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Experimenting pre-processing procedure using MRI images to predict Alzheimer's Disease

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Abstract: Alzheimer's Disease(AD) has been proved as a deadly disease with most of the population being affected by it, especially old-aged people. As a result, the diagnosing field is in dire need of a computer-aided diagnosis model that can predict and classify patients accurately. For a better diagnosing model, the medical input must provide clear information to the model. This paper aim at pre-processing of the inputs, thereby reducing the dimensionality, differentiating parts of the brain and tuning them to contribute to the improvement in accuracy for the classification model

Keywords: Pre-processing, Classification, Modalities, Computer-aided Diagnosis, Alzheimer's Disease

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I. INTRODUCTION

Alzheimer's disease has been realized to be the most common among people especially old-aged. The disease's symptoms have been usually misunderstood as a sign of old age or inattentiveness and ignored carelessly. This disease produces a death rate more than breast cancer and prostate cancer combined, every 1 in 3 senior citizens develops it and more shocking is that every 66 seconds someone develops AD in the United States according to a recent survey [1]. Getting microscopic into the brain, each nerve cell (neuron) in the brain is connected to each other in the form of communication networks and groups of neurons are responsible for the functioning of various tasks in our brain. AD causes damage in these nerve cells, mainly due to:

- **Plaques** are deposits of a protein fragment called beta-amyloid that build up in the spaces between nerve cells.
- **Tangles** are twisted fibers of another protein called tau that builds up inside cells.

Clearer screening of the brain provides better accuracy in the diagnosing model, so the steps for pre-processing the MRI images that have to be injected into the model has been experimented. Bhagya Shree and Sheshadri (2014) [28] have highlighted in their paper, about the importance of good pre-processing of the image. They have given a brief insight into a method in which pre-processing can be done. The main aim of pre-processing an image is to improve the data, suppressing the noises, reducing the size and reconstruction.

The paper proceeds further giving an insight into the works surveyed in section II, the architecture enlightening the steps of pre-processing in section III, the results of the steps being discussed in section IV and finally concluding the work with future work in section V.

II. LITERATURE SURVEY

Features act as the attributes based on which the classification of the patients can be done whether they are healthy or in the case being affected, their stage of progression. The features may be either the parts of the input, pattern or content value etc., The features are obtained from various biomarkers that are sensitive to the Alzheimer's Disease.

Some of the modalities that are sensitive to AD/MCI diagnosis: [15]

- **Magnetic Resonance Imaging(MRI):** Brain atrophy measurement is given by Structural and functional MRI.
- **Cerebrospinal Fluid(CSF):** CSF gives the quantification of proteins.
- **Blood Samples:** The protein content in the body is measured from the blood samples.
- **Positron Emission Tomography(PET):** The glucose content is measured with PET and Fluorodeoxyglucose PET.
- **Electro-Encephalogram(EEG):** EEG is used to analyze the brain activity.

- **Genetic information:** The main cause of the disease is by genes, including this will give more accuracy to the diagnosis.

The data received from the modalities must undergo the pre-processing procedure, making it suitable for applying various methods or techniques. Various approaches have been proposed by researchers for the pre-processing phenomena, each differs by the type of input format it needs and tools used.

Zhang et al (2011) [35], Liu et al (2014) [20] and Chen Zu et al (2016) [37] have implemented image analysis with MATLAB and tools like Brain Surface Extractor(BSE), Brain Extraction Tool(BET), FAST in FSL package in their works. The procedures followed are Anterior Commissure(AC)-Posterior Commissure(PC) with N3 intensity homogeneity correction, skull stripping, cerebellum removal, segmentation, registration, labeling and computing volume of Grey Matter(GM) into ROI (Regions of Interest) by Atlas Warping. Jie et al (2015) [17] has done the same with spatial distortion.

Shuai Huang et al (2011) [14] normalized (affine transformation, subsequent non-linear wrapping algorithm) MRI and PET with SPM (Statistical Parametric Mapping) to Montreal Neurological Institute(MNI) template. This undergoes Automated anatomical labeling technique to segment whole brain into 116 brain regions and used as features.

The input collected for the model needs to undergo various steps of pre-processing, to convert it into a format that the model can easily apply its techniques like feature extraction, feature selection, and classification. So the inputs have to be represented in such a way that the features can be extracted from it.

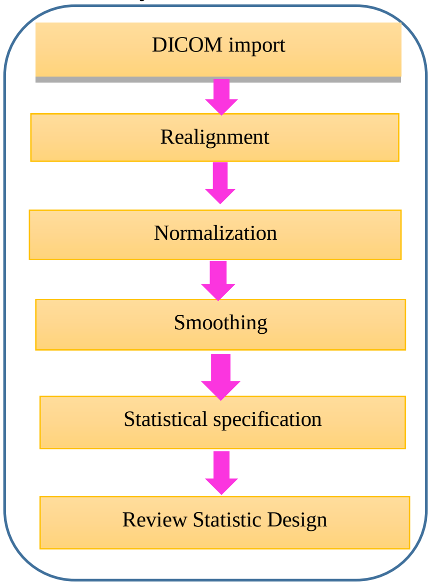


Fig.1. Steps in Pre-processing the MRI images

Fig.1 depicts the flow of data in the pre-processing procedure that has been followed in this paper [2].

III. METHOD

A. DICOM import

Digital Imaging and Communications in Medicine(DICOM) is a standard for storing and transmitting medical images enabling the integration of medical imaging devices such as scanners, servers, workstations, printers, network hardware, and picture archiving. The DICOM format is a very complex file forming at to handle, thus converting the DICOM files into SPM suitable format is done while importing it into SPM. The images for each subject has obtained a series of slices of the brain.

B. Realignment

Each slice of the brain, imported as DICOM files need to be realigned since each will be in an asynchronous manner. The rest of the images get aligned with respect to the first slice of the image so that all the slices get synchronized to the first image slice. Each subject's slices being organized makes the classification process a neat procedure.

- Realign (estimate): tells how much to rotate and move images to synchronize it with the first image of the sequence of the images. Changes name of metadata or header information giving the position of data in space. Image data remains same, only the orientations change.
- Realign (resize): creates a new set of realigned imaged
- Realign (est & res)

- Realign and unwarp

C. Normalization

Normalizing and warping the brain images, so that all images are of the same template and shape voxel by voxel.

- Normalize (estimate): Change one image to another
- Normalize (write): Create a new image
- Normalize (est & wri): Combining both estimate and write.

Each human brain differs by size and shape; spatial normalization deforms brain scans so that a location in one subject's brain scan matches the same location in another subject's brain scans. This is helpful while performing an observation on many subjects. Following a template makes it a standard process of classification.

D. Smoothing

After normalization, the images need to be smoothed before specifying statistics. Each voxel is being given a new value, which makes the smoothed images look blurry. It creates an approximation function that attempts to capture important patterns in data while leaving the noises. The data points that are high are reduced and low points are increased leading to smooth signals. In data analysis, it enhances extraction of more information and provides flexible and robust data analysis. Every data collection, not only contains the needed data but mostly has the possibility of containing noises (unwanted data), this brings a drastic change in the classification accuracy.

E. Statistical Specification

- Specify 1st level: This provides a within-subject analysis of images
- Specify 2nd level: This provides a summary analysis of the subject responses on images.

The design matrix is produced as a result of this analysis which defines the experimental design. The model design gives an outline of the data involved in the model.

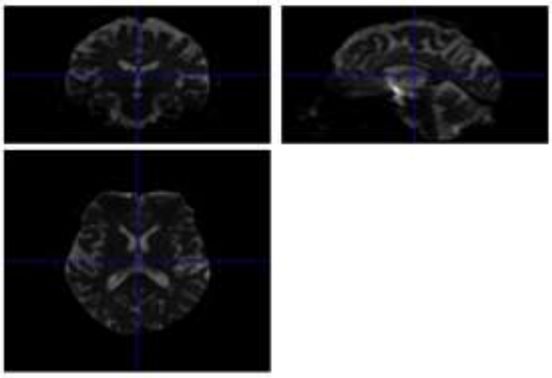
F. Review Statistic Design

The statistical design is being reviewed. The statistical design thus obtained from the statistical specifications is explored and analyzed. The experimental variance is checked after passing through a high-pass filter.

IV. Results And Discussion

The before said pre-processing procedure was experimented using SPM in MATLAB. Samples of the step's results are given along with a concise inference about it.

A. DICOM import



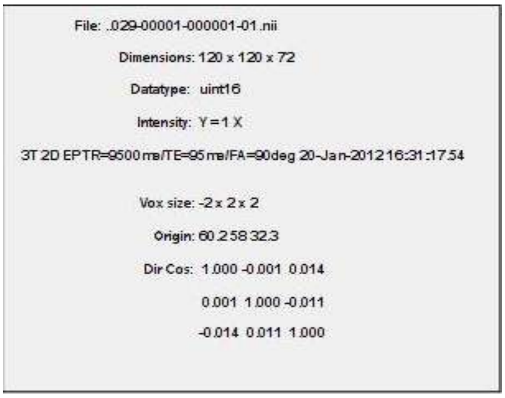


Fig. 2. Functional DICOM images

Fig.2 displays the functional DICOM images and their details. Importing the MRI images from DICOM viewer that's used to display the series of slices of a single subject. The DICOM images are converted into the SPM compatible format during this process. This step also gives the distinct structural and functional images of MRI scan images.

B. Realignment

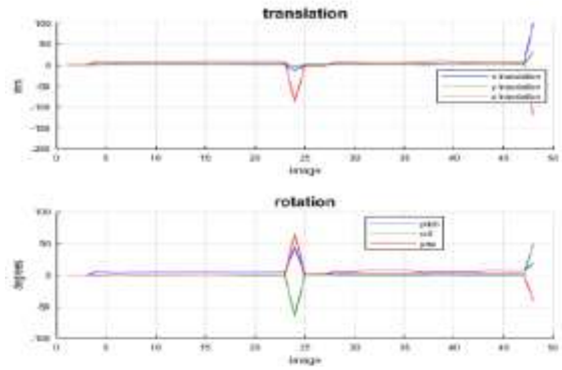


Fig. 3. Realigned images

Fig.3 displays the rotation and movement undergone by the images to synchronize the remaining slices with the first image of the subject so that each subject can be classified better with all their slices synchronized.

C. Normalization

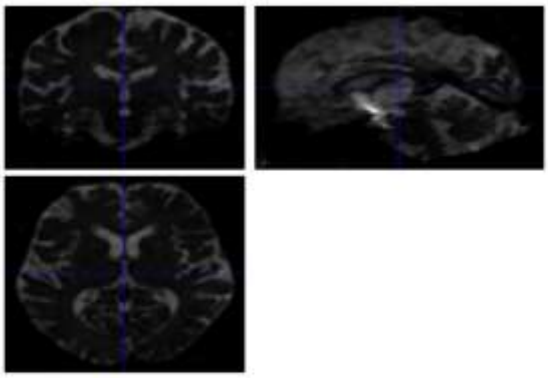


Fig. 4. Normalized images

Fig.4 displays the result of normalized images. The shape and size of the human brains, which varies from human to human are made uniform. The reduction in the dimensions has been achieved here.

D. Smoothing

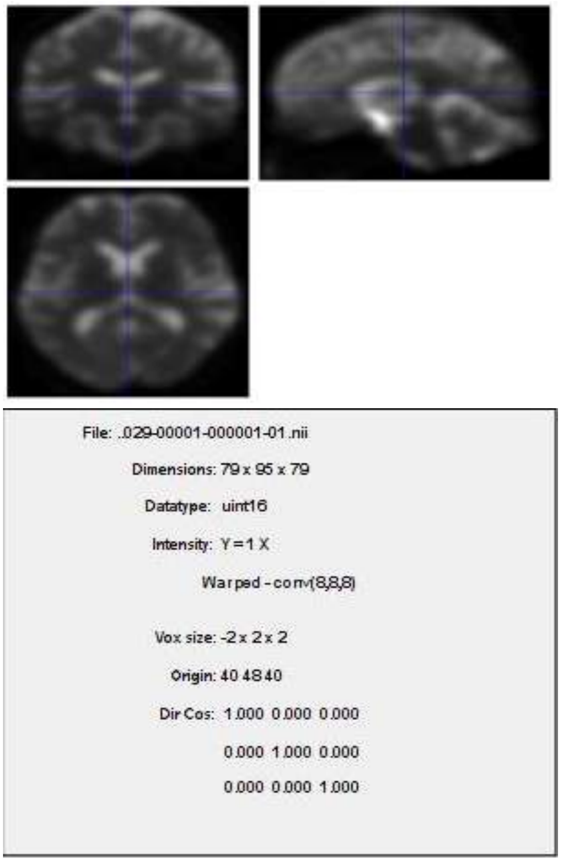


Fig. 5. Smoothed images

Fig.5 displays the result of images that have been smoothed. The images have been blurred as a result of smoothing to reduce noises. The ups and downs in the data signals are reduced/increased respectively to smooth the signals.

E. Statistical Specification

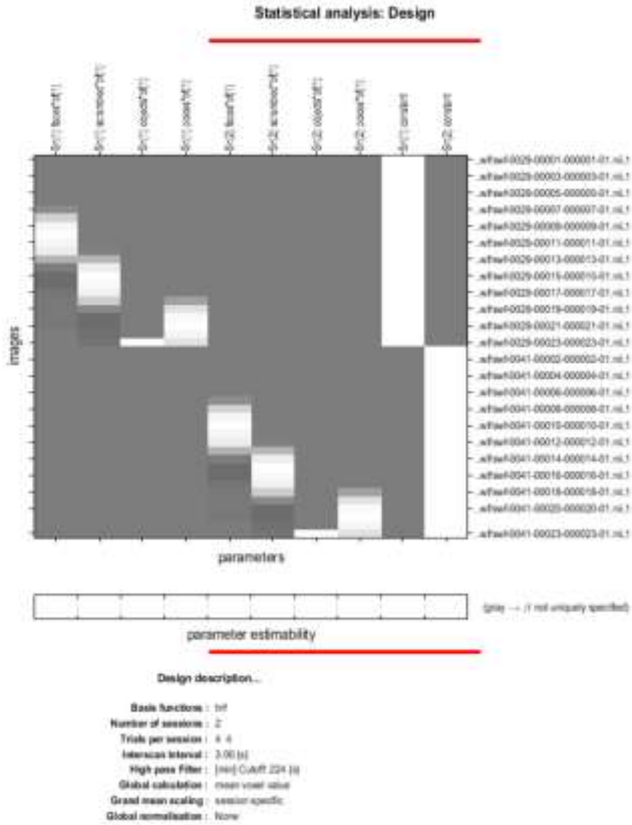
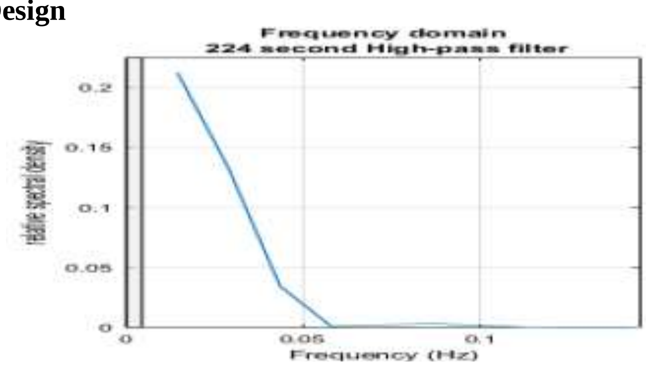


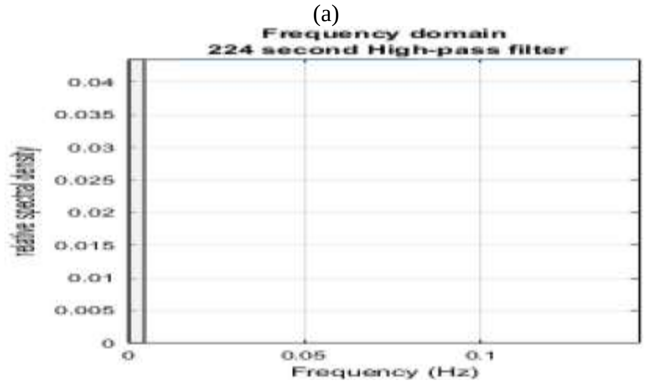
Fig. 6. Statistical specification

Fig.6 shows the statistical specification of the model. There are 2 sessions and four experimental conditions for each session: Faces, Scrambled, Objects and Places. Each row stands for one fMRI scan. The last two columns depict the average activity in each session.

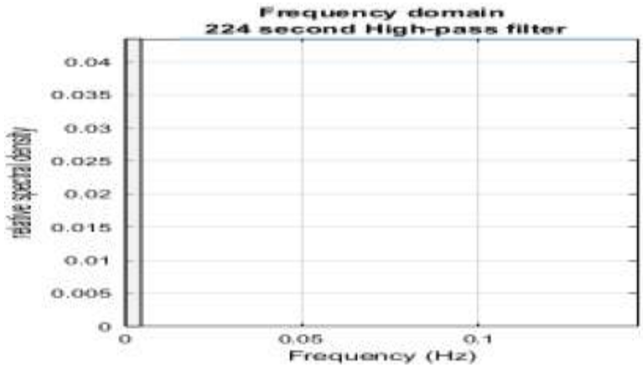
F. Review Statistic Design



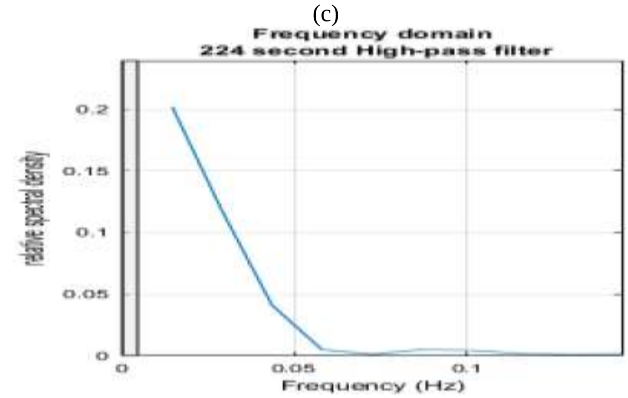
(a)



(b)



(c)



(d)

Fig.7. Review Statistic Design (a)Faces (b)Scrambled (c)Objects (d)Places

Fig.7. is indicating the part of images taken into account. The frequency domain graph is used to check that experimental variance is not removed while passing through a high-pass filtering.

The DICOM images imported from DICOM viewer are converted to a compatible format suitable to use in SPM. The image slices are realigned to synchronize all the slices of brain image of a single subject. The images obtained after realignment are normalized, which contributes to the brain images of different subjects being compared thus standardizing the subject's images. These images are then smoothed to reduce the noises. The statistical specification is done to analyze the images and provide an outline of the data involved in the model. This is then reviewed to check the experimental variance of the model. The preprocessing of input modality is an impactful procedure to the classification model. A computer shows more efficiency based on the input given to it, so giving a better input contributes to the better working of the model. The classification model would be better if the images are preprocessed and used, which gives a clear vision of the subjects involved in the model.

V. CONCLUSION AND FUTURE WORK

The pre-processing procedure for MRI images was experimented using the SPM tool in MATLAB and the images were realigned, normalized, smoothed, model specified and reviewed. By this procedure, the images got reduced in noise and dimensionality, rotated and moved with respect to the first slice of the images. The work can be extended by applying this procedure to other modalities and also increasing the steps of pre-processing.

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