Further results on Alzheimer Disease Detection on structural MRI features

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- 1 Introduction
- 2 Alzheimer Disease database
- 3 Relevance Vector Machine
- 4 Computational Experiments Results
- 5 Conclusions

Introduction

- Application of Computational Intelligence and Machine Learning algorithms for the automatic detection of Alzheimer's Disease (AD) from the analysis of Magnetic Resonance Imaging (MRI) T1 weighted images.
- In previous works, we have introduced a feature extraction method based on Voxel Based Morphometry (VBM).
- These features have been used as the input for several Artificial Neural Network (ANN) architectures and kernel based classifiers.
- In this work, we obtain more classification results appliying the Relevance Vector Machines (RVM) algorithm.



- 2 Alzheimer Disease database
- 3 Relevance Vector Machine
- 4 Computational Experiments Results
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Alzheimer Disease feature database

- AD is a neurodegenerative disorder, which is one of the most common cause of dementia in old people.
- Ninety eight right-handed women (aged 65-96 yr) were selected from the Open Access Series of Imaging Studies (OASIS) database.
- In this sample, 49 subjects have been diagnosed with very mild to mild AD and 49 are non-demented.

Feature Extraction process

- It is based on Voxel Based Morphometry (VBM), a neuroanatomical computational approach that measures differences in local concentrations of brain tissue, through a voxel-wise comparison of multiple brain images.
- Procedure:
 - Spatial normalization of subject images into a standard space.
 - Segmentation of tissue classes using a priori probability maps.
 - Smoothing to correct noise and small variations.
 - Voxel-wise statistical tests based on the General Linear Model (GLM).
 - This computation provides a Statistical Parametric Map (SPM), which is thresholded according to the Random Field theory.

Feature Extraction process diagram

SUBJECTS GM VBM Analysis Feature Extraction Voxel Intensities Voxel Values Classification Validation Classification Results

Figure: Feature extraction process diagram from the GM segmentation volumes (rectangles correspond to processes and ellipses to data).

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RVM Introduction

- Relevance Vector Machine (RVM) is a Bayesian sparse kernel technique for classification and regression.
- It is a sparse Bayesian model that provides probabilistic predictions through Bayesian inference.
- The benefit of a sparser classifier is that its results are more generalizable.

Basic Problem

Given a data set of input-target pairs $\{\mathbf{x}_n, t_n\}_{n=1}^N$ where $\mathbf{x}_n \in \mathbb{R}^d$ and $t_n \in \{0, 1\}$, a RVM classifier output is the posterior probability of membership of one of the classes given the input \mathbf{x} . Predictions are based in a function y(x) defined over the input space:

$$y(\mathbf{x}; \mathbf{w}) = \sum_{i=1}^{N} w_i K(\mathbf{x}, \mathbf{x}_i) + w_0, \qquad (1)$$

where $K(\mathbf{x}, \mathbf{x}_i)$ is the *kernel* function that defines a basis function for each sample in the training set.

Classification

To obtain a crisp classification, the probability output is tested against a threshold:

$$\hat{t}(\boldsymbol{\theta}) = \begin{cases} 1, & P(t=1 \mid \mathbf{x}, \mathbf{w}) > \boldsymbol{\theta} \\ 0, & P(t=1 \mid \mathbf{x}, \mathbf{w}) \le \boldsymbol{\theta} \end{cases},$$
(2)

unless stated otherwise, usually heta=0.5 when classification results are reported. 011111000011110010117

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- 1 Introduction
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- 3 Relevance Vector Machine
- 4 Computational Experiments Results
- 5 Conclusions

Methodology

- To evaluate the performance of the classifier, we use 10-fold cross-validation, repeated 50 times.
- To quantify the results, we measured the Accuracy, Sensitivity and Specificity.
- We have labelled patients as class 0 and controls as class 1.

Approaches

• Tested approaches are:

- RVM and SVM with linear and Gaussian kernels.
- Multilayer perceptron trained with backpropagation algorithm (MLP-BP).
- Radial Basis Function (RBF) with a linear output layer.
- Nearest Neighbor (1-NN) and the Probabilistic Neural Networks (PNN).
- A separate SVM has been trained for each VBM cluster and the results of the independent SVM classifiers are fused by majority voting.

RVM vs previous results

Classifier	Accuracy	Sensitivity	Specificity
Linear RVM	0.76	0.77	0.75
rbf RVM	0.76	0.76	0.77
Linear SVM	0.73	0.72	0.75
rbf SVM	0.76	0.77	0.76
Indep. linear SVM	0.77	0.74	0.80
Indep. rbf SVM	0.78	0.76	0.80
MLP-BP	0.78	0.72	0.84
RBF	0.72	0.65	0.80
1-NN	0.70	0.61	0.79
PNN	0.74	0.68	0.81

Table: RVM vs previous results.

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Conclusions

- We have explored the application of RVM to this feature database finding the accuracy results comparable with other state of the art classifiers.
- The sensitivity and specificity results are well balanced, contrary to other classifiers that show some bias towards one of them.

Further work

- The consideration of features extracted on the basis of information obtained from other morphological measurement techniques, such as Deformation-based Morphometry and Tensor-based Morphometry.
- Use additional image modalities (PET, fMRI, DTI) and additional clinical data. Additional image modalities imply the mutual registration of volumes and the fusion of the diverse information sources. Additional clinical data may be used as covariates in the GLM resolution within the VBM analysis.
- Using new classification strategies, such as the ones based on Lattice Computing or other soft-computing approaches.

Thanks

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