Texture Analysis Using Gabor Filter Based on Transcranial Sonography Image

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Abstract. Transcranial sonography (TCS) is a new tool for the diagnosis of Parkinson's disease (PD) at a very early state. The TCS image of the mesencephalon shows a distinct hyperechogenic pattern in about 90% PD patients. This pattern is usually manually segmented and the substantia nigra (SN) region can be used as an early PD indicator. However this method is based on manual evaluation of examined images. We propose a texture analysis method using Gabor filters for the early PD risk assessment. The features are based on the local spectrum, which is obtained by a bank of Gabor filters, and the performance of these features is evaluated by feature selection method. The results show that the accuracy of the classification with the feature subset is reaching 92.73 %.

1 Introduction

Early diagnosis of Parkinson's disease (PD) is of great importance, since clinical symptoms do not occur until the substantia nigra (SN) neurons in the brain stem have been irreparably damaged [1]. Early diagnosis of PD may have two different purposes: it can be used as the earliest possible PD diagnosis when first motor symptoms are present or it is used in preclinical diagnosis of predisposed individuals before first parkinsonian motor symptoms appear [2]. Nowadays, it is possible to determine the formation of idiopathic PD as well as monogenic forms of parkinsonism at an early state by means of transcranial sonography (TCS) [3]. In TCS images of the mesencephalon, the SN shows a distinct hyperechogenic pattern in about 90% of patients with PD, despite [4].

However, this finding is still subject to manual evaluation of the examined images. For quantitative analysis of SN hyperechogenicity, only the area of SN rather than the other image characteristics have been considered. Our goal is to reduce investigator dependence of the diagnosis by extracting multiple features from the manually segmented ipsilateral mesencephalon wing, which is close to the ultrasound probe as shown in Fig. 1. The moment of inertia and the 1st Hu-moment were found by Kier et al. [1] as good parameters for separating control subjects from parkin mutation carriers. A hybrid feature extraction method which includes statistical, geometrical and texture features for the early PD risk assessment was proposed in [5], which shows that the performance of

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texture features, especially Gabor features [6], were better than the others. Grey-Level Co-occurrence Matrix (GLCM) texture measurements were proposed by Haralick [7]. In this paper, we propose a texture analysis method which applies a bank of Gabor filters on the half of mesencephalon, and extracts texture features for the early PD risk assessment. GLCM texture features are measured as well and combined with Gabor features. These features are classified with SVMs, and feature selection methods such as sequential backward selection (SBS), sequential forward selection (SFS) and sequential forward floating selection (SFFS) are applied to obtain the best feature subset [8].

2 Feature Extraction

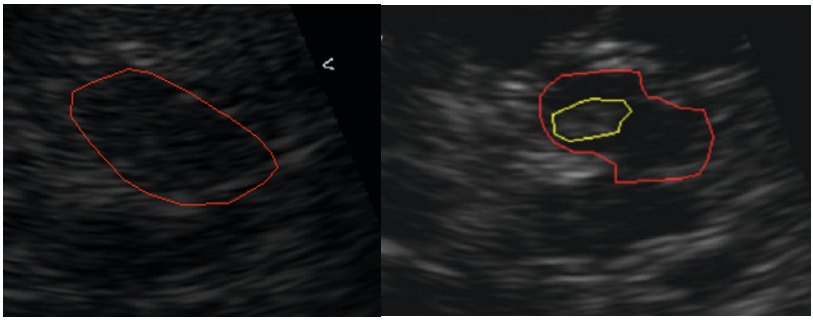
Feature extraction is used to reduce the dimension of the input data and minimize the training time taken by the classifier. Seven moments defined by Hu [9] were computed based on the segmented regions of interest (ROI) [1]. Texture features which are extracted by a bank of Gabor filters from the region of interest (ROI) are shown in Fig. 2 (a,c). Given an image $I(x, y)$ with size $P \times Q$, its discrete Gabor wavelet transform is then defined by a convolution

$$G_{mn}(x, y) = \sum_{\xi} \sum_{\eta} I(x - \xi, y - \eta)\mathbf{g}^*_{mn}(\xi, \eta) \tag{1}$$

where $*$ indicates the complex conjugate of g_{mn} [10]. The filter mask size is indicated by ξ and η. The two dimensional Gabor function $g(\xi, \eta)$ is

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

where W is called the modulation frequency, and ξ and η range from -30 to 30, the filter mask size is 61×61. The generating function is



(a) A healthy subject (b) A PD affected subject

Fig. 1. TCS images, manually segmented upper half of the mesencephalon (red) in a healthy, and a PD affected subject. The SN area (yellow) appears a bright spot in (b).

$$g(\xi,\eta) = a^{-m}\mathbf{g}_{mn}(\tilde{\xi},\tilde{\eta}) \tag{3}$$

$$\tilde{\xi} = a^{-m}(\xi cos\theta + \eta sin\theta); \qquad \tilde{\eta} = a^{-m}(-\xi sin\theta + \eta cos\theta) \tag{4}$$

where m and n specify the scale and orientation respectively, $a > 1$ and $\theta = n\pi/N$. N is the total number of orientations. Moreover,

$$a = (U_h/U_l)^{\frac{1}{M-1}}; \qquad W_{m,n} = a^m U_l \tag{5}$$

$$\sigma_\xi = \frac{(a+1)\sqrt{2\ln 2}}{2\pi a^m(a-1)U_l}; \qquad \sigma_\eta = \frac{1}{2\pi tan(\frac{\pi}{2N})\sqrt{\frac{U_h^2}{2\ln 2} - (\frac{1}{2\pi\sigma_\xi})^2}} \tag{6}$$

It is assumed that the SN region in the ROI (half mesencephalon) has homogenous texture, therefore the mean μ_{mn} and the standard deviation σ_{mn} of the transform coefficients magnitude are used to represent the texture features

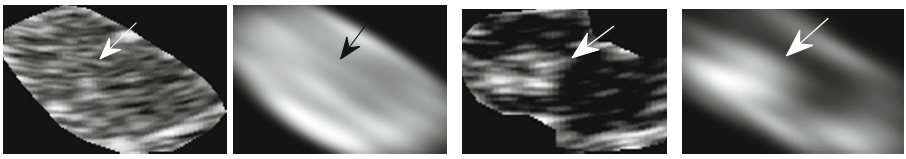
$$\mu_{mn} = \frac{\sum_x \sum_y \mid G_{mn}(x,y) \mid}{P \times Q} \tag{7}$$

$$\sigma_{mn} = \frac{\sqrt{\sum_x \sum_y (\mid G_{mn}(x,y) \mid -\mu_{mn})^2}}{P \times Q} \tag{8}$$

The Gabor feature vector f is composed by μ_{mn} and σ_{mn} as feature components [6]. Five scales and six orientations have been used in the experiments

$$f = (\mu_{00}, \sigma_{00}, \mu_{01}, \sigma_{01}, ..., \mu_{45}, \sigma_{45}); \tag{9}$$

The Gabor filter (scale 0, orientation 1) processing results are given in Figs. 2 (b,d).The multiple GLCMs were created with four directions, the window size was chosen as 3 by 3, and the GLCM feature vector g was composed by four features, such as contrast (inertia), correlation, energy (angular second moment) and homogeneity. Contrast and homogeneity are approximately the inverse of each other to some extent. The other two texture features, average gray level and average contrast, were computed as in [11].



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

Fig. 2. TCS images, ROI in a healthy subject (a), a PD affected subject (c) and Gabor filter (scale 0, orientation 1) processing results (b,d). The SN area in (d) appears more clearly than in (b).

3 Feature Selection

The goal of feature selection is to automatically select the best feature subset for classification purposes given a feature vector. In our case, the complete feature vector F has 85 dimensions, which consists of Hu moments, average gray level, average contrast, Gabor feature vector f and GLCM feature vector g. The features F1 to F85 are extracted as follows

- $F(1...7, 8, 9)$: 7 Hu moments, average gray level and average contrast;
- $F(10...69)$: 60 Gabor texture features $f(1...60)$;
- $F(70...85)$: 16 GLCM texture features $g(1...16)$.

Sequential feature selection is a common feature selection method which includes two components. One is a criterion function, which is to be minimized over all possible feature subsets. In this work, the misclassification rate of SVMs was set as the criterion, the Gaussian radial basis function (RBF) was selected as the kernel function. The sequential minimal optimization method (SMO) was specified to find the separating hyperplane. Another component is a sequential search strategy, which evaluates the criterion to establish the best feature subset. For the sequential forward selection (SFS), features are selected successively by adding the locally best feature, which provides the lowest criterion value, to an empty candidate set. In SBS, the feature that has the highest criterion is sequentially removed from a full candidate set until removal of further features increases the misclassification rate. However both of these methods are generally suboptimal and suffer from the "nesting effect" [8], therefore SFFS characterized by a dynamical changing of features at each step was implemented. It was shown to give good results and to be more effective than the SBS and SFS.

4 Experimental Results

A clinical study was conducted to evaluate whether the above mentioned features can be used as an early PD indicator. The study included 36 healthy controls (subjects without mutation and symptoms of PD) and 19 Parkin mutation carriers. All these 55 subjects underwent a detailed neurological examination. Therefore, the diagnosis result can be considered as ground truth to compare and evaluate the classification in this work.

The SVMs classification was cross validated by the leave one out method. This gave the accuracies of 90.91% and 92.73% when SFS and SFFS were used, respectively, to minimize the best feature subset. We could not obtain a small feature subset by SBS. The feature subset $F(17, 77)$ obtained by SFFS gave the highest classification rate of 92.73% ($F(17)$, Gabor feature $f(8)$ and $F(77)$ is GLCM feature $g(8)$). In this feature subset, the GLCM features $F(73, 77)$ had a good preformance of 90.91%. The detailed results of the implementation of these feature sets are given in Table 1.

Table 1. Classification rates (%) of SVMs cross-validation.

Method	Feature set	%	Specificity	Sensitivity
-	All features	65.45	1	0
SBS	-	-	-	-
SFS	$F(73, 77)$	90.91	88.89	94.74
SFFS	$F(17, 77)$	92.73	91.67	94.74

5 Summary and Conclusions

This paper concentrates on texture analysis using Gabor filters and GLCMs for PD detection. SFFS was implemented and two features including Gabor $f(8)$ and GLCM $g(8)$ texture features were found to be the best parameters to separate control subjects from Parkin mutation carriers. However, this method based on the the manual segmentation of the mesencephalon. Gabor and GLCM features greatly depend on the filter window size. Future work will firstly be focused on using a large number of subjects as ground truth datasets to validate the performance of the selected features. Secondly the adaptive window size of Gabor and GLCM will be investigated. At last we plan to develop a semi-automatic segmentation algorithm based on Gabor and GLCM texture features to eliminate the investigator-dependence.

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