Alzheimer's Detection at Early Stage Using Modified LGS (M-LGS) on MRI

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Abstract: Alzheimer's Disease (AD) is the most common cause of dementia, which is a non-curable after a certain stage. The nerve cells, which are very essential to carry messages in the brain, particularly those responsible for storing memories, slowly get damaged due to the formation of tangles and plaques made from protein fragments in damaged areas of the brain. This paper focuses on early detection of Alzheimer's disease using Magnetic Resonance Imaging (MRI), so that effective medication is possible. The minute changes in the Gray Matter (GM) and white is observed there in the MRI and the processing of this will be an aid to the expert for the correct diagnosis. The GM and WM are segmented from the image and the texture information is extracted using different variants of the Local Binary Pattern (LBP). It is observed that the Modified Local graph structure with the inclusion of grayscale information is a good descriptor for classifying AD and Mild Cognitive Impairment (MCI). The accuracy of the classification is improved by the inclusion of the proper threshold in the formation of local pattern.

Keywords: Alzheimer's disease, Local patterns, Magnetic resonance imaging, Mild cognitive impairment, Normal aging, Support vector machine.

I. Introduction

Alzheimer's is a dementia that causes problems of life such as thinking, memory and behavior. The Symptoms develops very slowly and day by day it gets worse and it becomes severe enough to interfere in day-to-day tasks. There is no definitive clinical test to determine whether a person has Alzheimer's disease. Usually several tests are performed to rule out any other cause of dementia. The only definitive method of diagnosis is examination of brain tissue obtained from a biopsy or autopsy [1]. However, if the current accepted criterion established by the NINCDS-ADRDA Work Group (National Institute of Neurological and Communicative Disorders and the Alzheimer's disease and Related Disorders Association) is used, diagnosis before death is considered about 90% accurate [2]. Clinical examination for Alzheimer's disease are extremely difficult to set up in a meaningful way, because the disease is only diagnosed when extensive damage to the nervous system has already occurred (enters moderately severe cognitive decline) and the atrophy changes are explicitly observed in Brain MRI. For a new drug and medicines to be tested broadly, the participants should be in the early stages of a disease, because it is then that most drugs have the greatest benefit [4]. Being able to identify people few years before the onsetof symptoms should make it easier to set up effective human studies. Change in behavior has nothing to deal at the early stage and an alternative method has to be devised. In this context MRI/S can be employed to identify the minute changes in the frontal lobes during the very mild cognitive decline stages which could greatly contribute to treating them effectively. Table 1 shows the stages of AD progression. The minute changes in the MRI/S are understood only if it is processed or localized. Since MRI is locally smooth, Texture classification via Local measures can be used for effective classification of GM. Local Pattern analysis plays an important role in Image analysis applications using few computational resources. An image texture is a set of metrics calculated in image processing designed to quantify the perceived texture of an image and it can uniquely identify them. Textual operators should be cheap and robust against variations caused by uneven illumination, different viewing positions, scaling, viewpoint and shadows in appearance of a texture [3].

There are varieties of techniques to identify AD from MRI and some of the methods are portrayed here. Neuroimaging tools to rate regional atrophy, ubcortical cerebro vascular disease, and regional cerebral blood flow and metabolism for detecting regional atrophy, cerebro vascular disease, and regional brain function opens up theregion of neurodegenerative disorder [10]. The work on Global and local gray matter loss in mild cognitive impairment and Alzheimer's disease which analyzes Global GM volume using segmentation by VBM also emphasis that severe GM loss occurs in MTL regions [11]. Detection of pro-dromal Alzheimer's disease via pattern classification [12] of magnetic resonance imaging by Segmenting image in to Grey Matter, White Matter and cerebrospinal fluid and spatially transforming the segmented image in to stero-taxic space is pattern analysis and classification method based on Voxel-by-voxel analysis of Pearson correlation coefficient states that the

Disease duration of less than 4 years was mainly characterized by atrophy in the MTL region, while disease duration of more than 4 years (hence higher probability of having true AD clinical picture) showed extension to other structures like the caudate nucleus, parietal-occipital regions, and frontal and parietal lobes. Using Volume Features and Shape Features for Alzheimer's disease Diagnosis by Volume estimation by 3-D volumetric features and statistical analysis by 2-D shape features are done. Principle component analysis (PCA) was utilized to decrease the dimensions of feature space. SVM classifier was trained for AD classification proves that the Left hemisphere shows atrophy greater than the right [13]. Cortial change [14] in AD detected with Disease-Specific Population-based Atlas is used for Tissue classification this is implemented by extracting cortial surface and gyral pattern matching the recognition is implemented by distinguishing variations in grey matter and the distribution from variations in Gyral patterns are encoded in these variation in Brain atlas and maps are created localizing grey matter differences explains the fact that the Left penisylvian language regions would exhibit greatest spatial variability and the entorhinal and medial temporal lobes show the earliest signs of atrophy in MCI, with fontal atrophy typically occurring later. Longitudinal Change of the Grey Matter of Mild Cognitive Impairment Patients over 3 years by Using Voxel-Based Morphometry done by normalizing the image based on Statistical analysis. Evaluation of different stages of AD using unsupervised clustering technique and voxel based morphometry is also studied for structural change in grey matter considering the GM loss [15]. Another work Computer-aided diagnostic reporting of FDG PET for the diagnosis of Alzheimer's disease is based on bio-marker's which involves the statistical voxel by - voxel comparison of F-FDG uptake compared to normative dataset. The Longitudinal Evaluation of Structural Changes in Fronto temporal Dementia Using Artificial Neural Networks Post Feature Extraction and preprocessing tissue classification is employed using ANN and is a Model Learning technique suggest that the phenomenon of neuron destruction reflects volume changes on brain tissues such as gray matter, white matter and cerebro-spinal fluid. White matter loss is associated with neuro degenerative disorders [16]. The discrimination between Alzheimer's disease, Mild Cognitive Impairment and Normal Aging Using ANN Based MR Brain Image Segmentation and realization of Back Propagation ANN identifies the structural changes after pre processing like skull stripping and feature extraction using Gabor filters [17].

The major region that gets affected by MCI in MRI is Median Temporal Lobe. This region shows commendable Grey matter volume loss and also white matter loss. This region is the Bio Marker in this Project. The other region that gets affected are Cerebellum posterior Lobe, Para-central Lobe, Inferior semi-lunar lobule, cerebellum anterior Lobe, Anterior cingulate, Frontal Lobe. Remaining of the paper is organized as follows, Section 2: Description of the System and Section 3: Results and Conclusion.

Table I: Seven Stages of AD

Stage	Impairment	Life Time	Visibility
1	No Impairment	Not Defined	Not Visible
2	Very Mild Cognitive Decline	Not Defined	Visible only after processing MRI
3	Mild Cognitive Decline	2 – 7 Yrs	
4	Moderate Cognitive Decline	2 Yrs	
5	Mod. Severe Cognitive Decline	18 Month	Visible explicitly in MRI
6	Severe Cognitive Decline	3 Yrs	
7	Very Severe Cognitive Decline	1 – 3 Yrs	

II. Materials and Method

The overview of proposed system is shown in Fig. 1. The database contains MRI images sliced at MTL region and the GM is segmented from it. The Local patterns portrayed above are extracted and fed in to Search and Retrieval System. When a new target image is queried on classification, the GM extraction takes place and followed by Local Measure extraction and the final classification result based on the distance of the target image across the images in the database.

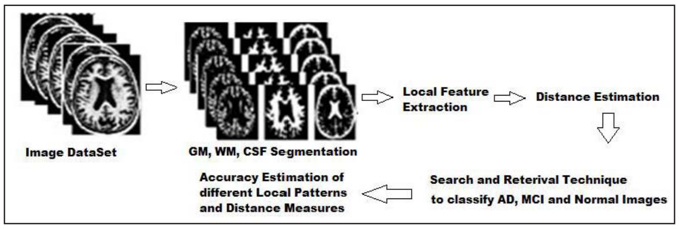

Fig. 1: Overview of System

A. Segmentation

The aim is to segment GM, WM and CSF (Cerebro Spinal Fluid) from MRI brain image. Statistical Parameter Mapping (SPM) version 8 [18] is used for this purpose. It is a fully automatic system for model based tissue classification of MRI. This system interleaves classification with evaluation of the model parameters and also improves the classification in each iteration. The algorithm segments single - and multispectral MRI/S and corrects for MR signal in homogeneities by Markov Random Fields (MRF) and also integrates appropriate information by means of Markov Random Fields. A digital brain atlas containing prior prospect about the spatial location of tissue classes is used to initialize the algorithm. This makes the system fully automatic and therefore it presents objective and reproducible segmentations. Initializing intensities in the brain as 1D array, n is the Number of voxel and the segmentation is denoted as, Z is the type of tissue the voxel belong to. Assuming there are K tissue types, k.

The segmentation is the estimation problem, where hidden segmentation has to be estimated from the observed intensity. The MRI image is viewed and the MTL region is sliced and post slicing the segmentation is performed on that particular slice.

B. Modified LGS - Feature Extraction

Post Segmentation the local patterns are extracted from the Grey Matter. The Local Patterns used in this study are Local Binary Pattern (LBP), Local Ternary Pattern (LTP) [5], Dominant Local Binary Pattern and variants (DLBP) [6], Complete Local Binary Pattern and variants (CLBP) [7], Adaptive Local Binary Pattern (ALBP) [8], Local Quinary Pattern (LQP) [5], Local Graph Structure (LGS) [9] and some Variant of LBP [1]. Local Graph Structure and M-LGS has been studied in detail and their distribution is analyzed on Grey Matter and White Matter.

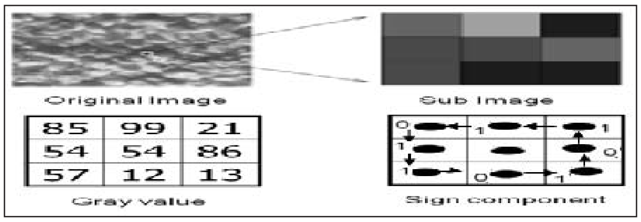

Fig. 2: Structure of M-LGS

This Modified LGS structure is formed out of the same principle but with the minor change. The target pixel (T) is the representation of the difference in magnitude of the pixel intensity in all the direction. The structure is just a proposed structure and in budding stage of implementation. The effect of this structure is analyzed on the MRI image and the accuracy is presented for the same.

Local Graph Structure (LGS (8, 1)) which is formed with 8 neighbors of a pixel, obtained by moving anticlockwise at the left region of the centre pixel and then right region of the central pixel. If the neighborhood pixel has a higher gray level value, assign the value 1 to the edge connecting the two vertices, else assign a value 0. It is formed using the equation

$$LGS = \sum_{k=0}^{7} s(g_a - g_b)2^k \left\{ s(x) = \begin{matrix} 1, x \geq 0 \\ 0.x < 0 \end{matrix} \right\} \quad (1)$$

Whereand are the two consecutive gray levels in the structure given in Fig. 2.

Table II: Demographics of GM – M-LGS

Type	Distribution	Mean	Variance	SD	Kurtosis
Normal	Mostly Dagum	175 - 182	5400 - 6100	70 - 80	(-) 0.80 – 0.90
AD	Mostly Gen Gamma	170 - 185	5200 – 5600	72 - 78	(-) 0.93 – 0.99
MCI	Dagum	160 - 173	5100 - 5700	71 - 76	(-) 0.99 – 1.1

Table III: Demographics of WM – M-LGS

Type	Distribution	Mean	Variance	SD	Kurtosis
Normal	Mostly Log- Logistic	194- 213	4700- 6020	68 - 78	(-) 0.4 – 0.70
AD	Mostly Pearson6	190-202	5500 – 6300	73 - 79	(-) 0.1 – 0.9
MCI	Mostly Log-Logistic	190 - 213	4900 - 6000	68 - 78	(-) 0.05 – 0.8

The Table 2 and 3 shows the demographics of the performance of Grey Matter and White Matter in M-LGS. The table proves that the structure follows some pattern and can be used for Classification of MCI, AD and Normal Images.

C. Distance Measures

In distance measure, post the feature extraction the features of every single image is compared with every other image in the database and this distance is preserved and applied for classification. The distance measures studied are Manhattan, Minkowski, Hamming, Chebychev, Euclidean, Jaccard, Spearman and Cosine.

III. Results and Discussion

The MRI used in the system is T1 - Weighted - 3T MRI Scanner's using protocol - TR= 3000, FOV = 240*240 mm2, with 256*256*170 mm3- acquisition matrix in X Y Z dimensions-slice thickness 1.2 mm, Siemens 3T MR Scanner - 176 slices [20]. The participants in this study were taken from ADNI. A Total of 300 MRI images are taken for training state such that each category – Normal, MCI and AD has 100 images each and 75 new images for testing (25 in each category). ADNI is a ten year old consortium for Neuro Imaging study following NINCDS/ADRA criteria [20]. Table 4 shows the demographics of the data used in our system.

Table IV: Demographics

Group	MCI	AD	NORMAL
AGE	69.3	64.9	65.3
MMSE	26.5	~7.8	27.9
CDR	0.6	1.3	0

In recent years AD identification at earlier stage carries lots of importance and Table 3 shows the accuracy of SVM Classifier in Classifying between Normal Aging, AD and MCI. The experiments were designed in Matlab 8.1.0 package with Medical Image Processing Toolbox. The results have been validated by the CDR provided in the ADNI dataset.

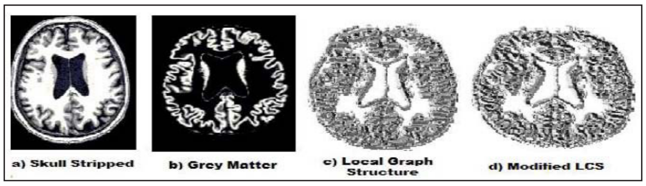

Fig. 3: Structural Evaluation of Normal Aging

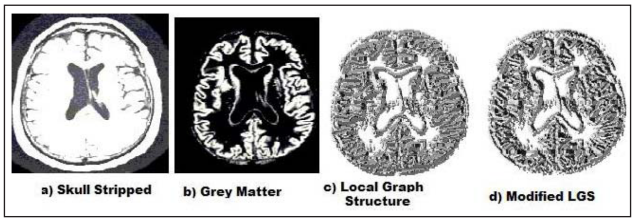

Fig. 4: Structural Evaluation of MCI Patients

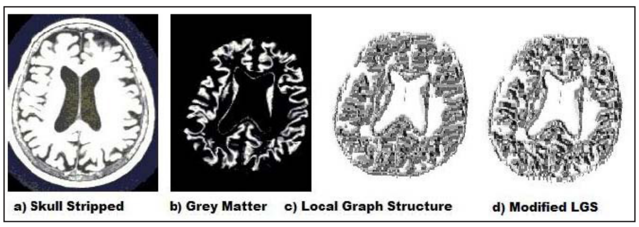

Fig. 5: Structural Evaluation of AD Patients

The Structural evaluation shows the skull stripped (a), Grey matter (b) LGS (c) M-LGS (d) of MTL region of Normal Aging, MCI and AD Patients MRI/S. The Z axis of Normal image is 126, MCI is 132 and AD is 132.This is the coronal axis of MRI. The table given below shows the comparative study of different local patterns.

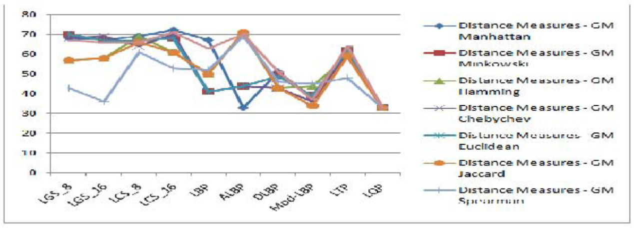

Fig. 6: Comparison of Local Patterns Based on Search and Reterival Mechanism

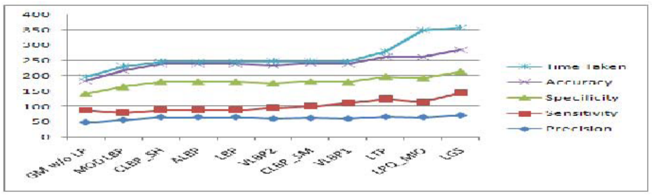

Fig. 7: Comparison of Local Patterns Based on SVM

The *x*-axis in Fig. 6 is the different patterns and the y axis is the percentage of accuracy across the different distances.

The Local Quinary Pattern shows the greater accuracy in classification while using SVM and similar is the Local Graph Structure and Modified Local Graph Structure while using the search and retrieval technique. Since the Graph pattern could encode large details compared to other patterns, the future work would be Quinary encoding on LGS. Apart from details, LGS and LCS is also capable of handling other features like Scaling, Transformation and Rotation.

IV. Conclusion

The proposed system is an approach for the longitudinal analysis of GM changes in MCI, AD and Normal aging patients. MCI progresses faster than AD. Hence the analysis would be helpful for the clinicians to understand the progression of MCI. The proposed approach is a new system for identifying MCI Patients so that the disease can be treated in early stage. The obtained results have extended clinical applications such as to detect diagnostically relevant changes in MCI patient's overtime. The classification accuracy of LGS is 71 % and that of LCS is 70%.

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