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Diagnosis of Alzheimer's disease in Brain Images using Pulse Coupled Neural Network

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Abstract- Alzheimer's disease is most commonly occurring type of disease in elderly patients. An automatic computer-aided diagnosis tool that supports the interpretation of functional brain images is proposed in this paper for the diagnosis of the Alzheimer's disease. This new technique is based on Pulse Coupled Neural Network (PCNN) for image classification. In Alzheimer's disease diagnosis mainly two databases are selected: a Single photon emission computed tomography (SPECT) database and Positron emission tomography (PET) images, both contains details for Alzheimer's disease patients(AD) and healthy references (NOR). The major steps in detection of Alzheimer's disease are feature extraction, feature reduction and classification of these features for making correct decision. The features from the images are extracted using wavelet packet transform (WPT). The reduction & selection of the most relevant features is done using non-negative matrix factorization (NMF). The resulting sets of data, which contain a reduced number of features, are classified by means of a Pulse Coupled Neural Network - based classifier for decision. This novel technique provides high classification accuracy and also reduces time consumption compared to existing methods.

Key Terms—Alzheimer's disease, wavelet packet tree, positron emission tomography (PET), single photon emission computed tomography (SPECT), pulse coupled neural network (PCNN).

I. INTRODUCTION

Alzheimer's disease (AD) is a neuro-degenerative disease that causes others loss of memory, changes in behavior and cognitive impairment. Mainly elderly are affected by this disease. The effect of this disease affects economic growth of many developing nations due to the growth of older population and is expected to increase in coming years. Alzheimer's disease is usually diagnosed clinically from the historical details of patients, collateral history and clinical observations, based on the neurological and neuropsychological characteristics and the absence of alternative conditions. Advanced medical imaging uses emission computed tomography such as single photon emission computed tomography (SPECT) or positron emission tomography (PET) to exclude other cerebral pathology. It may predict changes from mild cognitive impairment to Alzheimer's disease. The SPECT and PET provide information about physiological phenomena and their location in the body and these techniques are noninvasive nuclear medicine imaging techniques which produce a three-dimensional image of functional processes in the body, by means of emitting radionuclides.

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A. Computer Aided Diagnosis Techniques

There are varieties of techniques applied to different kind of medical data, such as to medical images, to assist the diagnosis work. These techniques are commonly known as Computer aided diagnosis. There exist many approaches for designing CAD systems for the Alzheimer's disease diagnosis. One approach widely used in neuroscience is the statistical parametric mapping tool developed for comparing groups of images. The classical multivariate techniques require the number of available observations to be greater than the number of components, so it is a univariate approach. The other approach is based on the analysis of the images, the analysis of regions of interest (ROI), feature extraction and posterior classification in different classes by means of some discriminative functions. The small sample size problem is one of the main problem faced by multivariate approaches, that is, the number of available samples is much lower than the number of features used in the training step. The dimensionality reduction and feature selection is an issue in these techniques. The fact that images represent large amounts of data and most imaging studies have relatively few subjects restricted the exploration of statistical learning classification methods and CAD tools.
The important stages of a supervised learning-based CAD system applied to functional imaging consist of:

- functional image collection and normalization;
- feature extraction and reduction;
- classification based on test strategy

II. FEATURE EXTRACTION

The functional brain images contain information about the brain point at each voxels. By using voxel information two groups of subjects can be defined: Alzheimer's disease patients labeled as AD and other with healthy reference labeled as NOR. An initial feature selection based on discrimination capability is selected, obtaining a vector of discriminant voxels for each participant and the selected discriminant voxel vectors can be projected onto a different subspace.

A. Intensity Normalization

A basic problem in the use of SPECT/PET images is the lack of an absolute signal level. There are mainly two types of variation of the measured signal among SPECT images: Global variation, Local variation. Global variations are caused by the differences in the dose of the radioactive tracer at the time of the image acquisition, sensitivity of the scanner, or the positioning of the patient with respect to the detectors.

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Local variations are caused due to the differences that occur normally between different subjects as well as within the same subject over time. Even though pathologies such as AD do cause differences - before analysis of the images global variations have to be corrected and local variations, especially those due to pathology, should be preserved. The standard approach is to assume the global cerebral blood flow to be the same for all subjects. This leads to the necessity of intensity normalization. Here, in order to avoid these normalization errors, intensity normalization based on the mean value of a group of voxels with the highest intensity values is applied and based on this the mean value of the 0.1% voxels with the highest intensity levels is selected for the intensity normalization.

B. Feature Extraction Using Wavelet Packet transform

Wavelet is a well-known image analysis technique, when used provides richer feature space ie; it provides excellent time and frequency resolution. The resulting wavelet coefficient yields a smaller set of more robust features, which can improve the probability of correct classification. The concept behind wavelet is to analyze the signal at different scales or resolutions, which is called multi-resolution. Otherwise wavelets can be defined as the class of functions used to localize a given signal in both space and scaling domains. Many wavelets can be constructed from mother wavelet. A mother wavelet can be stretched or compressed to change the size of the window. So, wavelets can automatically adapt to both the high frequency and the low frequency components of a signal by different sizes of windows. Wavelets mean small waves that segments data into different frequency components and transfer each component with different resolution that is matched to its scale.

In this work, the feature extraction is performed using wavelet-packet transform. It differs from conventional wavelet transform by recursively decomposing the high frequency components. Thus it constructs a tree-structured multi-brand extension of the wavelet transform. A wavelet packet transform decomposes an image into four sub images using high pass filters and low pass filters. Then the filtered outputs are down sampled by a factor of two and the size of the image becomes one-fourth of the previous image. Since the decomposition is an orthogonal representation of the image there is no loss and redundancy of data between different levels.

C. Feature Reduction Using NMF

Nonnegative matrix factorization (NMF) technique that decomposes a non-negative matrix into pair of non-negative matrix is used for feature reduction. It is a useful decomposition tool for multivariate data. This technique is especially suitable for non-negative data sets such as functional images and is suitable for the reduction of features obtained from Positron emission tomography (PET) and Single photon emission computed tomography (SPECT) brain images, where all the variables consist of positive values

NMF is a linear, non-negative data representation where the original database $A=[A_1,A_2,\ldots.A_M]$ which consists of M measurements of N nonnegative scalar variables, is approximated by a nonnegative matrix product as

$$A \approx WH \quad (1)$$

where $W=[W_1,W_2,\ldots\ldots W_K]$ with dimension N×K and $H=[H_1,H_2,\ldots\ldots\ldots H_K]$ with dimension K×M. K is usually chosen such that K<<min(M,N) in which case WH can be seen as a compressed form of the data in A. This provides a reduced-variable matrix H that represents A in terms of the NMF basis matrix W.

The relative error (%) of the factorization can be understood by means of comparison of matrix A and the approximation WH. Some of the error functions are:

$$Err_1 = 1/NM\|A-WH\|^2 = 1/NM\sum_{nm}(A_{nm}-(WH)_{nm})^2 \quad (2)$$

$$Err_2 = D(A\|WH) \quad (3)$$

where first error function is Forbenius norm and second error function is Kullback-Leibler divergence.

Different approaches for NMF Algorithms are: Multiplicative update rule and Alternating least square algorithm or Additive update rule. Due to their fast convergence and lower iteration Alternative Least Square Algorithm is taken.

III. PCNN BASED CLASSIFIER WITH BOUNDS OF CONFIDENCE

The PCNN was originally presented in order to explain the synchronous neuronal burst phenomena in the cat visual cortex. The information of the input is converted to a set of pulse images which present the objects and edges of the images, so pulse-coupled means that the image is analyzed by looking multiple times at different coupled pixels. The pulse-coupled neural network is a neural network that has the ability to perform extraction of edges, texture information from images and image segmentation. The PCNN is very generic. Only a few changes are necessary for effectively operate on different types of data. This is an advantage over other image segmentation algorithms which generally require information about the target before they are effective. But the parameters still have to be set manually. When we compare to other artificial neural network models the Pulse coupled neural network is significantly different in both structure and operation. The processing layer consists of many neurons and each neuron correspond to an image pixel or a set of neighboring image pixels. These are the feeding inputs and are linked to nearby neurons called the linking inputs. The feeding inputs are repeatedly processed and both these inputs together produce a pulse train. The Pulse coupled neural network neuron includes dendritic tree, linking modulation, and pulse generator part. The dendritic tree receives the inputs from two types of channels ie; the linking and the feeding. The linking receives external stimulus while the feeding receives external stimulus and local stimulus. The classification based on Pulse Coupled Neural Network is performed using the following equations:

$$F_{i,j}[n] = e^{-\alpha f}F_{i,j}[n-1] + S_{i,j} + F_f\sum_{kl} m_{ijkl}Y_{kl}[n-1] \quad (4)$$

$$L_{ij}[n] = e^{-\alpha L}L_{ij}[n-1] + V_l\sum_{kl} w_{ijkl}Y_{kl}[n-1] \quad (5)$$

$$U_{ij}[n] = S_{ij}[n](1+\beta L_{ij}[n]) \quad (6)$$

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$$\theta_{ij}[n] = e^{-\alpha\theta}\theta_{ij}[n-1] + V_{\theta}Y_{kl}[n-1] \quad (7)$$

$$Y_{ij}[n] = \begin{cases} 1, if\ U_{ij}[n] > \theta_{ij}[n] \\ 0, otherwise \end{cases} \quad (8)$$

L_{ij}, F_{ij}, U_{ij} and T_{ij} are the linking input, feeding input, internal activity and dynamic threshold respectively. Y_{ij} is the pulse output generated by the pulse coupled neuron. m and w are the constant weight matrices and depend on the linking fields. β is the linking coefficient constant.α is the attenuation time constant for linking, feeding and threshold. V_F, V_L, V_θ are inherent voltage potentials.

IV. EXPERIMENTAL RESULTS AND DISCUSSION

The database taken consist of a set of 3D SPECT brain images produced with an injected gamma emitting 99mTc-ECD and Positron emission tomography (PET) brain images. The Single photon emission computed tomography (SPECT) scan can be obtained by means of a three-head gamma camera Picker Prism 3000. The brain images are then reconstructed from projection data by filtered back projection along with a Butterworth noise filter. These two databases contain spatially normalized functional brain images of different subjects. This normalization step ensures that a given voxel in one patient refers to the same brain position than the same voxel in another patient. Now the intensities of the functional images are normalized to the maximum intensity. This normalization is computed for each image individually by referring each voxel to the average value of the %0.1 highest intensity voxels, in order to allow statistical comparison among different subjects.

The normalized image is then taken for feature extraction and reduction by the method of wavelet packet transform and non-negative matrix factorization. The resulting features are then classified using Pulse Coupled Neural Network and the classified results categorizes the image into Alzheimer's disease (AD) or No Alzheimer's disease (NOR).

The accuracy rate was used to evaluate the performance of classification. It was calculated based on the overlap of the standard manually labeled reference image by an expert and a collection of segmentation results obtained with the Pulse Coupled Neural Network approach. The accuracy rate, which represents the accuracy rate of the segmented area in class k relative to the area in the standard reference image was quantified as the overlap fraction and is defined as:

Accuracy= SA(K)∩SeA(K)/SA(K) (9)

where SA(k) and SeA(k) are the standard and the segmented image, respectively. While SA(k)∩SeA(k) represents the intersection areas of class k between the classified image and the standard image, and the denominator represents the area in class k in the standard image.

The sensitivity and specificity are obtained for the evaluation of PCNN based CAD tool and is given by

Sens=TP/TP+FN (10)

Spec=TN/TN+FP (11)

where TP is the number of true positives and TN is the number of true negatives; FP is the number of false positives and FN is the number of false negatives.

TABLE I

Performance of VAF-SVM as reference, NMF-SVM tool and NMF-PCNN

	VAF-SVM	NMF-SVM	NMF-PCNN
Acc	69.54	83.80	88.20
Sens	71.13	83.01	88.51
Spec	67.76	84.61	90.11

Table I provides the comparison of approaches available for the diagnosis of the Alzheimer's disease with proposed system. The voxels as features along with Support Vector Machine is taken as the reference for comparison. The Non-negative matrix factorization with SVM technique is the existing system with which the comparison is made. Table I shows nearly 5 percent improvement in accuracy specificity and sensitivity and also low consumption time compared to existing.

IV. CONCLUSION

The PCNN based CAD technique used for diagnosis of Alzheimer's disease uses wavelet packet transform (WPT) and non-negative matrix factorization for feature extraction and reduction and pulse coupled neural network (PCNN) with bounds of confidence for classification. The feature reduction step provides a reduced set of variables representing the original data. The PCNN based Computer Aided Diagnosis (CAD) tool, along with its variations, is validated with two brain functional image databases: a Single Photon Emission Computed Tomography data set which provides information about the blood perfusion in the brain and a Positron Emission Tomography data set which yields information about the glucose metabolism. The validation results of the proposed NMF-PCNN method yields high classification accuracy with high sensitivity and specificity values (increase of 5 percent) for both data sets compared to NMF-SVM. It also provide low time consumption.

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