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Content Based Image Retrieval Using Texture Structure Histogram and Texture Features

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Abstract

In Content Based Image Retrieval one of the most important features is texture. In this paper we present a image retrieval based on Texture Structure Histogram (TSH) and Gabor texture feature extraction. In TSH technique to describe the texture feature, we use the edge orientation and color information method. The HSV color space will be used in this technique for humans visual perception mechanism. To make the image content more reasonable non-equal interval quantization scheme will be used. One of the important texture feature analysis method is Gabor texture feature extraction. Using the mean and variation of Gabor filtered image the image texture will be retrieved. To get the same dominant direction rotation normalization will be used. In this paper the comparison of both the texture techniques will be discussed. This mechanism gives a good retrieval performance and more efficient techniques.

Keywords: CBIR, TSH, Feature Representation, and Gabor filter, Edge Orientation.

I. INTRODUCTION

In recent years, with the rapid development of digital image processing technology, helping the user to find the multimedia information what they need quickly and effectively becomes a hot research topic at present. Image retrieval is a major component of multimedia information retrieval technology, and also one of the basic theory of video information retrieval, it play a significant role in the field of information retrieval. Image retrieval is based on users' query requests, extract an image or image set that related to the query image from the image dataset. Generally, three categories of methods for image retrieval are used: text-based, content-based and semantic-based. The content-based image retrieval (CBIR) has been proposed in the early 1990's. This approach is to retrieve images using low-level features like color, texture and shape that can represent an image.

Texture is one of the most important characteristics of an image. Texture features are also widely used in CBIR systems. Various algorithms have been designed for texture analysis, such as gray level co-occurrence matrices, the Tamura texture feature, the Markov random field model, Gabor filtering, and local binary patterns. Tamura et al., based on human visual psychology research put forward some different methods to describe the texture feature, give a description of several different terms: coarseness contrast and directionality, line likeness, regularity, roughness, etc. This paper uses the color and edge orientation feature that describe the texture information correctly.

Gabor filter (or Gabor wavelet) is widely adopted to extract texture features from the images for image retrieval, and has been shown to be very efficient. 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.

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, objects 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 achieves 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.

2. HSV COLOR SPACE AND QUANTIZATION

Color information is the bottom and intuitive physical characteristics. Because color is robust to the effects of noise, size and orientation of image, so color feature is most commonly used in content-based image retrieval. Color quantization is closely related to the color space. A lot kinds of color spaces have been proposed and used for image retrieval. However, different color space has different application, we usually hard to decide which kind of color space is most suitable for our image retrieval algorithm. The HSV color space could mimic human color perception well.

Color Non-Equal Interval Quantization in HSV Color Space

In order to cut down the computing complexity and extract the color features in efficient way, we use HSV color space and quantize it into non-equal interval 72 bins, thus we get the color index image C(x, y). As is known to all, quantizing the H, S and V channels uniformly is not suitable for human's visual perception and recognition. We give our non-equal interval quantization scheme as follows. Fig.1 shows that our quantization scheme is better than the equal interval scheme.

a. RGB image b. equal interval c. non-equal interval

Fig. 1 HSV quantization scheme

Edge Orientation Quantization in HSV Color Space

Edge orientation also plays an important role in content-based image retrieval. Edge orientation information can represent the object's shape and boundaries perfectly. In this paper, we use a simple and effective method for edge orientation detection.

Let $a = (H_x S_x, V_x)$ and $b = (H_y, S_y, V_y)$, where H_x, S_x and V_x denotes the gradient in H, S and V channel along horizontal direction respectively, and H_y, S_y and V_y denotes the gradient in H, S and V channel along vertical direction respectively.

After the edge orientation θ(x,y) of each pixel has been computed, the orientations are uniformly quantized into 18 bins with each corresponding to angle of 20°. It is most reasonable according to the experiments.

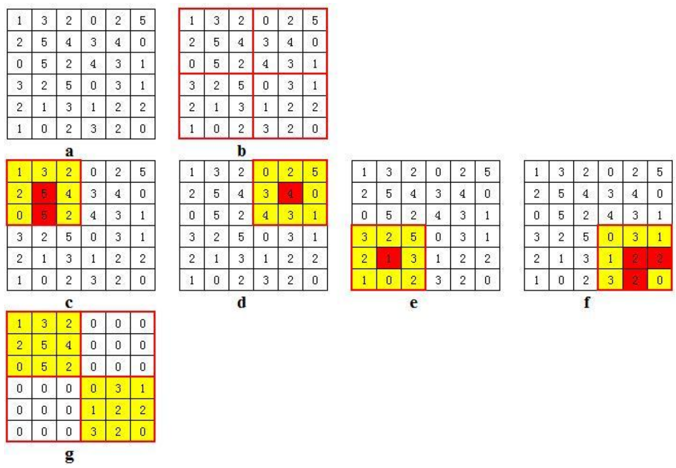
Thus we get the edge orientation index image $\theta(x, y)$

3. FEATURE EXTRACTION

Structure Map Construction and Feature Representation

According to the color index image, we build the color structure map. Similarly, we can build the edge orientation structure map and we omit it here. The details of the process are illustrated in Fig.2. For the color index image, a 3×3 block filter throughout the image from left to right and top to bottom with 3-step length. Then, we consider the value of central point of the 3×3 block and the values of its four neighborhoods. If the value of central point equals to that of its four neighborhoods, then the values of the 3×3 block will be remained, otherwise, the values will be set to zero. Finally, we get the color structure map $T(x, y)$. Similarly, the edge orientation structure map $O(x,y)$. Fig.2 shows the processing of the color information detection.

After previous operation, we can obtain the color structure map $T(x, y)$ and its index value is denoted as p 0, 1, ... , P 1 . For each point (x_0, y_0) in $T(x, y)$, we denote its index value$T(x_0, y_0)p0$ and the index values are $T(xi,yi)\ pi$, $(i1,2,3,4)$.



3.1 Feature Fusion

For some images, its texture information is very rich. However, for some kinds of images, its edge orientation information seems to be much richer. Thus we give different weights to the two features according to the attribute of images. According to the experiment, we train the parameters to get the most suitable one whose precision is the highest.

H_{color} (T (x, y)) and H_{ori}(O(x, y)) as the final feature vector H, namely Texture Structure Histogram (TSH).

4. GABOR FILTER (WAVELET)

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

$$Gmn(x, y) = \sum\sum I(x - s, y - t)\psi mn * (s, t)$$

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:

$$\psi\ (x, y)\ = \frac{n1\ exp\ [\ -1(x2\ +\ y2)]\ \cdot exp(\ j2\pi Wx)x}{2\pi\sigma x\sigma y\ 2\ \sigma x2\ \sigma y2}$$

where W is called the modulation frequency.

The self-similar Gabor wavelets are obtained through the generating function:

$$\psi mn(x, y)\ =\ a\frac{\overline{m}{\sim}{\sim}}{\psi(x, y)}$$

where m and n specify the *scale* and *orientation* of the wavelet respectively, with m = 0, 1, …M-1, n = 0, 1, …, N-1, and

$$\tilde{x} = a - m\ (xcos\theta +\ \ ysin\theta\ )$$

$$\tilde{v} = a - m\ (-xsin\theta +\ \ ycos\theta\ )$$

Where a>1 and $\theta = n\pi/N$. and 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 from 0 to 60, i.e, filter mask size is 60x60

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

Texture representation

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

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

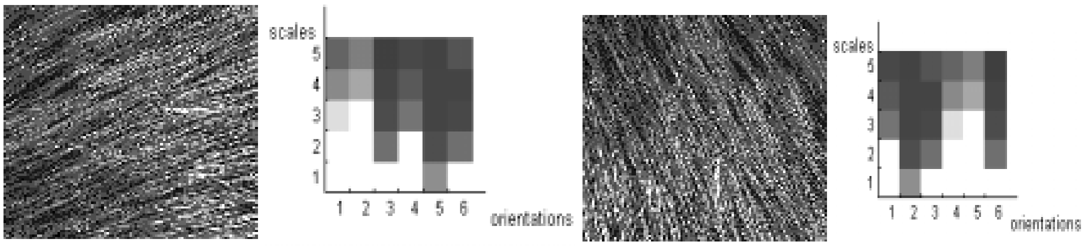
$m = 0, 1, \ldots, M\text{-}1;\ n = 0, 1, \ldots, N\text{-}1$

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 $\sigma_{mn}$and standard deviation σ_{mn} of the magnitude of the transformed coefficients are used to represent the homogenous texture feature of the region

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

$$f\ = (\propto 00, \sigma 00, \propto 01, \sigma 01, \ldots\ldots\ \propto 45, \sigma 45,)$$

Rotation invariant similarity measurement



(a) straw image. (b) Energy map (c) rotated image (d) energy map

Figure 3:

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

$$\mathrm{D(Q,T)} \ = \sum_{\mathrm{m}} \sum_{n} d_{mn}\ (\mathrm{Q,T})$$

Where

$$d_{mn} = \ \sqrt{(\propto mnQ - \propto mnT\ )^2 + \ (\sigma\, mnQ\ -\ \sigma\, mnT\ )^2}$$

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 Figure.3 (a) and Figure.3(c) are the same image with different orientation but will have very big distance if the above measurement is applied directly.

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 $\boldsymbol{f}$. 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 rotating180^o.),

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 $I'(x, y)$:

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

Reorder the above distribution according to orientation values, we have

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

This 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 degree of the first image. It is shown in the feature maps that image (a) has a dominant direction feature in orientation 2 (60degree), while in image (b), this dominant direction feature has moved to orientation 5 (150 degree) and features in other directions are circularly shifted accordingly. Compared with rotation invariant methods in [10, 11], our algorithm is simple and intuitive

5. CONCLUSION

In this paper, we propose a novel image feature representation method, namely, texture structure histogram (TSH). It is an effective image feature for image retrieval. First, the HSV color space is used; because HSV color space conforms to people's subjective judgment of color similarity, that is to say, HSV color space conforms to human visual perception. Then, we propose a novel non-equal interval quantization scheme that according to the different attribute and distribution of the H, S and V channels. Building texture structure map is also a key step, which provides a good feature representation for the texture information of image. TSH integrates the advantages of both color and texture features, and shows a good retrieval performance. 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. The experimental results demonstrate that the proposed algorithms have a better performance for image retrieval.

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