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Robust Feature for Transcranial Sonography Image Classification Using Rotation-invariant Gabor Filter

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Motivation

Transcranial sonography (TCS) is used for the diagnosis of Parkinson's disease (PD) especially in early stages. Several feature analysis algorithms were implemented for PD detection from half of mesencephalon (HoM). However the challenge of the classification of the TCS images is that orientations and shapes of the HoM are different from one PD patient to another.

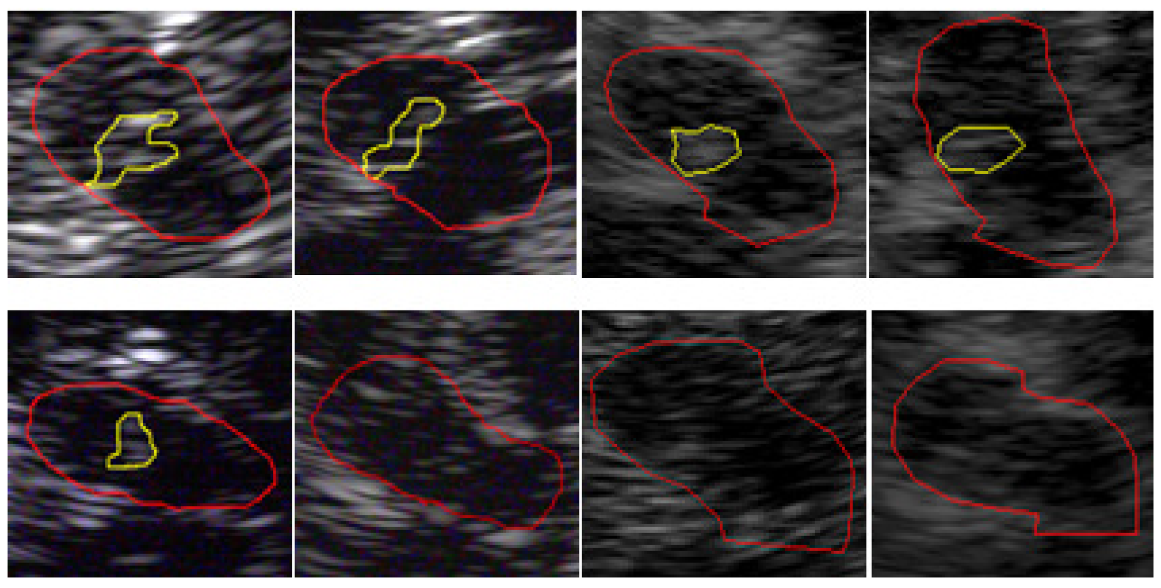

Fig 1. Manually segmented TCS images from PD (1st row) and healthy control (2nd row) with Philips SONOS 5500.

Method

Our goal is to develop Gabor features that are invariant to the direction of HoM, the brightness and the contrast changes from the different user settings. We propose a texture analysis method that applies a rotation-invariant Gabor filter bank on the TCS images and computes the robust feature for the classification.

Conventional Gabor filter bank

Let I(x,y) be an image, its discrete Gabor wavelet transform:

$$G(x,y)=\sum_{\xi}\sum_{\eta} I(x-\xi, y-\eta)g_{mn}(\xi,\eta) \qquad (1)$$

where m, n specify the scale and orientation, respectively. The 2D Gabor function:

$$g(\xi,\eta)=\frac{1}{2\pi\sigma_{\xi}\sigma_{\eta}}\exp\left[-\frac{1}{2}\left(\frac{\xi^2}{\sigma_{\xi}^2}+\frac{\eta^2}{\eta_{\eta}^2}\right)\right]\cdot\exp[2\pi jW\xi] \qquad (2)$$

Rotation-invariant Gabor filter

Method 1: The summation of the Gabor filter responses under different orientations along the same scale could yield a rotation-invariant Gabor filter:

$$g_m^R(\xi,\eta)=\sum_{n=0}^{K-1} g_{m,n}(\xi,\eta),\ m=0,1,\ldots,S-1 \qquad (3)$$

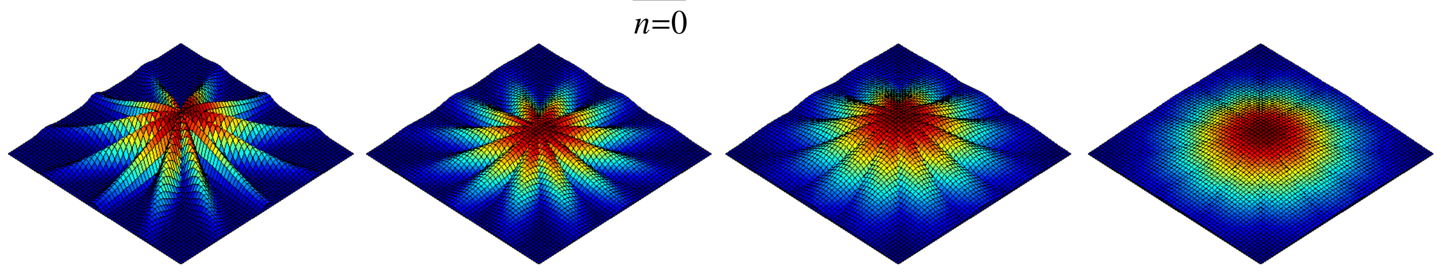

Fig 2. The summation of Gabor filters with six orientations at scale 1, 2, 3, 4.

Method 2: The Gabor features are sorted by the total energy of the corresponding filtered images over the orientation at the same scale. Then, the rotation-invariant Gabor features were extracted and shifted by the dominant direction.

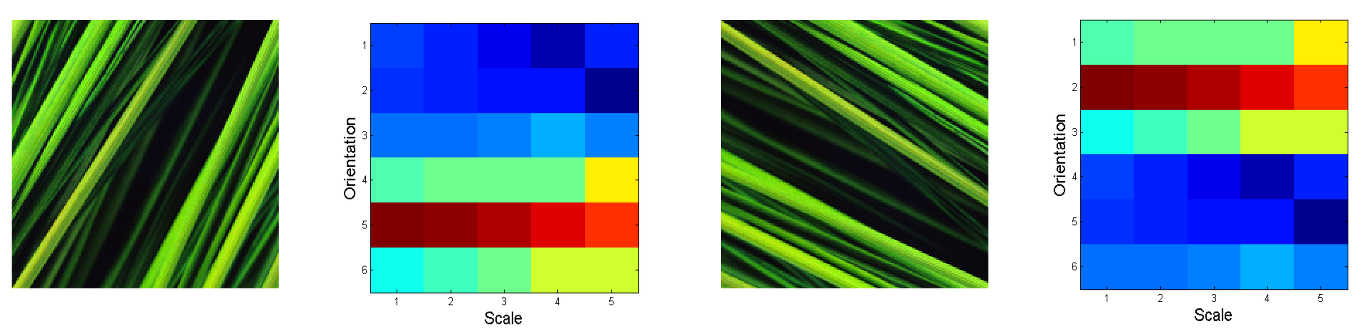

Fig 3. The energy maps of the texture image and the rotated image.

The conventional Gabor feature vector with five scales and six orientations is given by

$$f_c=(\mu_{00},\sigma_{00},\mu_{01},\sigma_{01},\ldots,\mu_{45},\sigma_{45}) \qquad (4)$$

The element in feature vector with the dominant direction is moved to the first position, and the others are circularly shifted accordingly. If 'c' is at the dominant direction then the shifted feature vector is:

$$f_r=(c,d,e,a,b)\,,\ f_c=(a,b,c,d,e)$$

Robust feature extraction

In gerenal, the conventional Gabor features, the mean and the standard deviation (std) are calculated from the intensity values of the filtered image directionly. Here, we compute the entropy from the histogram of the filtered image. The fixed Δ is used in all the calculations.

$$H(x)=-\sum_{x\in S} hist_{norm}(x)\log_2(hist_{norm}(x)) \qquad (5)$$

$$H(x)=\sum_{-\infty}^{+\infty}\Delta p(x_i)\log_2 p(x_i)-\log_2\Delta \qquad (6)$$

Evaluation

The normalization process is simulated for different user settings. First, zero mean and unit variance. Second, to rescale each image to [0,255]. Third, to apply the contrast-limited adaptive histogram equalization (CLAHE) to match the histogram with a desired shape (exponential and Rayleigh distributions).

Experimental Results

Experiment 1: We compared the rotation-invariant Gabor filter algorithms based on the UIUC database, two rotated texture sets T01(bark1) , T15(brick2) , each one containing 40 samples.

Table 1. Performance of Gabor filter banks on UIUC database.

Classification	Gabor filter	Method 1	Method 2 [3]
Accuracy (%)	72.00	72.00	**76.00**
Confusion matrix	$\begin{pmatrix}39 & 1\\ 21 & 19\end{pmatrix}$	$\begin{pmatrix}38 & 2\\ 20 & 20\end{pmatrix}$	$\begin{pmatrix}40 & 0\\ 19 & 21\end{pmatrix}$

Experiment 2: TCS images were obtained by Philips SONOS 5500 with different examiners. Totally, 67 images from 38 PD patients and 71 images from 39 healthy subjects were included. All 77 subjects underwent a neurological examination. The rotation-invariant Gabor filter bank was applied to the ROI of TCS images. Then the Gabor features, mean, std and entropy, were calculated and evaluated by SVMs with linear kernel. At last, the sequential forward floating selection (SFFS) method was implemented to select the feature subset which achieved the best classification rate.

Table 2. Performance of Gabor features, mean, std and entropy based on different normalized TCS images.

Normalized data	F(1,5,7) %	F(61,77) %	**F(66,3)** %
$\frac{x-\mu}{\sigma}$	67.39	**60.08**	70.29
[0,255]	65.94	**61.59**	70.29
Exponential	63.76	**60.14**	78.26
Rayleigh	30.43	**68.84**	77.53

The results in Table 2 show that the entropy features F(61, 77) are more stable than mean and std, F(1, 5, 7). F(66, 3) obtained by SFFS gave the highest classification rate of **81.88%**.

Conclusions

This paper has concentrated on the texture analysis by using rotation-invariant Gabor filters and selecting the feature subset for TCS images classification. The results show that the rotation-invariant Gabor filter is better than the conventional Gabor filter and that the feature entropy is more stable than mean and std in the monotonic change of the gray scale.

References

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[3] D Zhang MI A Wong, Lu G. Content-based Image Retrieval Using Gabor Texture Features. In: IEEE Transactions PAMI; 2000. p. 13–15.