images. In (b) all the 18 similar textures in the database are retrieved in the first 18 images and the remaining are also relevant. Same textures with different orientations have been ranked most highly, it demonstrates our retrieval algorithm is rotation invariant.

Figures 2(c) (d) are conducted on color image database which is composed of 360 different kind of images of flower, landscape, computer generated animation images etc. Figure 2(c) shows the retrieval result for a query using a flower image. The 5 images with same flowers in the database are all retrieved out in the first 24 ranked images. Images with similar flower pattern are also found in the upper rank. The fifth flower image with similar flower pattern to the query image is ranked very low because its background texture is very different from that of the query image.

Figure 2(d) is a query using a landscape image. As can be seen, most of the first 25 retrieved images are images with similar landscape to that in the query image. It shows that the proposed method works well for retrieval of images with overall homogeneous texture.

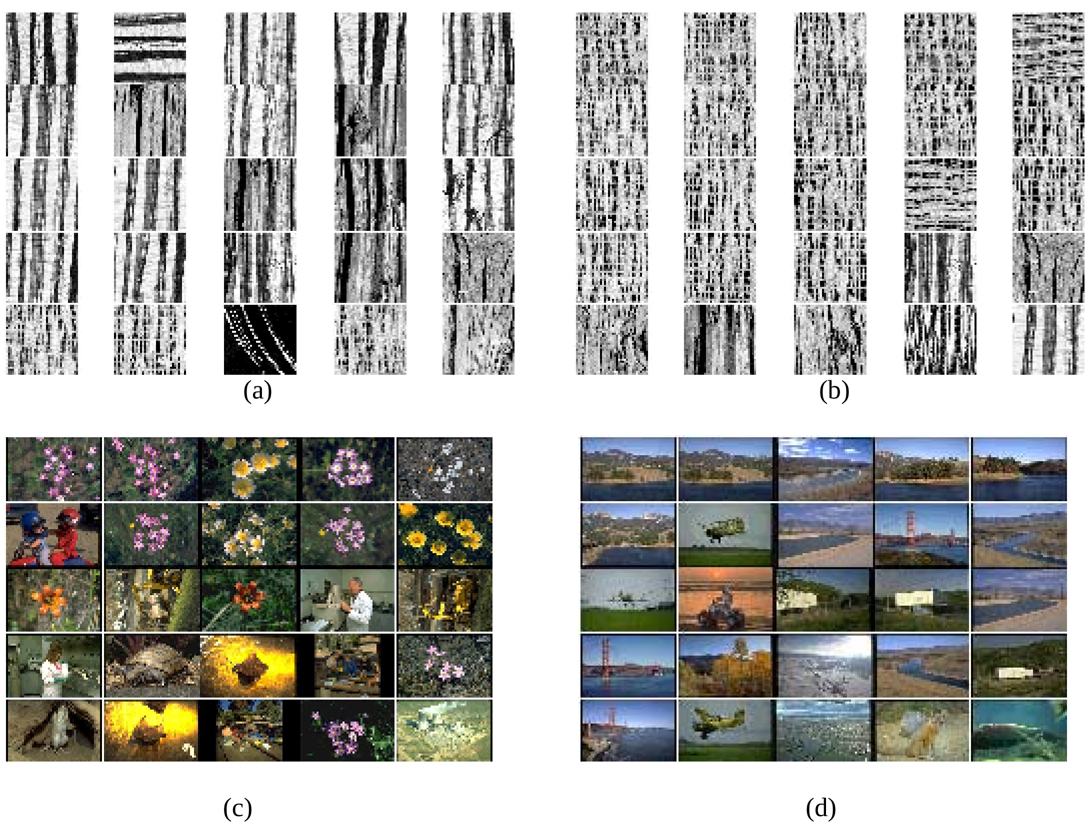


Figure 2. Image retrieval results using Gabor texture features

5. Conclusions and future work

In this paper we have presented an image retrieval method based on Gabor texture features of the images. The preliminary retrieval results have been shown and examined. Our retrieval algorithm is rotation invariant. In the paper, global texture features are extracted from the entire image, the extracted texture features are then used to measure the similarity between images. This method is most useful if the entire image or main part of the image has a uniform texture. In reality, an image may be considered as a mosaic of different texture regions. As such, texture-based image retrieval can be conducted after images have been segmented using texture features. After segmentation, images can be compared region by region. Furthermore, since texture is hard to describe or define, in a retrieval system, users are often given examples to select for retrieval, the example textures are usually homogeneous and correspond to different parts of images. Therefore, texture retrieval is very useful for region-based retrieval. In our future work, texture segmentation will be incorporated into our system to facilitate texture-based retrieval. Scale invariance will also be considered.

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