Information Extraction from Raw DTI Data Using Texture Based Analysis: A Preliminary Study of Classification and Regression

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Abstract

This study presents a texture based analysis, Local Binary Pattern on Three Orthogonal Planes (LBP-TOP), to extract simple and effective features from raw diffusion tensor image (DTI) data. Examples of sex classification and age estimation using various DTI data were used to demonstrate the performance of this method. A total 204(age-range from 4 to 85, 120 males) subjects downloaded from public-access NKI/Rockland Samples were used to evaluate those approaches. Our results show that the mean diffusivity (MD) can provide most information in these two examples. The best sex classification accuracy is 0.81, and the best age estimation mean average error is 6.32 years. Those results show that LBP-TOP is capable of extracting effective information from DTI data and could be a good candidate for classifying or evaluating various neurological diseases based on DTI information.

Introduction

Diffusion tensor image (DTI) provides unique and complex information of brain white matter structure. Because of the complexity, few neuroimaging classification studies used the information from it. In this study, we introduce a simple and efficient texture operator, Local Binary Pattern on Three Orthogonal Planes (LBP-TOP), to extract useful information from the raw and unmodified DTI data.

Local Binary Pattern (LBP) is a simple and efficient texture operator introduced by Ojala [1]. Fig. 1 shows the steps of mapping each voxel to LBP space. After defining a local window with P neighborhood pixels and radius R, LBP code can be computed by thresholding the neighborhoods of each pixel with the value of the center pixel and encodes the result as a binary number. Combining LBP on three orthogonal planes (LBP-TOP) can be used to be a simplified descriptor of 3D data [2].

Materials & Methods

NKI/Rockland Samples downloaded from INDI [3] were used in this study. A total 204(age-range from 4 to 85, 35.22±20.07 years, 120 males) subjects are used in this work. All preprocessing were performed using both FSL [4] and AFNI [5]. The analysis of DTI was conducted by DTIFIT of FSL. The results were separated to fractional anisotropy (FA), mean diffusivity (MD), and eigenvectors (V1) to compute specific LBP-TOP mapping (Fig. 2). Only LBP-TOP with eight neighbors and different radius (1, 2, and 3 voxels) were computed. Raw data was rigid transformed to same orientation and resolution (2mm isotropic). Then a non-linear transformation performed by ART (Automatic Registration Toolbox)[6] was used to build transform models from ICBM152 2mm T2 weighted brain template to skull stripped T2 weighted brains of subjects. The result model was used to transform atlases to the brain of each subject and get the spacial context of the specific subject. To introduce spacial information, we use four probabilistic parcellations provided by FSL. Those atlases, Harvard-Oxford cortical structural atlas and subcortical structural atlas, probabilistic cerebellar atlas, and JHU DTI-based white-matter atlases, were threshold by zero percentages to build binary overlapped masks. The resulting overlapped 177 masks were used to separate image data in this study. After computing the LBP-TOP mapping of each brain image, histogram of distant special context is calculated by those masks.

For sex classification, a linear SVM was used to train and test the data. For age estimation, we use linear SVR as a feature ranking tool to select the most important features. Then we train new models using top 2n important features and evaluate. To evaluate results, 10-fold cross-validation was used.

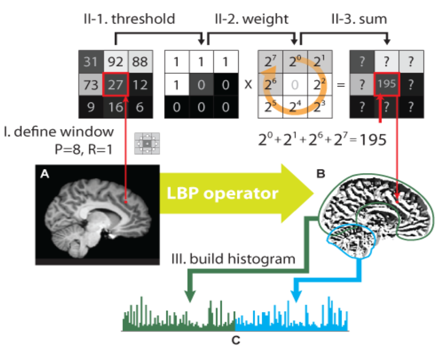

Fig. 1. Illustration of local binary pattern(LBP) operator.

Table 1. Accuracy results of sex classification.

Radius	FA	MD	V1	VL1
1 voxel	0.78	0.80	0.77	0.74
2 voxels	0.76	0.78	0.75	0.76
3 voxels	0.75	0.81	0.73	0.75

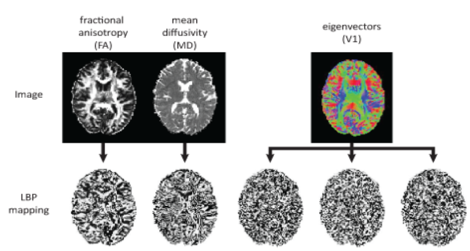

Fig. 2. Information extracted by LBP-TOP from DTI data.

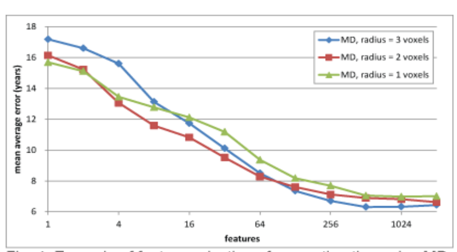

Fig. 4. Example of feature selection of age estimation using MD data.

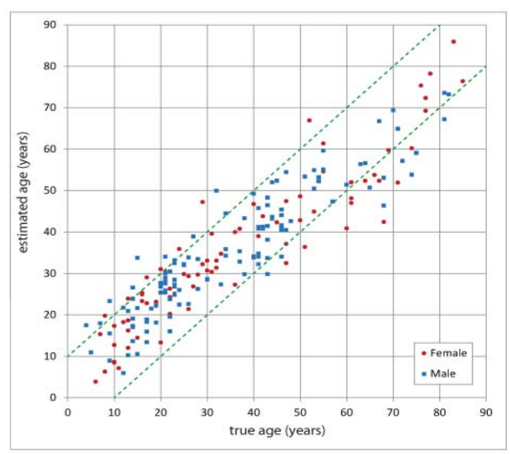

Fig. 3. Brain age estimation by MD with radius of 3 voxels and using top 1024 features. The green dashed line indicates the real age± 10 years.

Results&Conclusion

Table 1 shows the resulting sex classification. Radius with one voxel can build better models in most cases. FA and MD can provide more information for classifying sex. MD show best results in age estimation. Fig. 3 demonstrate the specific results of age estimation by MD. Because of the unbalanced age distribution of the source data, age of some elder subjects is under-estimated. Fig. 4 shows the feature selection result of MD with different radius.

In this study, we demonstrated a feature extraction method based on texture analysis to extract effective information from brain DTI data without the needed of modifying the raw images. Our results show the capability of this method by build sex classification and age estimation model using linear SVM. We demonstrated that LBP-TOP could be a good candidate for disease classification and regression using DTI data in clinical usage.

References [1]Ojala, T., Pietikäinen, M. &Mäenpää, T. IEEE Transactions on pattern analysis and machine intelligence 971-987 (2002). [2] Zhao, G. IEEE transactions on pattern analysis and machine intelligence 915-928 (2007). [3] Nathan Kline Institute (NKI) / Rockland Sample (http://fcon_1000.projects.nitrc.org/indi/pro/nki.html). [4] FMRIB Software Library (FSL, http://www.fmrib.ox.ac.uk/fsl/). [5] Analysis of Functional NeuroImages (AFNI, http://afni.nimh.nih.gov/afni). [6] Ardekani, B.A. et al. Journal of neuroscience methods 142, 67-76 (2005).