Detecting Parkinson's brain changes using local feature based regional SVM ensemble on MRI images

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Introduction:
Brain anatomical structural difference in Parkinson's Disease (PD) subjects at the group level has been studied through neuropathology and Voxel Based Morphometry [1], but automatic detection of the structural local feature remains challenging. Local features, e.g. Scale Invariant Feature Transform (SIFT) [2] which can locate and encode the salient and robust keypoints in 2D brain images as gradient histogram has recently demonstrated its promise in Feature Based Morphometry [3] when applied to Alzheimer's MRI pattern detection. However, SIFT is high dimensional and hard to be discriminated by human. We develop a local feature based regional Kernel Support Vector Machine (SVM) [4] ensemble method, outlined in Figure 1, that can identify discriminative regions based on local features, by maximizing classification hyperplane margin between regional local features of PD and healthy controls (HC) (Figure 2). Furthermore, the regional SVM ensemble constructs a reliable predictive model for classifying PD's MRI brain images. Our preliminary results show that the identified high discriminative regions measured by Area Under Receiver Operating Characteristics Curve (AUC) scores are consistent with previous neuropathologic studies, and may serve as potential PD markers.

Methods:
Ten early unmedicated patients with PD and ten age and gender matched healthy controls were recruited into the study. All brain MRI images were obtained from a Varian (Palo Alto, CA) 4-Tesla MRI Scanner using a 3D-MDEFT pulse sequence. Each volume image was reformatted to 161x191x151 voxels and aligned to the Talaraich coordinate using AFNI software.

We used a data-driven statistical machine learning approach to 1) automatically detect discriminative cerebral regions in PD patients, quantified by AUC score of each regional SVM 2) construct a strong predictive ensemble classifier that can differentiate MRI images of PD from HC. In addition, different kernels were experimented to determine which performs better.

More specifically, the algorithm works as follows: 1) Segment each brain MRI into cubes size of 20x20x20 voxels; 2) Reslice the cross-sectional 2D images along each orientation of Sagittal, coronal, and axial; 3) For slice of 2D images, extract SIFT features; 4) Gather the SIFTs from both PD and HC that fall into each cube, which forms a bag of features that describe the regional structures; 5) Construct a SIFT feature set for each cube that contains more than 200 SIFT keypoints; 6) For each cube a regional SVM is trained by its feature set which optimally classifies PD from HC. The data dimensionality is 130, consisting of 128 bins from the SIFT descriptor,
1 from scale and 1 from orientation. On average each cube contains 800 SIFTs; 7) ROC curve and AUC of 10-fold cross validation are reported. (8) High AUC regional SVM's are selected to form the ensemble that can predict if a MRI volume is PD or HC.

**Results:**

In general, our results show that polynomial kernel consistently outperforms linear kernel for about 15% improvement, e.g. the average Top 10 AUC score 0.891 (polynomial) vs. 0.748 (linear) in coronal view (Figure 4). Coronal view is the most discriminative with 6% higher AUC than the other two views, suggesting that coronal images provide more anatomic features for identifying PD neuropathology. Different regions have different discriminative powers. Structural different cerebral regions found by our method are consistent with neuropathology [1]. Thalamas, Anterior cingulated, Hippocampus have elevated AUC scores (Figure 3). Regions with high AUC, e.g. Putamen (AUC 0.852), suggest that limbic areas are involved in PD mechanism.

**Conclusions:**

We developed a data-driven approach combining local feature and regional SVMs, which demonstrates its advantage in identifying and predicting PD related regions. Extensive experiments are carried out and regions found by our approach will advance the understanding of PD neuropathology.

**Modeling and Analysis Methods**

Classification and Predictive Modeling

**Abstract Information**

**References**

Each MRI brain volume is segmented into smaller regions, e.g. 20x20x20 voxels. For each region in each view, SIFT features are extracted, and gathered into the PD and HC as regional feature set. Then the regional SVM is trained by each regional feature set. A regional SVM ensemble can be constructed as a committee of regional SVM's with high AUC scores.
Figure 2, SIFT feature examples for PD and HC subjects in the same region.

The first and last 10 images are from PD and HC, respectively. Each 4x4 grid is one SIFT feature from the same cube. The green point denotes SIFT center, the size of the grid denotes the scale, and in each small grid there is an 8-bin orientation gradient histogram. The SIFT feature can robustly locate the salient key points in an image, and encode the covered region into 128 bin gradient histogram which is unaffected by global intensity changes but only captures the differential local structures. Though it is capable of encoding the brain structures, it is not visually straightforward to see the differences between PD and HC, therefore we need to utilize machine learning algorithms to find the optimal classifier.
<table>
<thead>
<tr>
<th>Block</th>
<th>Linear SVM AUC</th>
<th>Polynomial SVM AUC</th>
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<tr>
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<td>Average (Std)</td>
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<tr>
<td>Axial</td>
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<td>0.768</td>
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<tr>
<td>Coronal</td>
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<td>0.796</td>
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</tbody>
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**Figure 3, performance analysis of different kernel SVM in different views.**

Statistics of top 10 regional SVM’s are reported as Table on the left and ROC curves on the right. All experiments are done in 10 fold cross validation. Polynomial kernel consistently outperforms linear kernel, and coronal view has higher AUC than other views.
Figure 4, AUC brain map

Each colored block in the AUC map illustrates the AUC score, ranges from 0 (blue) to 1 (red). AUC maps for Sagittal, axial and coronal views are shown. Thalama, Anterior cingulated, Hippocampus regions [1] are highlighted in light blue, blue, purple, respectively, and their corresponding peak AUC scores are 0.847, 0.892, and 0.855 respectively, significantly higher than average. Interestingly the coronal shows the highest average AUC scores. Furthermore, Putamen region has AUC of 0.852 which suggests limbic areas are involved in PD mechanism.