Hepatic CT image query using Gabor features

Chenguang Zhao (赵晨光)[1], Hongyan Cheng (程红岩)[2], and Tiange Zhuang (庄天戈)[1]

[1]*Department of Biomedical Engineering, shanghai Jiaotong University, Shanghai 200030*
[2]*Department of Radiology, Hepatobiliary Surgery Hospital, Shanghai 200030*

Received April 19, 2004

A retrieval scheme for liver computerize tomography (CT) images based on Gabor texture is presented. For each hepatic CT image, we manually delineate abnormal regions within liver area. Then, a continuous Gabor transform is utilized to analyze the texture of the pathology bearing region and extract the corresponding feature vectors. For a given sample image, we compare its feature vector with those of other images. Similar images with the highest rank are retrieved. In experiments, 45 liver CT images are collected, and the effectiveness of Gabor texture for content based retrieval is verified.

OCIS codes: 100.2000, 100.2960, 100.6950, 100.7410.

In medicine, texture information is very useful when computerize tomography (CT) images are used for diagnosis. A successful content based CT image retrieval (CBIR) system[1−3] for medical use must incorporate texture features. When texture analysis is a main concern, Gabor scheme is a powerful tool, because primitives of image representation in vision have a wavelet form similar to Gabor elementary functions (EFs)[4]. Gabor functions are often used in current models of image representation in the visual cortex because they are good approximations to the receptive fields of simple cortical cells. According to the Gabor approach, an image $\phi(x,y)$ can be represented as a linear combination of EFs[5]

$$\phi(x,y)=\sum_{m_x n_x m_y n_y} a_{m_x n_x m_y n_y} f_{m_x n_x m_y n_y}(x,y), \quad (1)$$

where $f_{m_x n_x m_y n_y}$ is the EF of the order $(m_x n_x m_y n_y)$,

$$f_{m_x n_x m_y n_y}=g(x-m_x D_x, y-m_y D_y) \times \exp(in_x W_x x+in_y W_y y), \quad (2)$$

and $g(\cdot,\cdot)$ is a two-dimensional normalized window function.

The function $f_{m_x n_x m_y n_y}(x,y)$ is situated at the point $(x=m_x D_x,\ y=m_y D_y)$ of the Gabor lattice and has a spatial frequency of $(\omega_x=n_x W_x,\ \omega_y=n_y W_y)$. The constants D_x, D_y and W_x, W_y are the basic sampling intervals along the spatial and spatial-frequency axes respectively. $a_{m_x n_x m_y n_y}$ is the coefficient of the order $(m_x n_x m_y n_y)$, representing the relative weight of the respective EF in the image $\phi(x,y)$.

When a Gaussian window function is employed as $g(\cdot,\cdot)$, the Gabor EFs are not orthogonal. The coefficients $\{a_{m_x n_x m_y n_y}\}$ are calculated using an auxiliary function $\gamma(\cdot,\cdot)$, which is biorthogonal in a certain sense to the window function $g(\cdot,\cdot)$, defined as

$$a_{m_x n_x m_y n_y}=\iint \phi(x,y)\gamma^*(x-m_x D_x, y-m_y D_y) \times \exp(-in_x W_x x-in_y W_y y)\,\mathrm{d}x\mathrm{d}y. \quad (3)$$

When a square window function is used, the resultant function $f_{m_x n_x m_y n_y}$ is orthogonal and the functions $g(\cdot,\cdot)$ and $\gamma(\cdot,\cdot)$ are identical, thus simplifying the computation process. For simplicity, the square window function is used in this paper.

Texture analysis takes the form of inner product or correlation of Gabor EFs with images. Features characterizing texture are defined in relation to the EF parameters. The six features defined by Porat and Zeevi are dominant localized frequency (denoted by F), variance of the dominant localized frequency (VF), dominant orientation (T), variance of the dominant orientation (VT), mean of the localized intensity level (L), and variance of the localized intensity level (VL), and are respectively expressed as

$$F_{m_x m_y}=\frac{\sum_{n_x=1}^{N-1}\sum_{n_y=1}^{N-1}\left|a_{m_x n_x m_y n_y}\right|\sqrt{n_x^2+n_y^2}}{\sum_{n_z=1}^{N-1}\sum_{n_y=1}^{N-1}\left|a_{m_x n_x m_y n_y}\right|}, \quad (4)$$

$$VF_{m_x m_y}=\frac{\sum_{n_x=1}^{N-1}\sum_{n_y=1}^{N-1}\left|\sqrt{n_x^2+n_y^2}-F_{m_x m_y}\right|}{N^2}, \quad (5)$$

$$T_{m_x m_y}=\frac{\sum_{n_x=1}^{N-1}\sum_{n_y=1}^{N-1}\left|a_{m_x n_x m_y n_y}\right|\theta(n_x,n_y)}{\sum_{n_z=1}^{N-1}\sum_{n_y=1}^{N-1}\left|a_{m_x n_x m_y n_y}\right|}, \quad (6)$$

$$VT_{m_x m_y}=\frac{\sum_{n_x=1}^{N-1}\sum_{n_y=1}^{N-1}\left|\theta(n_x,n_y)-T_{m_x m_y}\right|}{N^2}, \quad (7)$$

$$L_{m_x m_y}=\frac{1}{K}\sum_{x,y\in A(m_x m_y)}\phi(x,y), \quad (8)$$

$$VL_{m_x m_y}=\frac{1}{K}\sum_{x,y\in A(m_x m_y)}\left|\phi(x,y)-L_{m_x m_y}\right|, \quad (9)$$

where $a_{m_x n_x m_y n_y}$ is defined in Eq. (3), $\theta(n_x,n_y)$ indicates the wavelet orientation satisfying $\tan[\theta(n_x,n_y)]=n_y/n_x$ for $n_x\neq 0$ and $\tan[\theta(n_x,n_y)]=\pi/2$ for $n_x=0$, and $A(m_x m_y)$ is the set of K pixels belonging to the area defined by the window function centered according to m_x, m_y.

Here, to testify the feasibility of Gabor approach in querying liver CT images, 45 images, with 4 types of hepatic CT manifestations, were collected. They are 14 images of low attenuation, with infiltration, 5 images of uniformly low attenuation, 13 images of multi-focal nodular type, and 13 images of lipiodol retention. For each image, we manually delineate the abnormal regions to generate an image segment.

Porat and Zeevi have used the six texture features defined in Eqs. (4)−(9) to classify the natural textures, and the results are satisfactory. Unfortunately, these features show inability when applied to classification of hepatic pathology bearing patches. In Fig. 1, we divide the six features into 3 pairs, that is, (F, VF), (T, VT), and (L, VL). Taking each pair as a coordinates system, we plot the 2-tuple feature vectors as markers on it. Of the four types of CT manifestations, samples with lipiodol retention can be identified easily using F or L (they are not plotted in the figure), but other types of samples are mixed together. As a result of hepatic lobule and hepatic plate imaging, a liver in a CT image presents a granular texture, including high frequency components in it. So, features defined by F, VF, and VL failed to differentiate different CT findings because of the interference of these high frequency components.

To adopt Gabor scheme to liver texture retrieval, we introduce the other two features based on Gabor transform,

$$F^1_{m_x m_y} = \left(a_{m_x 0 m_y 1} + a_{m_x 1 m_y 0}\right)/2 \tag{10}$$

and

$$F^2_{m_x m_y} = a_{m_x 1 m_y 1}. \tag{11}$$

They are Gabor coefficients with low frequencies. Using $F^1_{m_x m_y}$, $F^2_{m_x m_y}$, and L, defined in Eqs. (10), (11), and (8), respectively, we associate with each sample a 3-tuple

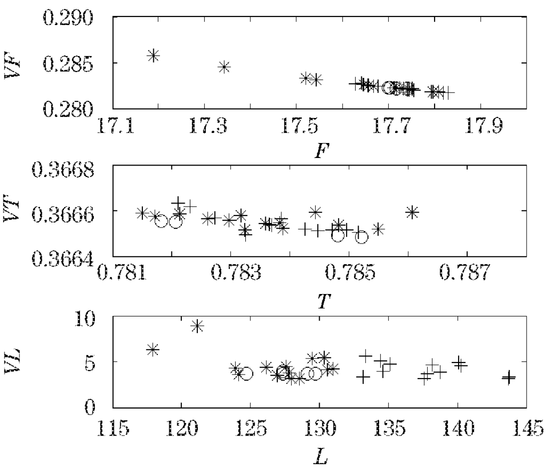

Fig. 1. Hepatic texture classification using features defined in Eqs. (4)−(9) when 16×16 square window size is used. Asterisks: low attenuation with infiltration; crosses: multi-focal nodular; circles: uniformly low attenuation.

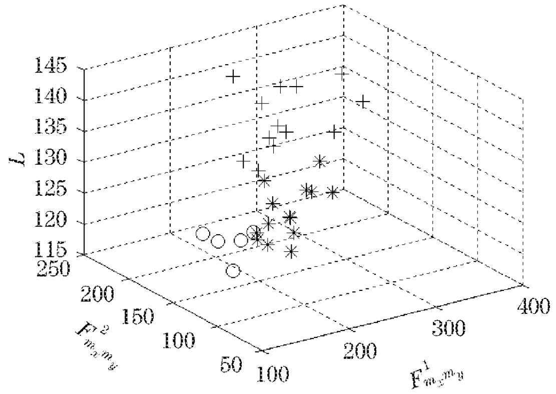

Fig. 2. Hepatic texture classification using features defined in Eqs. (10), (11), and (8) when 16×16 square window size is used. Asterisks: low attenuation with infiltration; crosses: multi-focal nodular; circles: uniformly low attenuation.

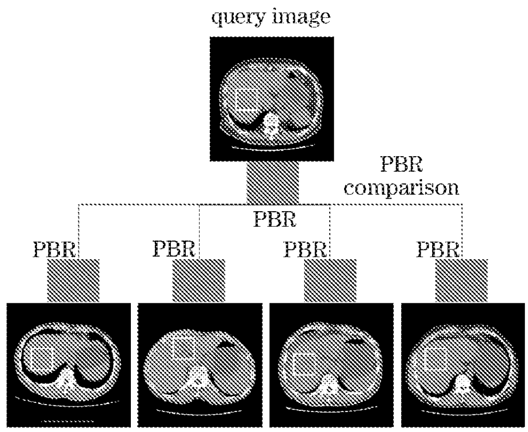

Fig. 3. Liver CT image retrieval based on Gabor texture of PBRs.

Table 1. Mean Number of Correct Retrievals for Each Category

	Correct Retrievals	Percent of Total
Low Attenuation with Infiltration	3.29	0.82
Uniformly Low Attenuation	2.80	0.70
Multi-Focal Nodular Type	3.54	0.88
Lipiodol Retention	4.00	1.00

feature vector. The distribution of these samples in the feature space is shown in Fig. 2. We can see that the new feature vector is capable of classifying the samples into different groups, which is the precondition of successful retrieval schemes.

To show the effectiveness of the 3-tuple feature vector in hepatic CT image retrieval, we take each CT image segment as a query sample and compare the feature vector of its pathology bearing region (PBR) with those of others using Euclidean distance (see Fig. 3). The four most similar samples are retrieved. For each category, we show the mean of the number of retrieved samples that share the same category with the query sample (see Table 1).

In conclusion, we present a CBIR scheme for hepatic image data. For each image, we manually delineate its PBR. Then, we use Gabor analysis to calculate the texture features. In query procedure, the feature vector of the query image is compared with other feature vectors using Euclidean distance metric, and the four images with the highest similar rank are retrieved. In experiments, the effectiveness of Gabor features is verified.

This work was supported by the National Natural Science Foundation of China under Grant No. 60272081. C. Zhao's e-mail address is zhao_c_g@263.net.

References

1. A. Pentland, R. W. Picard, and S. Sclaroff, Proc. SPIE **2185,** 34 (1994).
2. M. Flickner, H. Sawhney, W. Niblack, J. Ashley, Q. Huang, B. Dom, M. Gorkani, J. Hafner, D. Lee, D. Petkovic, D. Steele, and P. Yanker, IEEE Computer **28,** 23 (1995).
3. C. Shyu, C. E. Brodley, A. C. Kak, A. Kosaka, A. M. Aisen, and L. S. Broderick, Computer Vision and Image Understanding **75,** 111 (1999).
4. M. Porat and Y. Y. Zeevi, IEEE Trans. Biomedical Engineering **36,** 115 (1989).
5. M. Porat and Y. Y. Zeevi, IEEE Trans. Pattern Analysis and Machine Intelligence **10,** 452 (1988).