MULTIPLE FEATURE EXTRACTION FOR EARLY PARKINSON RISK ASSESSMENT BASED ON TRANSCRANIAL SONOGRAPHY IMAGE

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ABSTRACT

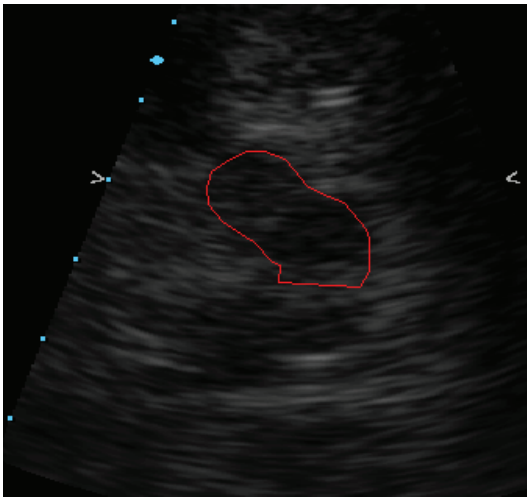
Transcranial sonography (TCS) is a new tool for the diagnosis of Parkinson's disease (PD) at a very early state. The TCS image of mesencephalon shows a distinct hyperechogenic pattern in about 90% PD patients. This pattern is usually manually segmented and the substantia nigra (SN) region can be used as an early PD indicator. However this method is based on manual evaluation of examined images. The extraction of multiple features from TCS images characterizing the half mesencephalon morphology and structure can be used to validate the observer-independent PD indicator. We propose hybrid feature extraction methods which includes statistical, geometrical and texture features for the early PD risk assessment. These features are tested with support vector machines (SVMs). Furthermore five features are selected with the sequential feature selection methods. The results show that the correct rate of the classification with these five features is reaching 96%.

Index Terms— Early diagnosis, Parkinson's Disease, Transcranial sonography, classification, texture analysis

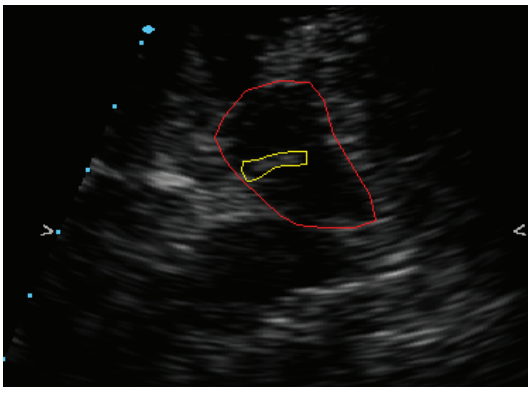
1. INTRODUCTION

Early diagnosis of Parkinson's disease 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 meanings: the earliest possible PD diagnosis when first motor symptoms are present or 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 TCS [3]. In TCS images of the mesencephalon, the SN shows a distinct hyperechogenic pattern in about 90% of patients with Parkinson's disease (PD), despite its normal appearance on CT and MRI scans [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 Hu1-moment were found by Kier et al. [1] as good parameters for separat-



(a) The mesencephalon in a healthy subject.



(b) The SN area (indicated by a yellow contour) in the mesencephalon of a PD affected subject.

Fig. 1. Manually segmented upper half of the mesencephalon (red) in healthy (top) and PD affected subjects (bottom).

ing control subjects from parkin mutation carriers. In this paper, we propose hybrid feature extraction methods which include statistical, geometrical and texture features for the early PD risk assessment. These features are used with an SVM classifier. The performance of SVMs did not increase with the growth of the feature set, therefore the feature selection methods such as sequential backward selection (SBS) and sequential forward selection (SFS) are applied to obtain the best feature subset.

2. FEATURE EXTRACTION

The feature extraction is used to reduce the dimension of the input data and minimize the training time taken by the classifier. Multiple features which include geometrical moments, statistical moments and texture moments are extracted from the region of interest (ROI). The ultrasound images of the upper half of the mesencephalon are shown in Fig. 2 (a) and (c), which are manually segmented from Fig. 1 by physicians.

2.1. Statistical Moments

The basic idea is to characterize the 'content' of an image histogram using some descriptors. Therefore, the following statistical features [5] of the histogram were calculated for quantitative analysis of the gray-level distribution in the ROI:

F1: Mean value
F2: Variance value
F3: 3rd order moment
⋮
F10: 10th order moment
F11: Energy
F12: Entropy
F13: Skewness
F14: Kurtosis
F15: Gray mode

Gray mode is the global max in a histogram.

2.2. Geometrical Moments

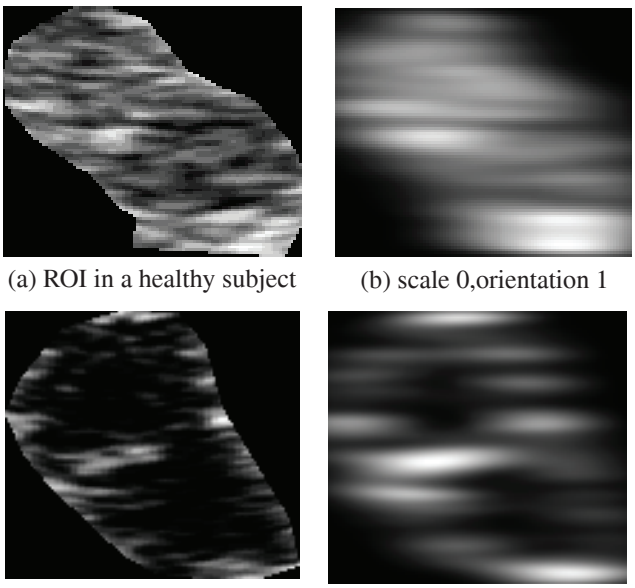
Seven moments defined by Hu [6] were computed based on the segmented ROIs. Hu moments have been proven to be invariant to object scale, position and orientation. The moment of inertia is adapted to image processing by interpreting intensity values as inertia values and varies strongly between a uniform and a centrical distribution of the ROI [1]. Used geometrical moments are as follows:

F16: Moment of inertia
F17: 1st order Hu moments
⋮
F23: 7th order Hu moments

2.3. Texture Features

Gabor filters are effective to extract texture features [7]. Given an image $I(x, y)$ with size $P \times Q$, its discrete Gabor wavelet transform is defined by the convolution

$$\mathrm{G}_{mn}(x, y) = \sum_{\xi} \sum_{\eta} I(x - \xi, y - \eta) g^*_{mn}(\xi, \eta) \qquad (1)$$



(a) ROI in a healthy subject (b) scale 0,orientation 1

(c) ROI of PD affected subject (d) scale 0, orientation 1

Fig. 2. Half of the mesencephalon in healthy (top) and PD affected subjects (bottom); The original gray-level image (left) and Gabor filter processing result (right).

where $*$ indicates the complex conjugate of g_{mn}. It is assumed that the local area is spatially homogeneous [8]. The filter mask size is indicated by ξ and η. The two-dimensional Gabor function $g(\xi, \eta)$ can be written as

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

where W is called the modulation frequency [8]. ξ and η range from -30 to 30, the filter mask size is 61×61. The other constants are chosen as in [8].

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 for the classification purpose [8]:

$$\mu_{mn} = \frac{\sum_x \sum_y \mid G_{mn}(x, y) \mid}{P \times Q}, \qquad (3)$$

$$\sigma_{mn} = \frac{\sqrt{\sum_x \sum_y (\mid G_{mn}(x, y) \mid - \mu_{mn})^2}}{P \times Q}. \qquad (4)$$

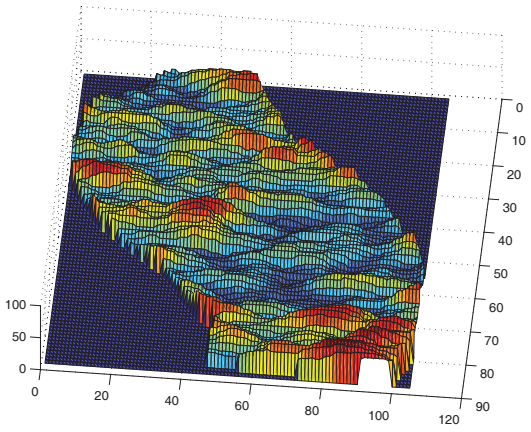
The Gabor feature vector f is composed by μ_{mn} and σ_{mn} as feature components [7]. Five scales and six orientations have been used in the experiments:

$$\mathrm{f} = (\mu_{00}, \sigma_{00}, \mu_{01}, \sigma_{01}, ..., \mu_{45}, \sigma_{45}); \qquad (5)$$

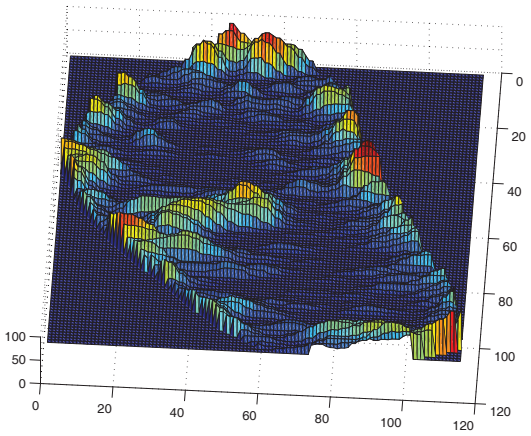
The other two texture features, average gray level and average contrast were computed as in [9]. The Gabor filter

(scale 0, orientation 1) processing results are given in Fig. 2 (b) and (d). The features F24 to F85 are extracted as follows:

F24: Average gray level
F25: Average contrast
F26: Mean of the magnitude $f(1)$
F27: Standard deviation of the magnitude $f(2)$
...
F85: Standard deviation of the magnitude $f(60)$



(a) Healthy subject



(b) PD affected subject

Fig. 3. Surface plot of the ROI in healthy (top) and PD affected subjects (bottom). (two same subjects with Fig. 2)

3. SUPPORT VECTOR MACHINES

SVMs, as introduced by Vapnik [10], classify the input data into one of two classes with a linear decision boundary of maximum margin. For non-linearly separable data, the kernel methods are used to transform the original input space into a higher-dimensional space where a separating hyperplane could be constructed. We consider the problem of the Ultrasound images classification where the input vector is the feature vector F with 85 dimensions, the Gaussian radial basis function (rbf) is selected as the kernel function.

4. FEATURE SELECTION

The goal of feature selection is to select the best feature subset automatically for classification purposes given a feature vector. The SVM classifier has been chosen to evaluate the effectiveness of feature subsets. The feature selection detects an optimal feature subset based on the feature vector F.

A general feature selection method, sequential feature selection includes two components. One is a criterion function, which is used to minimize over all possible feature subsets. In this work, the misclassification rate of SVMs is set as the criterion. 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 is the one that provides the lowest criterion value, to an empty candidate set. The SFS technique starts from the best individual feature (BIF) by identifying the first feature that has the highest discrimination power. The SFS stops until the further features does not decrease the criterion. The sequential backward selection (SBS) method is the 'bottom up' counterpart to SFS. In SBS, starting from a full candidate set, one sequentially removes the feature which has the highest criterion until the removal of any further features may lead to an increase of the misclassification rate.

5. EXPERIMENTAL RESULTS

A clinical study has been conducted to evaluate whether the image features can be used as an early PD indicator. The study consisted of 36 healthy controls (subjects without mutation and symptoms of PD) and 42 Parkin mutation carriers. All these 78 subjects underwent a detailed neurological examination. Therefore the diagnosis result can be considered as the ground truth to compare and evaluate the classification. In each image the half mesencephalon (ROI marked by red contour) and even the SN (yellow contour) area were manually segmented by two individual physicians as shown in Fig. 1.

This paper is trying to develop the features which can be used to recognize the TCS images of mesencephalon of two different categories called 'healthy controls' and 'PD'. The difference of gray value distributions between these two class images can be seen more clearly in the surface plot (Fig. 3) than in a gray image. Gabor filter bank is applied to the ROI of TCS images. Statistical moments, geometrical moments and Gabor texture features are extracted from the images. The algorithm structure can be seen from the flowchart in Fig. 4.

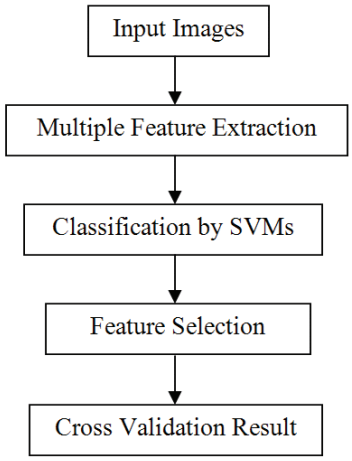


Fig. 4. The flow chart of proposed work

The SVMs classification has been cross-validated by the leave-one-out method. This gives the correct rates of 79.49%, 79.49% and 76.92% when statistical features, geometrical features and Gabor texture features are added successively into the feature vector. Then the SBS and the SFS are used, respectively, to minimize the best feature subset. Comparatively, the feature subset obtained by SFS gives the highest classification rate of 96.15%. In this feature subset, the Gabor features $f(1), f(2)$ have the best individual performance of 88.46%. The detailed results of implementation of these feature sets are given in Table 1.

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

Feature sets	%	Specificity	Sensitivity
$F(1...15)$	79.49	66.67	90.48
$F(1...23)$	79.49	66.67	90.48
$F(1...85)$	76.92	83.37	71.43
SBS,$F(12, 27, 80, 82...85)$	92.31	86.11	97.62
SFS,$F(17, 25, 26, 27, 29)$	96.15	94.44	97.62
Hu1,$F(17)$	83.33	80.56	85.71
Contrast,$F(25)$	58.97	61.11	57.14
Gabor,$f(1), f(2)$	88.46	80.56	95.24
Gabor,$f(4)$	87.18	77.78	95.24

6. SUMMARY AND CONCLUSIONS

This paper concentrates on selecting good combination of features and a classifier which suits for the Parkinson's disease risk assessment based on TCS images. We proposed hybrid feature extraction methods which include statistical, geometrical and texture features for the early PD risk assessment. The SVMs separate the input images into two classes by image characteristics other than the manual segmentation of substantia nigra. The SFS is implemented and five features including RMS contrast, Hu1-moment and other three Gabor texture features were found being the best parameters to separate control subjects from parkin mutation carriers.

Future work will firstly be focused on using a large number of subjects evaluated as ground truth datasets to validate the performance of selected features. Secondly we plan to eliminate the investigator dependence caused by the manual segmentation of the ipsilateral mesencephalic brain stem by a semi-automatic segmentation algorithm. At last a broader comparison to other texture features as well as other classifiers such as one-class classifier will be implemented in the future work.

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