Classification of Alzheimer’s disease subjects from MRI using the principle of consensus segmentation

Aymen Khlif and Max Mignotte

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Plan

❖ Introduction

❖ Contributions: Proposed classification model
   ➢ Dataset description
   ➢ MRI data preprocessing
   ➢ Prototypes NC and AD
   ➢ Hybrid classification

❖ Experiments and results

❖ Conclusion and perspectives
Introduction: Alzheimer's disease (AD)

- **Neurodegenerative and progressive disease**
  - Deterioration of cognitive functions
  - Memory, language and behavior disorders
  - Progressive loss of autonomy
  - Disorientation in time and space
Introduction: Statistics of Alzheimer’s Disease

- In 2050:
  - 115 million in the world, a new case every 7 seconds
  - 13.5 million in the USA (245454 new cases per year)

- Global economic impact: $600 billion in 2010

- Urgent issue:
  - Early diagnosis of AD
  - Implementation of a therapeutic
  - Slow down the neurodegenerative process

1 Association Alzheimer’s disease International
Introduction: Magnetic Resonance Imaging (MRI)

- Brain analysis: structural, functional and non-invasive
- Contributing to the early diagnosis of AD
  - Structural alterations
  - Metabolic alterations
- Detecting changes
  - Macro-structural \(\rightarrow\) IRM Anatomic/Structural
  - Micro-structural \(\rightarrow\) Diffusion Tensor Imaging
AD diagnosis methods

▪ Volumetric analysis / Area of interest
  ❖ Study the variation of the volume of a region
  ❖ Manual: time-consuming, depends on the observer (clinician)
  ❖ Automatic / semi-automatic: suffers from errors

▪ Voxel analysis / Voxel
  ❖ To detect significant differences in Grey Matter (GM) between two groups of subjects by voxel-to-voxel tests
  ❖ Do not require a priori assumptions about the location, the size or number of ROIs to be analyzed, since they provide voxel wise measures determined in the entire brain
  ❖ Help to detect structural changes in MRIs
  ❖ Do not depend on the clinician abilities

Methods for group analysis: Individual diagnosis?
Problematic

- Individual diagnosis = visual assessment of a new case
  - Learn about similar cases?
  - Detection and characterization of pathological targets?
  - To which class of known subjects can it be associated?
  - Lists of similar images?
Solution

Use recent advances made in segmentation and multimedia Indexing and classification for Content Based Visual Information Retrieval (CBVIR). More precisely, use the concept of consensus segmentation to build two segmentation prototypes (Prototype Normal Control and Prototype Alzheimer's Disease).

Tools

- Indexing by visual content of images
- Principle of consensus segmentation based atlas
- Using “Domain Knowledge” in:
  - Image acquisition MRI
  - Diagnosis of AD

principle of consensus segmentation

- A consensus segmentation is conceptually the compromise (in terms of level of details, contour accuracy, number of regions, etc.) exhibited by each segmentation map (or spatial clustering) belonging to a set of segmentations.

- In our case, the principle of consensus segmentation allows us to build two reliable segmentation-based prototypes, one corresponding to healthy individuals and the second one corresponding to unhealthy subjects (with AD).

- The segmentation into three kinds of regions has the merit to efficiently reduce the information content of a brain image and to suppress noise and artifacts which are not relevant for the AD detection.

- These two consensus segmentation-based prototypes allow us to suppress undesired components in the brain image (to be classified) such as the anatomical variability existing between individuals which are not relevant for the detection and quantification of AD.
Data description

- OASIS (Open Access Series of Imaging Studies: [www.oasis-brains.org](http://www.oasis-brains.org))
- Worldwide project
- Sharing data for research in the treatment and diagnosis of Alzheimer's disease
- We will consider a subset of the complete cross-sectional OASIS dataset, with 49 controls and 49 AD patients

<table>
<thead>
<tr>
<th></th>
<th>Very mild to mild AD</th>
<th>Normal Controls</th>
</tr>
</thead>
<tbody>
<tr>
<td>No. of subjects</td>
<td>49</td>
<td>49</td>
</tr>
<tr>
<td>Age</td>
<td>78.08 (66-96)</td>
<td>77.77 (65-94)</td>
</tr>
<tr>
<td>Education</td>
<td>2.63 (1-5)</td>
<td>2.87 (1-5)</td>
</tr>
<tr>
<td>Socioeconomic status</td>
<td>2.94 (1-5)</td>
<td>2.88 (1-5)</td>
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<tr>
<td>CDR (0.5/1/2)</td>
<td>31/17/1</td>
<td>0</td>
</tr>
<tr>
<td>MMSE</td>
<td>24 (15-30)</td>
<td>28.96 (26-30)</td>
</tr>
</tbody>
</table>

Table 1: Demographic information of the subjects in the two classification classes
MRI data preprocessing

Affine registration to template

Brain masking (BET)

Grey/White/CSF segmentation

Talairach atlas brain
Construction of prototypes

MRI Data (416 subjects)

K-Means by varying seeds and window size

Majority Vote fusion

Fusion of segmentations in healthy subjects with Majority Vote (316 subjects)

Fusion of segmentations in subjects with Alzheimer’s disease with Majority Vote (100 subjects)

Prototype_NC

Prototype_AD
Proposed classification model

Stage (1): Calculate distance

\[ D_{NC} = \text{Pott\_Distance} \text{ (Input MRI, Prototype\_NC)} \]
\[ D_{AD} = \text{Pott\_Distance} \text{ (Input MRI, Prototype\_AD)} \]

Stage (2): Classification

Choose the classifier

| \[ D_{NC} - D_{AD} > T \] |
| \[ D_{NC} - D_{AD} < T \] |

Classifier 1: based on Minimum distance

NC  AD

Classifier 2: based on KNN

NC  AD

Pott distances is the normalized number of labels differences in percentage
Comparison with morphometric methods (NC vs. AD)

<table>
<thead>
<tr>
<th>Classifier type</th>
<th>Accuracy</th>
<th>Sensitivity</th>
<th>Specificity</th>
</tr>
</thead>
<tbody>
<tr>
<td>MDC-KNN (our approach)</td>
<td>0.86</td>
<td>0.85</td>
<td>0.87</td>
</tr>
<tr>
<td>rbf-DAB-SVM</td>
<td>0.85</td>
<td>0.78</td>
<td>0.92</td>
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<tr>
<td>LVQ2</td>
<td>0.83</td>
<td>0.74</td>
<td>0.92</td>
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<tr>
<td>LVQ1</td>
<td>0.81</td>
<td>0.72</td>
<td>0.90</td>
</tr>
<tr>
<td>LC-KNN</td>
<td>0.80</td>
<td>0.80</td>
<td>0.79</td>
</tr>
<tr>
<td>rbf-AB-SVM</td>
<td>0.79</td>
<td>0.78</td>
<td>0.80</td>
</tr>
<tr>
<td>MLP-BP</td>
<td>0.78</td>
<td>0.69</td>
<td>0.88</td>
</tr>
<tr>
<td>PNN</td>
<td>0.78</td>
<td>0.62</td>
<td>0.94</td>
</tr>
<tr>
<td>Linear SVM</td>
<td>0.78</td>
<td>0.72</td>
<td>0.88</td>
</tr>
<tr>
<td>Indep-rbf-SVM</td>
<td>0.75</td>
<td>0.56</td>
<td>0.95</td>
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<tr>
<td>Kernel-LICA-DC</td>
<td>0.74</td>
<td>0.96</td>
<td>0.52</td>
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<tr>
<td>Indep-Linear-SVM</td>
<td>0.74</td>
<td>0.51</td>
<td>0.97</td>
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<tr>
<td>KNN-Pott-MV</td>
<td>0.73</td>
<td>0.61</td>
<td>0.85</td>
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<tr>
<td>Linear-AB-SVM</td>
<td>0.71</td>
<td>0.54</td>
<td>0.88</td>
</tr>
<tr>
<td>RBF</td>
<td>0.66</td>
<td>0.65</td>
<td>0.68</td>
</tr>
</tbody>
</table>
Conclusion

• Our approach is automatic and does not require the intervention of the clinician during the disease diagnosis

• It is extensible to other diseases that can be diagnosed by brain MRI such as Schizophrenia and brain tumors

Perspectives

• The method could be extended by combining axial, coronal, and sagittal MRI data for improving the classification accuracy

• Generalize the approach for the 3D case and compare it with 2D

• Classification in four classes (NC, Very mild AD, mild AD, moderate AD)

• Generalize the approach for other criteria for the consensus segmentation (e.g., VOI, GCE, PRI, FCR)
Perspectives

Stage (1): Calculate distance
\[ D_{NC} = \text{Pott Distance (Input MRI, Prototype_NC)} \]
\[ D_{AD} = \text{Pott Distance (Input MRI, Prototype_AD)} \]

Stage (2): Classification

Choose the classifier

\[ |D_{NC} - D_{AD}| > T \]
\[ |D_{NC} - D_{AD}| < T \]

Classifier 1: based on Minimum distance
- NC
- AD

MDC classification
Using three prototypes
- Very mild AD
- MODL AD
- Endstage AD

Classifier 2: based on KNN
- NC
- AD

MDC classification
Using three prototypes
- Very mild AD
- MODL AD
- Endstage AD

AD severity quantification step
Questions