Parallel Nonlinear Analysis of Weighted Brain's Gray and White Matter Images for Alzheimer's Dementia Diagnosis

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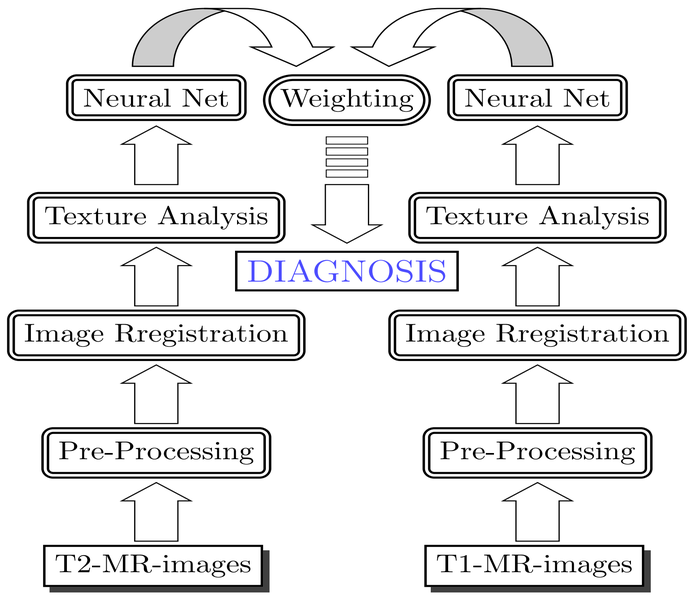
Introduction

We introduce a novel method for Alzheimer's dementia diagnosis. Our focus is on analysis of MRI because of its high resolution in brain tissues.We believe that the tissue analysis can be a reliable tool to diagnose various diseases. The novelty of this work is using both T1 and T2 images simultaneously after they are optimally weighted.

Brain Images Dataset

- 120 MRI's (including T1 and T2 images) for different cross-sections of the brain
- 52 images belong to the normal control group while the rest belongs to AD patients.
- Half of the images is T1 and the other half is T2.
- 60 percent of the images is used for training, and the rest is reserved to test and control the algorithm.
- Images dataset: The Whole Brain Atlas. Available on `http://www.med.harvard.edu/AANLIB/home.html`

Disease Diagnosis Method

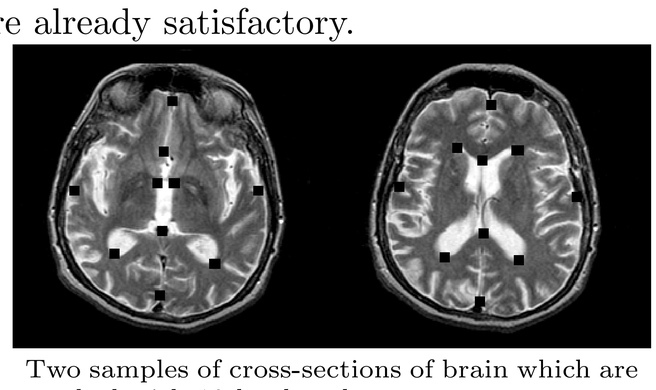


Phase I: preprocessing

Removing irrelevant information:

1. marginal parts of the images.
2. background.
3. other parts of brain, e.g. parts of eyes.

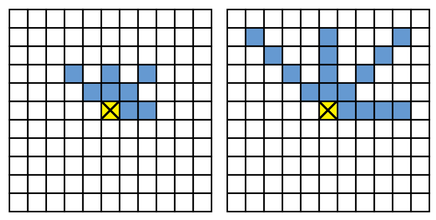
We registered each image on its corresponding image as precisely as possible using 10 landmarks. The landmarks are located and placed on those points of the brain which are geometrically and anatomically more important. Registration includes 1) pixel position interpolation and 2) gray-level interpolation. For performing interpolation process, radial basis function $r^2 \log r^2$ is used. The affine terms have not been used in the proposed algorithm, since the results were already satisfactory.



Two samples of cross-sections of brain which are marked with 10 landmarks.

Phase II: core processing

We extracted features which can capture the properties of the brain tissue using Gray-Level Co-occurrence Matrix (GLCM) which helps scan the tissue in order to give a sense of how the relationship between different pixels of an image is.



Definition of neighborhood for the central point in T1 images (right figure) and T2 images (left figure).

Considering the fact that AD defects the white and gray regions of brain more than its black and marginal regions, and also since T1-weighted has more medical data of white and gray regions than T2-weighted images, we believe that T1 images have more data than T2 images, thus we define neighborhood of T1 and T2 differently.

The desired Statistical features are as follows: 1) Energy, 2) Contrast, 3) Homogeneity, and 4) Correlation

Correlation in the GLC matrix:

$$f_1 = \frac{HXY - HXY1}{max\{HX, HY\}}$$

$$f_2 = \sqrt{1 - \exp\{-2(HXY2 - HXY)\}}$$

C(i, j) is an element of GLC matrix and N is number of gray-levels.

$C_x(i) = \sum_{j=1}^{N} C(i,j), \quad C_y(i) = \sum_{i=1}^{N} C(i,j)$

$HXY = -\sum_{i=1}^{N}\sum_{j=1}^{N} C(i,j)\log\{C(i,j)\}$

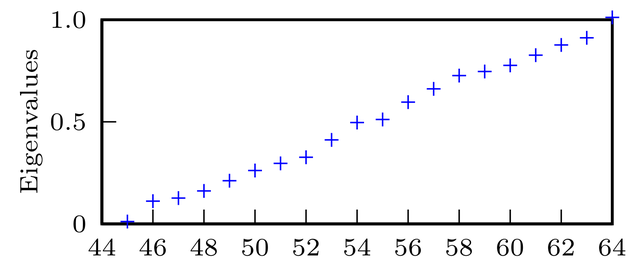
$HXY1 = -\sum_{i=1}^{N}\sum_{j=1}^{N} C(i,j)\log\{C_x(i) \times C_y(j)\}$

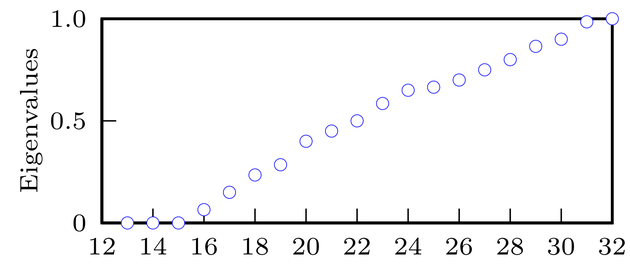
$HXY2 = -\sum_{i=1}^{N}\sum_{j=1}^{N} C_x(i) \times C_y(j)\log\{C_x(i) \times C_y(j)\}$

4*16 features from T1 and 4*8 features from T2 are extracted.

Feature Extraction

We reduce two vectors, one for T1 images and another one for T2 images that using PCA. We chose 19 first eigenvalues with the largest values for T1 image, and also 17 eigenvalues with the largest values for T2 images.





Trends of changes in eigenvalues of two input vectors.

Discrimination

Two feed-forward neural networks are tuned and used with 19 and 17 inputs for analysis of T1 and T2 images respectively. Both networks have a hidden layer with 10 nodes equipped with Sigmoid transfer function.

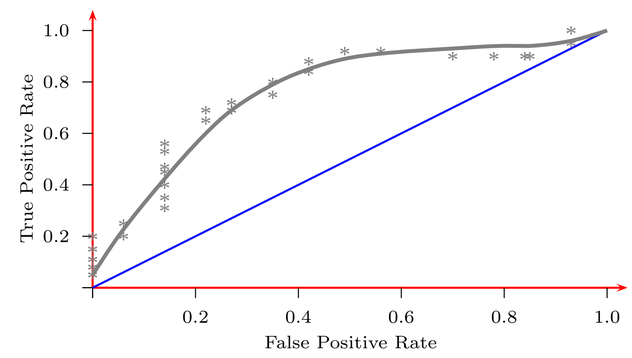
We multiply the first neural network's output by weighting factor 0.63, and also multiply the second neural network's output by weighting factor 0.37, that were initialized and determined during the training of the classifier system.

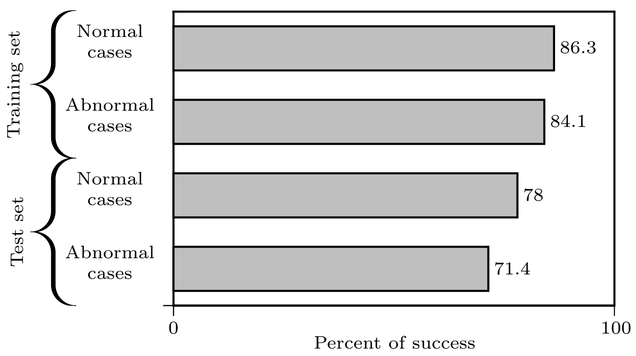
Results

In order to give a more clear measure of the performance of the classifier system, consisting of two parallel neural networks, the right-top figure illustrates an ROC graph.

However, higher accuracies in separation of training data can cause a better result in our database, but this increases the number of layers and nodes of the neural networks which may lead to overtraining of the system and thus, it may reduce the classification accuracy of test images. Therefore, we believe that the response shown here is an optimal one.

In the future research, we try to, in addition to improving the diagnosis of AD, produce initially independent features in order to increase the speed of process to have a real-time classifier system.





The final results of the AD diagnosis system.

References

[1] M. Torabi, H. Moradzadeh, R. Vaziri, S. M. J. Razavian, R. Dehestani Ardekani, M. Rahmandoost, A. Taalimi, and E. Fatemizadeh, "Development of Alzheimer's Disease Recognition Using Semiautomatic Analysis of Statistical Parameters Based on Frequency Characteristics of Medical Images," in *Proc. of IEEE Int. Conf. Signal Proc. & Communication*, Nov 2007, pp. 868–871.

[2] M. Torabi, R. Dehestani Ardekani, and E. Fatemizadeh, "Discriminationnation between Alzheimer's Disease and Control Group in MR-Images Based on Texture Analysis Using Artificial Neural Network," in *Proc. of Int. Conf. Bio. & Pharm. Eng.*, Dec 2006, pp. 79–83.

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The main concept of this work is inspired by the ideas of the philosopher Majid Jafari-Tabar.