A Feature based Detection method using segmented MRI images for Alzheimer's disease diagnosis

Deepika V*, M.Suchetha
School of Electronics Engineering, Vellore Institute of Technology, Chennai, India
***Corresponding author: E-Mail: deepika.v2014@vit.ac.in**

ABSTRACT

Computer Aided Diagnosis (CAD) is useful to detect Alzheimer's disease (AD) at an early stage. For detecting the presence of Alzheimer's disease Magnetic Resonance Imaging is very useful. In this paper, a novel method for distinguishing between Mild cognitive impairment (MCI), Normal control (NC) and Alzheimer disease (AD) subjects is proposed based on Multivariate techniques such as Partial Least Square (PLS) and Principal Component Analysis (PCA). Median filtering is preferred due to its excellent noise removal characteristics. K-means clustering is preferred to segment the image into different anatomical structures and to yield better segmentation. Feature extraction is done using Haralick texture parameters. Support Vector Machine (SVM) classifier is used to validate the efficiency and performance of the proposed method.

KEY WORDS: Computer Aided Diagnosis, Alzheimer disease, Principal Component Analysis, Support Vector Machine.

1. INTRODUCTION

Alzheimer's disease is one of the important forms of brain disorder. It is a kind of dementia. It occurs in old people where they fail to remember some familiar things such as personal things, relationship etc. It starts with memory loss. Magnetic Resonance Imaging is preferred as a imaging method for early detection and diagnosis of Alzheimer's disease. The aim of our study is to develop a novel method for discriminating between Mild cognitive impairment, Normal control and Alzheimer's disease patients based on Multivariate techniques applied to images, such as Partial Least Square (PLS) and Principal Component Analysis (PCA). The three steps for implementing the algorithm are, i) Preprocessing of the input image ii) feature extraction iii) Classification from the resultant features.

2. PROPOSED METHODS

Image Preprocessing: MRI Images are prone to a type of noise called Rician noise. MRI images were de noised using Median filter. It is a nonlinear filter. It helped in smoothing the image. After de noising the image realignment and spatial normalization were done to resize images into sagittal, axial and coronal with voxel sizes are 121x145x 121. Segmentation is done using K-means clustering.

K-means Clustering: It is an iterative procedure that is used to partition *n* observations into *k* clusters. Its function is represented as

$$J = \sum_{j=1}^{k} \sum_{i \in c_j} \left\| x_i - \mu_j \right\|^2 \quad (1)$$

Where c_j is the j^{th} cluster and μ_j is the centroid of the cluster c_j. In statistical signal processing and machine learning method, *k*-means clustering is a technique of cluster analysis that aims to partition *n* observations into *k* clusters. Each observation in this clustering algorithm belongs to the cluster with the neighbouring mean. The function *k-means will* partition data into *k* mutually exclusive clusters. Each observation is then assigned to the index of the clusters. k-means clustering operates only on actual observations but not on a larger set of dissimilarity measures. Thus it creates a single level of clusters rather than hierarchical clustering.

The basic algorithm is:

a) Pick *k* cluster canters, either randomly or based on some heuristic
b) Assign each pixel in the image to the cluster that helps in minimizing the distance between the pixel and the cluster center
c) Re-compute the cluster centers by averaging all of the pixels in the cluster
d) Repeat steps 2 & 3 until convergence is attained (e.g. no pixels change clusters).

k-means algorithm is preferred due to its efficiency in segmenting the image into clusters. It further indicates in which cluster the desired information is contained. It helps to highlight the features of the given image. Different anatomical structures like Grey Matter (GM), Cerebro Spinal Fluid (CSF) and White Matter (WM) and is obtained as a result of k-means algorithm. Further the feature extraction process is performed on the segmented image using PLS, PCA techniques.

Texture features: The texture features in images quantify gray level differences and defined size of area where changes occur. Texture features could provide cues for identifying objects or classifying patterns at feature extraction and classification stage. Texture feature manipulations use the contents of the Gray Level Co-occurance Matrix (GLCM) to provide a quantity of the variation in intensity at the pixel of interest. A statistical method aims at determining the gray level transition between two pixels is Gray Level Co-occurance Matrix. This method constructs a co-occurrence matrix thereby calculating the pixel frequently with a particular gray level intensity value, *i* occur in a specific spatial association to a pixel with a value, *j* with a definite distance, *d* and θ as the orientation. The number of rows and columns of a GLCM matrix depends on the gray levels *G* in the texture of an image. The relative frequency of a matrix $P(i,j\,|\,\Delta x,\Delta y)$ is parted by a pixel distance $(\Delta x,\Delta y)$. $P(i,j\,|\,d,\theta)$ is a matrix element that comprises the probability values of second order for gray level *i* and *j* at distance *d* and with orientation θ.

$$p_x(i)=\sum_{j=0}^{G-1} p(i,j) \qquad (2)$$

$$p_x(j)=\sum_{i=0}^{G-1} p(i,j) \qquad (3)$$

Where the i_{th} and j_{th} entry that is obtained by summing the rows of *p(i,j)*. Various features can be extracted from the GLCM, μ the mean value of *p*, σ is the standard deviation of *P*. The different textural features contained in the co-occurrence matrices are calculated by Haralick. Various statistical measures are estimated in this paper. Haralick texture parameters are used to extract the features.

Partial Least Square (PLS): Partial Least Square is observed by means of latent variable. Its objective is to maximize covariance between different sets of variables. PLS helps in decomposing n X N matrix of zero mean variables X and n X N matrix of zero mean variable Y into regression models form

$$X=TP^{T}+E \qquad (4)$$

$$Y=UQ^{T}+F \qquad (5)$$

T and U are nXp matrices. In M x p matrix Q signifies matrices of loadings with number of columns being number of PLS components. n x N matrix E and n xM matrix F are the residual matrices. PLS is particularly suited when matrix of predictor has more variables compared to observations. PLS is a weight of covariance structure between predictors. PLS can extend to multiple outcomes and allows for dimension reduction. PLS is useful to predict set of dependent variables from set of independent variables.

Principal Component Analysis: It is a proficient tool for extracting most significant features in image. It generates orthonormal basis vector that maximizes scatter of all the projected samples. Let X=[X_1, X_2,....X_N] be sample set of these vectors where N is number of patients. After the normalization of vectors to unity norm and subtracting large average new vector set Y= [Y_1, Y2,...Y_N]

$$\sum y=\frac{1}{n}\sum_{n=1}^{N} Y_i Y_i^t=\frac{1}{N}YY^t$$

YY^t is n x n matrix and Y^tY is NxN matrix

PCA is used to describe variation of a set of multivariate data in terms of uncorrelated variables. PCA derives new variables in decreasing order. PCA reduces dimensionality by reflecting low variance features. PCA is used in data reduction and interpretation.

Automated classification based on PLS, PCA with SVM classifier: PLS and PCA was used to compute score vectors. SVM was used to assess underlying class (AD, MCI, NC). This method diminishes input space dimensionality. First image is pre-processed and voxels are selected. It reduces initial number of voxels present in input space.

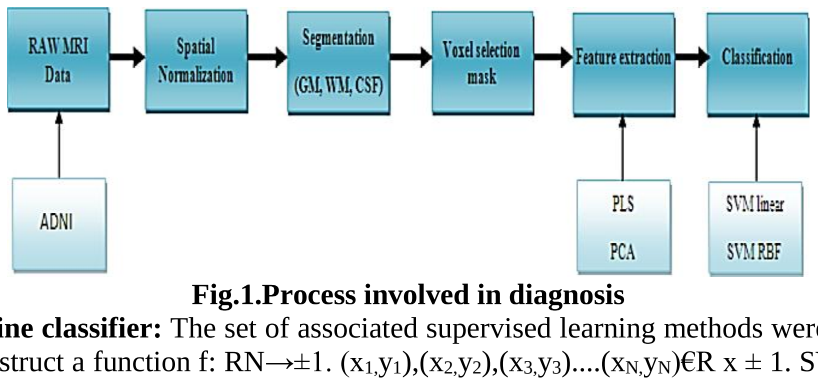

Fig.1.Process involved in diagnosis

Support vector machine classifier: The set of associated supervised learning methods were represented by SVM. The objective is to construct a function f: RN→±1. (x_1,y_1),(x_2,y_2),(x_3,y_3)....(x_N,y_N)€R x ± 1. SVM is computationally efficient. It demonstrates good classification performance. SVM is an extension of nonlinear model. Its properties have flexibility in choosing a feature selection process, similarity function, and the ability to handle large feature space. Kernel function corresponds to inner product in some extended feature space. SVM maximizes margin around separating hyper plane. Decision function is fully quantified by subset of training samples.

3. RESULTS AND DISCUSSION

The simulation results are obtained using MATLAB. The input images are taken from ADNI database to classify images into AD, MCI and NC patterns. Fig 2 shows original image. The axial, sagittal and coronal part is separated as shown in Fig 4. The original image is preprocessed using median filter as shown in Fig 5. Further the image is segmented into different anatomical structures using k-means clustering. White matter, Grey matter, and CSF outputs are obtained as shown from Fig 6 to Fig 8.

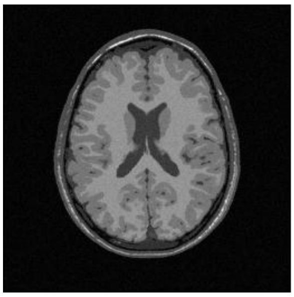

Fig.2. Input image

Fig.3.Sagittal slice

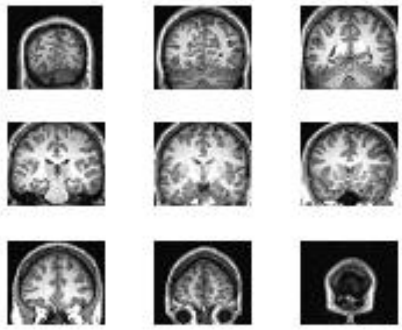

Fig.4 Axial, Coronal, Sagittal Slices

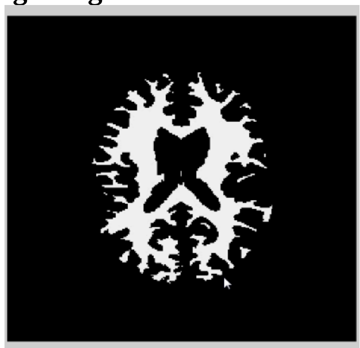

Fig.5.Preprocessed image

Fig.6.Grey matter

Fig.7.White matter

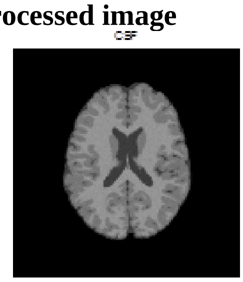

Fig.8.Cerebrospinal fluid

Texture parameters, PLS and PCA are used for feature extraction. Fig 9, Fig 10 and Fig 11 show normal control, Mild Cognitive impairment (MCI) and Alzheimer's disease image respectively.

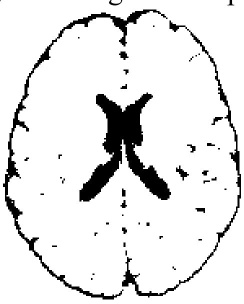

Fig.9.Normal image

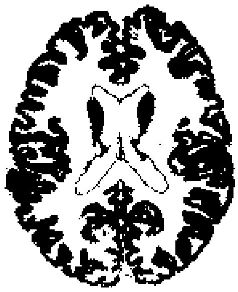

Fig .10.MCI

Fig.11.Alzheimer diseased image

Comparison plot of AD, MCI, NC are shown in Fig 12 and Fig 13. Fig 14 to 19 shows PLS and PCA components.

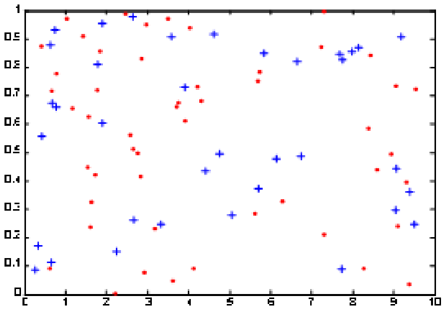

Fig.12. Comparison of AD,MCI,Normal using PLS

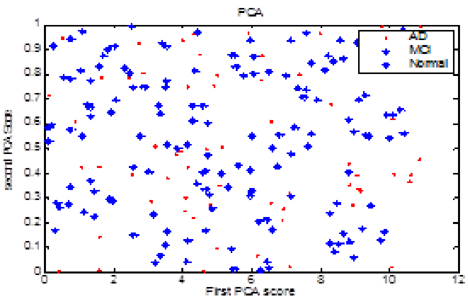

Fig.13.Comparison of AD,MCI,Normal using PCA

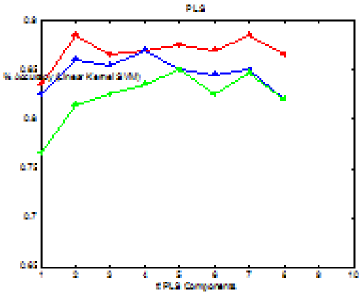

Fig.14.Accuracy

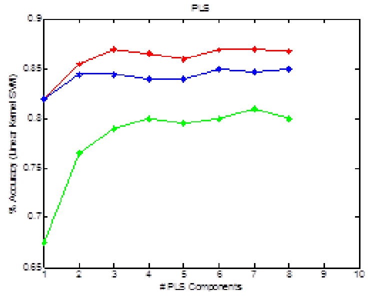

Fig.15.Accuracy

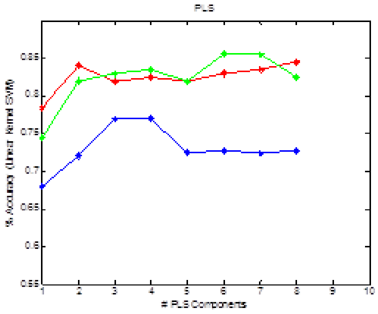

Fig.16. Accuracy

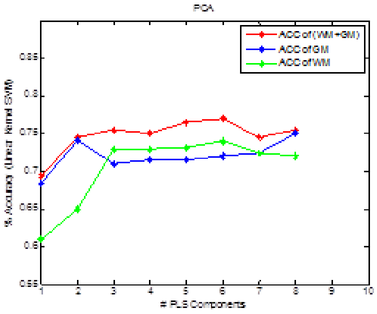

Fig.17.Accuracy

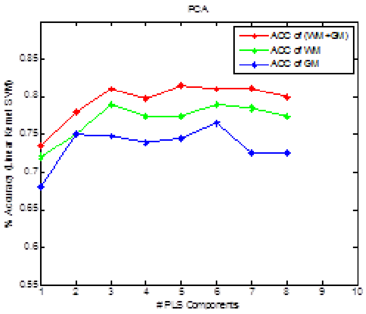

Fig.18.Accuracy

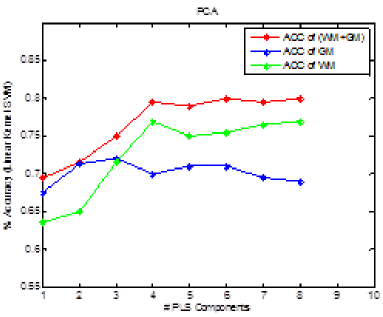

Fig.19.Accuracy

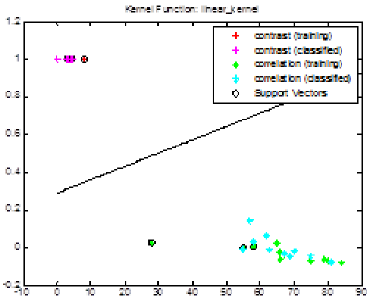

Fig.20

The classification of three stages differentiating its features is shown in Fig 20. In this work a CAD based system has been developed using two feature extraction methods and diverse SVM classifiers as NC, MCI and AD. In this approach the input data has been segmented and voxel selection process is performed. This method will reduce the input space dimensionality. Thus initially structural MRI images are normalized and segmented. After that different binary mask for each mater such as WM and GM is finished. This step helps to reduce the voxel numbers present in the input space. By analysing the methodologies to develop CAD system for detection better classification performance of PLS and PCA features are obtained . The extracted features are given as input to the linear SVM classifier . PLS performs better than PCA as feature extraction technique and yields peak values . Linear SVM classifier gives better performance in terms of accuracy compared to RBF.

Classification of Group 1(NC vs AD): Linear SVM yields higher accuracy rates for both PLS and PCA. Best accuracy rates are yielded by PLS, PCA and linear Kernal. Accuracy is 88.49% for PLS and linear Kernal.

Classification of Group 2(NC vs MCI): Combined features extracted from WM and GM yields highest accuracy of 81.89%.Feature extracted from GM alone yields accuracy of 77.57% .Feature extracted from WM alone yields accuracy of 80.54%.

Classification of Group 3(MCI vs AD): Combined features extracted from WM and GM yields highest accuracy of 85.41%.Feature extracted from GM alone yields accuracy of 77.03% .Feature extracted from WM alone yields accuracy of 87.03%.

4. CONCLUSION

Detection of Alzheimer disease helps to de noise the problem at early stage. Premature detection of Alzheimer's disease was supported using CAD. It uses two feature extraction methods PLS and PCA. PLS uses score vectors. PCA method performs initial reduction. SVM tests both classifiers. PCA method is used to reduce the input space. Better accuracy is achieved by PLS method compared to other method. In future combined features may be used to do the detection process and classification can be done to get better accuracy level.

REFERENCES

Alzhemier's Association, Alzheimer's disease facts and figures, Alzheimer's Dement, 9 (2), 2013, 208-245.

Bastien P,Vevinzi, Tenenhaus M, PLS generalized linear regression, comput.star.Data Anal., 48, 2005, 17-46.

Brien JTo, Role of imaging techniques in diagnosis of dementia, Br.J.Radiol., 80, 2007, 71-77.

Burges C.J.C, A tutorial on support vector machine for pattern recognition, Data Min. Knowl. Discov., 2 (2), 1998, 121-167.

Colliot O, Chetelat G, Chupin M, Pillon B, Deweer B, Dubois B, Marsault C, Amygdalohippocaml MR volume measurements in early stages of Alzheimer disease, AJNR Am.J.Neuroradial., 15, 1994, 929-937.

Jobin Christ, and Parvathi R.M.S, Segmentation of medical image using K-means clustering and marker controlled watershed algorithm, European Journal of Scientific Research, 71 (2), 2012, 190-194.

Killany R.J, Moss M.B, Albert Temporal M.S, Lobe regions on magnetic resonance imaging identify patients with early Alzheimer's disease, Arch,Neurol., 50, 1993, 949-954.

Lehericy S, Baulac M, Chiras J, Pierot L, Martin N, Pillon B, Deweer B, Dubois B, Marsault C, Amyadalohippocampal MR volume measurements in early stages of Alzheimer disease, AJNR Am.J.Neuroradial., 15, 1994, 929-937.

Segovia F, Gorriz J Ramrez J.M, Salas-Gonzalez D, Alvarez M Lopez, Chaves R, The Alzheimer Disease Neuroimaging Initiative, a comparative study of feature extraction methods for diagnosis of Alzhemier's disease using ADNI database, Neurocomputing, 75, 2012, 64-71.

Segovia F, Gorriz J.M, Ramrez J, Salas-Gonzalez D, Alvarez I, Early diagnosis of Alzheimer Disease based on partial least squares and support vector machine, Expert Syst.Appl., 40, 2013, 677-683.

Shawe-Taylor J, Cristianini N, Support vector machine and other Kernel Based, Learning Methods, Cambridge University Press, UK, 2000.

Xekardaki Aikaterini, Giannakopoulos Panteleimon, Haller Sven, White matter changes in bipolar disorder, Alzheimer disease, and mild cognitive impairment, new insights from DTI, J.Aging Res., 2011, 1-10.