Retrieval Image by Region Classification

RYSZARD S. CHORAS University of Technology and Agriculture S. Kaliskiego 7, 85-791 Bydgoszcz POLAND

ABSTRACT

The retrieval of images from a large database of images is an important and emerging area of research. Highresolution images in the physical database are decomposed into sets of image features which are stored in the logical database. Currently a few image retrieval systems combining color and texture as features to search images. In this paper 2D image is processed using a set of Gabor filter to derive a feature vector representing texture in the image. Color information in an image is represented by color histogram. This method is useful for processing large collections of image data.

KEY WORDS: Image retrieval, Texture, Gabor functions, Color histogram .

1. INTRODUCTION

In wide domains the majority of data is archival in the form of images. For the management of archived image data, an image database system which supports the analysis, storage and retrieval of images is needed (Fig.1). Much attention is done to the problems of how to retrieve images efficiently. Image matching and retrieval is based on some characteristic features. The input images are analyzed to extract the features and these features are stored in the database, along with the original images. Whenever an image is submitted for search its features are extracted. These extracted features are matched against those in the database.

Image data retrieval can be done using following_{ilte} features:

- low level features e.g. color, histogram, texture information,

- intermediate level features including shape primitives,

- highest level features including domain specific information.

We consider a color and texture information as the basic feature which are then used to retrieve images.

Pixels do not participate directly in the search process, and are only used for extraction of the features. For each image a feature vector is extracted and stored. Searching is done by sequentially going through each feature vector

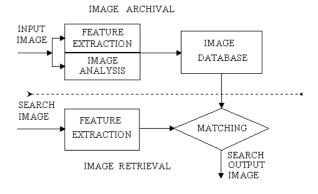


Fig.1. An image retrieval model

stored in the database and computing its distance to the input images feature vector.

Let

$$\{\underline{F}(x, y): x = 1, 2, \dots M, y = 1, 2, \dots N\}$$

be a 2D image pixel array. $\underline{F}(x, y)$ denotes the color value at pixel (x, y)

$$\underline{F}(x, y) = \{F_R(x, y), F_G(x, y), F_B(x, y)\}$$

for color images, and the gray scale intensity value at pixel (x, y) for monochrome images.

We propose the use of oriented multi-resolution Gabor filters to extract features from the database images.

2. COLOR FEATURES

Color is an important attribute for image retrieval. The pixels in the image are represented in the *RGB* space by which define the color features as the red, green and blue value at each pixel.

Regardless of the color space color information in an image can be represented either by a single 3D histogram or three separate 1D histograms. These color representation are essentially invariant under rotation and translation of the input images.

Color histograms are used as feature vectors for image. Describes the global color distribution in the image. Color histograms are created on the basis of each color features for each image in the image database by counting the number of times a discrete color feature.

If the colors in image *F* are quantized into *m* colors C_1, \ldots, C_m then the histogram is defined for $i \in [m]$ by

$$h_{c_i} = N \Pr[(x, y) \in F_{c_c}]$$

and

$$F_{c_i} = \{(x, y) | F(x, y) = c_i\}$$

Histogram h^Q derived from a query image Q is similar to histogram h^{F_k} constructed for each image F_k in the database and a similarity function is defined as

$$d(h^{\mathcal{Q}}, h^{F_k}) = \frac{\sum \min(h^{\mathcal{Q}}, h^{F_k})}{N}$$

We have also used cooccurrence feature which is given by

$$Co_{c_i,c_j}(F) = |F(x_1, y_1) = c_i, F(x_2, y_2) =$$

= $c_j |\max\{|x_1 - x_2|, |y_1 - y_2|\} = k |$

3. GABOR FILTER

Gabor filters are well recognized in the recent past as a joint spatial/spatial-frequency representation of textures. The 1D Gabor function was first defined by Gabor and later extended to 2D by Daugman. A 2D Gabor filter is an oriented complex sinusoidal grating modulated by a 2D Gaussian function, which is given by

$$G_{\sigma,\phi,\theta}(x,y) = g_{\sigma}(x,y) \exp[2\pi j\phi(x\cos\theta + y\sin\theta)]$$

where

$$g_{\sigma} = \frac{1}{2\pi\sigma^2} \exp\left[-\left(x^2 + y^2\right)/2\sigma^2\right]$$

The frequency is given by ϕ and orientation by θ . $g_{\sigma}(x, y)$ is the Gaussian function with scale parameter σ . The parameters of a Gabor filter are therefore given by the frequency ϕ , the orientation θ and the scale σ .

The Gabor filter $G_{\sigma,\phi,\theta}(x,y)$ forms complex valued function. Decomposing $G_{\sigma,\phi,\theta}(x,y)$ into real and imaginary parts gives

$$G_{\sigma,\phi,\theta}(x,y) = R_{\sigma,\phi,\theta}(x,y) + jI_{\sigma,\phi,\theta}(x,y)$$

where

$$R_{\sigma,\phi,\theta} = g_{\sigma} \cos[2\pi\phi(x\cos\theta + y\sin\theta)]$$

 $I_{\sigma,\phi,\theta} = g_{\sigma} \sin[2\pi\phi(x\cos\theta + y\sin\theta)]$

The Gabor filtered output of an image F(x, y) is obtained by the convolution of an image with the Gabor function $G_{\sigma,\phi,\theta}(x, y)$.. Given a window size $W \times W$ for W = 2l + 1, the discrete convolutions of F(x, y) with components of $G_{\sigma,\phi,\theta}(x, y)$ are

$$C_{R}(x, y \mid \sigma, \phi, \theta) = \sum_{w=-l}^{l} \sum_{v=-l}^{l} F(x + w, y + v) R_{\sigma, \phi, \theta}(w, v)$$

$$C_{I}(x, y \mid \sigma, \phi, \theta) = \sum_{w=-l}^{l} \sum_{v=-l}^{l} F(x + w, y + v) I_{\sigma, \phi, \theta}(w, v)$$

Define the energy $E(x, y | \sigma, \phi, \theta)$ at (x, y) as

$$E(x, y | \sigma, \phi, \theta) = C_R^2(x, y | \sigma, \phi, \theta) + C_I^2(x, y | \sigma, \phi, \theta)$$

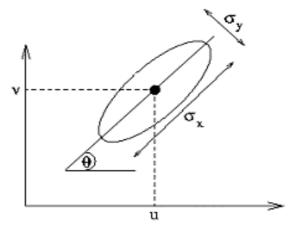


Fig.2. Parameters defining filter in the frequency domain.

See Fig.3 for examples of the filters at various orientations and scales.



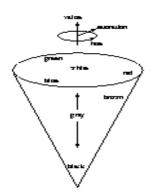
Fig.3. Real components of Gabor wavelet filters at different orientations and scales

Gabor features are calculated independently on each color band.

The RGB space has the major deficiency of not being perceptually uniform. We consider new color space which is reached from the RGB space. We transform the RGB image data to the HVS color model. Now

$$F^*(x,y) = S(x,y)e^{jH(x,y)}$$

where S(x, y) is saturation, and H(x, y) is hue (Fig.4)



REFERENCES

[1] P. Wu, B.S. Manjunath, S. Newsam, H.D. Shin, A texture descriptor for browsing and similarity retrieval, *Signal Processing: Image Communications, 16*, 2000, pp. 33-43.

[2] B.S. Manjunath, W.Y. Ma, Texture features for browsing and retrieval of image data, *IEEE Transaction on Pattern Analysis and Machine Intelligence*, *18* (8), 1996, pp. 837-842.

[3] T.P. Weldon, W.E. Higgins, D.F. Dunn, Efficient Gabor filter design for texture segmentation, *Pattern Recognition*, . 29(12), 1996, pp.2005-2015

[4] A. Jain, F. Farrokhma, Unsupervised texture segmentation using Gabor filters, *Journal of Pattern Recognition*, .24, 1991, pp.1167-1186

Fig.4. The color cones.

4. IMAGE RETRIEVAL PROCESS

The retrieval process is defined as follows:

1. Image F(x, y) in the database is represented by image matrix F and feature vector,

2. Search image is represented by feature vector,

3. Similarity between search image and the database image

is then evaluated by combining individual feature vector representation similarity,

4. The database images are ordered by their similarity

to search image,

5. The image with higher similarity is marked.

5. CONCLUDING REMARKS

We have presented a content based image retrieval ystem which is based on texture features. Textured images have space-varying local properties. The feature extraction is based on the mechanism of multichannel representation of the retinal images in the biological visual system. The local properties of the texture can be obtained using a set of Gabor filters. The proposed texture descriptor provides a robust representation of many images.