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Intensity diagnosis of Alzheimer's based on VBM

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ABSTRACT

The volume calculation of MR Image segmented and estimate the affected intensity of Alzheimer's disease is dealt with this paper. It is concerned with Voxel Based Morphometry to render the first part segmentation. The result gives an active region which further needs an estimation to justify the diagnosis. As in this case the image is in form of voxels. When properly processed, classified images can represent foundations for diagnostic purposes. A VBM - fuzzy approach was used to take advantage of Voxel Based Morphometry's ability to fine segmentation based on voxel comparisons of GM, WM & CSF and membership degrees andfunctions of fuzzy logic, respectively. The method of VBM is done with SPM. The method is based on the spatial properties of the MR Brain image features and makes use of SPM multi-scaled representations of the image. A fuzzy classifier is created on basis of the previous segmented data. The method showed high quality classification for images of complex components in determining the intensity of Alzheimer's and GUI is used as front end for the user comfort.

Introduction

Alzheimer's disease is a brain disorder named for German physician Alois Alzheimer, who first described it in 1906. It is a progressive and fatal brain disease, which destroys brain cells, causing memory loss and problems with thinking and behavior severe enough to affect work, lifelong hobbies or social life. Alzheimer's gets worse over time, and it is fatal. Like the rest of our Body organs, our brains change with age. The symptoms are, slowed thinking and occasional problems with remembering certain things.

However, serious memory loss, confusion and other major changes in the way our minds work are not a normal part of aging. They may be a sign that brain cells are failing. The brain has 100 billion nerve cells (neurons). These cells are involved in thinking, learning and remembering. Others help us see, hear and smell.

In Alzheimer's disease, increasing numbers of brain cells deteriorate and die. Two abnormal structures called plaques and tangles are prime suspects in damaging and killing nerve cells. The proper investigation of the affected area can help in its treatment. Thus MR brain volume calculation of the affected area becomes vital. First processing of MR Brain images is through VBM. Voxel-based morphometry (VBM), compare different brains on a voxel-by-voxel basis after the deformation fields have been used to spatially normalize the images. In this the entire brain, is examined rather than a particular structure. This approach therefore depends on the types of structural difference that are expected among the images.

A VBM-fuzzy approach as a combination of VBM and fuzzy logic is introduced to find the different intensity of affected area in an image. This paper implements the VBM-fuzzy approach to extract the MR brain image features voxel by voxel and classify them into various sets of classes for proper intensity identification of Alzheimer's. GUI is used to select the specific output.

Diagnosis of Alzhiemer's Disease

Earlier, several methods are used to diagnose the Alzheimer's disease.

Multiple Active Contour Models and Fuzzy Clustering

Automatic segmentation was combining fuzzy clustering and multipleactive contour models. An automatic initialization Algorithm based on fuzzy clustering is used to robustly identify and classify all possible seed regions in the image. These seeds are propagated outward simultaneously to localize the final contours of all objects.

In this, the level set approach is used in various imaging domains. The approach is based on the theory of curve evolution, geometric flows and their implementation using the level set based numerical algorithms proposed by other and sethian.

This can be used only in microscopy images.

Dynamically Dysfunctional Protein Interactions

This is based on the network-based method, reveal that the active pathways Tend to be more complicated during the development of disease. Also find that the disease proteins performing important functions are always located in the cooperation of the identified pathways. These results also demonstrate that the network-based analysis can provide knowledge and evidences on the dynamics and pathological pathways of the complex Alzheimer's disease

It can be only used for protein interactions not genotype mechanisms.

Stacked Generalization For Early Diagnosis OfAlzheimer's Disease

This is based on, multi resolution wavelet analysis is performed on event related potentials of the EEGs of a relatively larger cohort of 44 patients. Particular emphasis was on

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diagnosis at the earliest stage and feasibility of implementation in a community health clinic setting. Extracted features were then used to train an ensemble of classifiers based stacked generalization approach.

It uses electrodes, which cause discomfort to patient. This is preliminary test, not accurate.

MR Image Texture Analysis

This takes, the value of magnetic resonance (MR) image texture in Alzheimer's disease (AD) both as a diagnostic marker and as a measure of progression. T1-weighted MR scans.

Stepwise discriminate analysis was applied to the training set, to obtain a linear discriminate function.

This can be only used to track the Alzheimer disease.

Proposed System

The VBM -fuzzy system, with software programs the SPM5 & Mat lab toolboxes. The patient data is collected for processing. The toolbox of VBM is a collection of extensions to the segmentation algorithm of SPM5. The aim of VBM is to identify differences in the local composition of brain tissue, rather than large scale differences. This is achieved by spatially normalizing all the structural images to the same stereotactic space, segmenting the normalized images into gray and white matter, smoothing the gray and white matter images and finally performing a statistical analysis to localize significant differences between two or more experimental groups. The output is a statistical parametric map (SPM) showing regions where gray or white matter differs significantly among the groups. The VBM localizes the areas of brain affected by Alzheimer's. GUI is used as front end, which allows user to select the particular output.

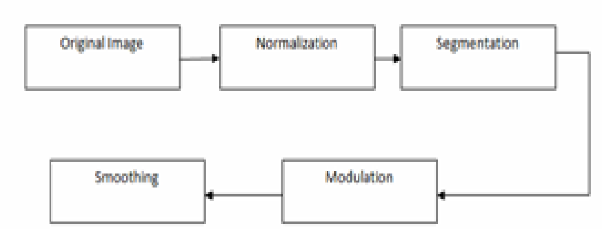

Figure 1. Flow Diagram

Spatial Normalization

Spatial normalization involves registering the individual MRI images to the same template image. A template consists of the average of a large number of MR images that have been registered in the same stereotactic space. In the SPM2 software, spatial normalization is achieved in two steps.

The first step involves estimating the optimum 12-parameter affine transformation that maps the individual MRI images to the template. Here, a Bayesian framework is used to compute the maximum a posteriori estimate of the spatial transformation based on the a priori knowledge of the normal brain size variability.

The second step accounts for global nonlinear shape differences, which are modeled by a linear combination of smooth spatial basis functions. This step involves estimating the coefficients of the basic functions that minimize the residual squared difference between the image and the template, while simultaneously maximizing the smoothness of the deformations.

The ensuing spatially-normalized images should have a relatively high-resolution (1mm or 1.5mm isotropic voxels), so that the segmentation of gray and white matter (described in the next section) is not excessively confounded by partial volume effects, that arise when voxels contain a mixture of different tissue types.

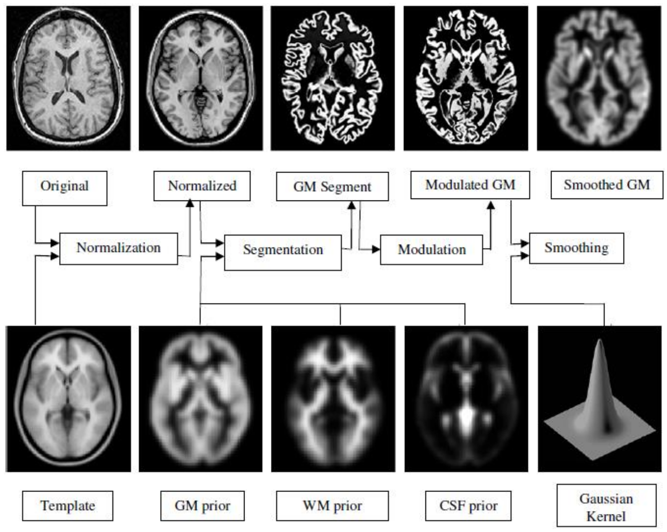

Figure 2. VBM flow diagram

Segmentation

The spatially normalized images are then segmented into gray matter, white matter, cerebrospinal fluid and three nonbrain partitions. This is generally achieved by combining a priori probability maps or "Bayesian priors", which encode the knowledge of the spatial distribution of different tissues in normal subjects, with a mixture model cluster analysis which identifies voxel intensity distributions of particular tissue types. The segmentation step also incorporates an image intensity non-uniformity correction to account for smooth intensity variations caused by different positions of cranial structures within the MRI coil.Here the spatial normalization of the control as well as the patient is carried out.

At first estimation of data is done, where raw data gets selected with controls. Then estimation options are carried out. It includes Tissue probability maps, Gaussians per class, affine regularization, warping regularization, warp frequency cutoff, bias regularization with very light regularization, bias FWHM with 70mm cutoff, sampling distance, setting the origin. Further writing options include GM,WM,CSF& Bias correction with native space, unmodulated normalized area, modulated normalized area.

Smoothing

The segmented gray and white matter images are now smoothed by convolving with an isotropic Gaussian kernel. The size of the smoothing kernel should be comparable to the size of the expected regional differences between the groups of brains, but most studies have employed a 12-mm FWHM kernel. The motivation for smoothing the images before the statistical analysis is three-fold. First, smoothing ensures that each voxel in the images contains the average amount of gray or white matter from around the voxel (where the region around the voxel is defined by the smoothing kernel). Second, the smoothing step has the effect of rendering the data more normally distributed by the central limit theorem, thus increasing the validity of parametric statistical tests. Third, smoothing helps compensate for the inexact nature of the spatial normalization. Smoothing also has the effect of reducing the effective number of statistical comparisons, thus making the correction for multiple comparisons less severe.

Statistical Analysis

Following the pre-processing, the final step of a VBM analysis involves a voxel-wise statistical analysis. This employs the general linear model (GLM), a flexible framework that allows a variety of different statistical tests such as group comparisons and correlations with covariates of interest. The standard parametric procedures (t tests and F tests) used are valid providing that the residuals, after fitting the model, are normally distributed. If the statistical model is appropriate, the residuals are most likely to be normally distributed once the segmented images have been smoothed.

The results of these standard parametric procedures are statistical parametric maps. Since a statistical parametric map comprises the results of many voxel-wise statistical tests, it is necessary to correct for multiple comparisons when assessing the significance of an effect in any given voxel.

Fuzzy color classification is a supervised learning method for segmentation of color images. This method assigns a color class to each pixel of an input image by applying a set of fuzzy rules on it. A set of training image pixels, for which the colors are known, are used to train the fuzzy system.

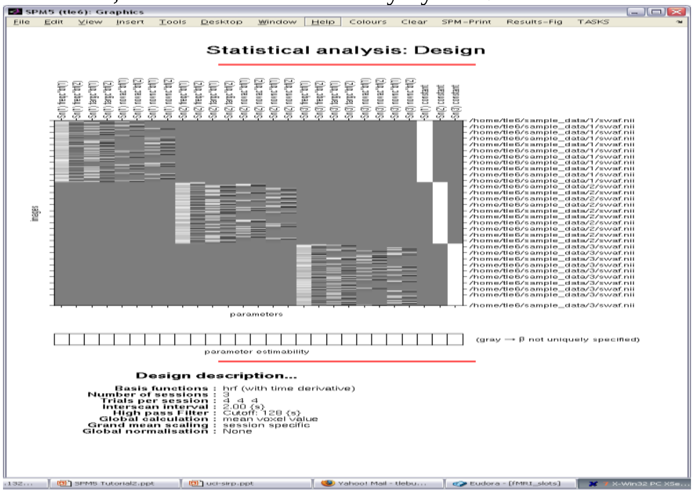

Figure 3. Statistical Analysis

Fuzzy Color Classification

Different color spaces like HSL, RGB, YIQ, etc. have been suggested in image processing, each suitable for different domains. HSL color space is used because a color in this space is represented in three dimensions: one which codes the color itself (H) and another two which explain details of the color, saturation (S) and lightness (L). Instead of assigning a specific hue value to each color around this circle, a fuzzy membership function can code for a color by giving it a range of hues each with different membership value. Thus, to model the fact that the distribution of colors is not uniform on circle of hues, Truck in , propose to represent them with trapezoidal or triangular Fuzzy Subsets. Several other works have been done in the field of none uniformly distributed scales: for example, Herrera and Martinez use Fuzzy Linguistic Hierarchies with more or less labels, depending on the desired granularity .

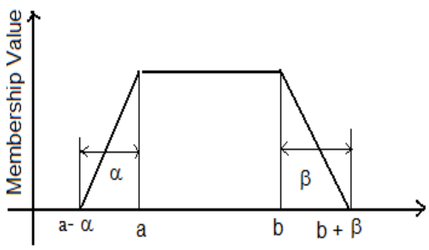

Figure 4. Trapezoidal membership function

Similarly, associated colors with fuzzy sets. Indeed, for each color, they built a Membership Function varying from 0 to 1. If this function is equal to 1, the corresponding color is a "true color".

Experimental Result

In this session proposed method results are shown.

We used MATLAB and fuzzy classifier to simulate the result.

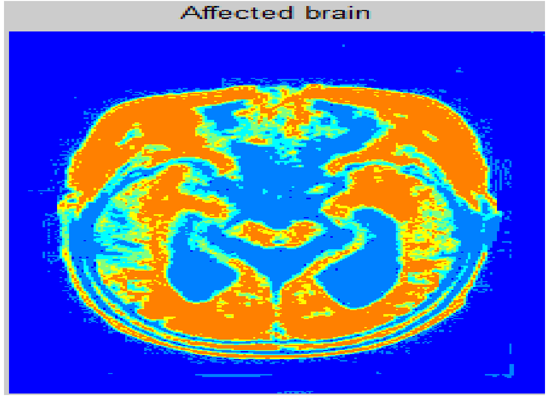

Figure 5. Simulated Output

Conclusion

The technology used here is mainly to extend a helping hand to medical community. In this paper a study on VBM with controls and patients were done. Existing methods limited the scope of diagnosis of Alzheimer's only with thedoctor's expertise. VBM method laid a path for finding the loss in GM. This encourages us to subject it to future improvement and enhancement that will enrich its contribution.

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