Classification of 3D Magnetic Resonance Images of Brain using Discrete Wavelet Transform

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ABSTRACT
Presented work is a feature-extraction and classification study for Alzheimer's disease (AD), Mild Cognitive Impaired (MCI) and Normal subjects. The proposed technique consists of three stages, namely, normalization of 3D MRI, feature extraction, and classification. In the first stage, we have normalized 3D MR images using VBM analysis, spatially filtered and slice averaged in order to obtain 2D MR slice. In the second stage, obtained the features related to MRI images using discrete wavelet transformation (DWT) with mother wavelets Haar and Daubechies. In the classification stage, a classifier based on feed forward backpropagation artificial neural network (FP-ANN). Classification is obtained with accuracies of 74% and 67% using Daubechies wavelet and Haar wavelet respectively. Used subjects from the ADNI database.

General Terms
Neurodegeneration, Dementia diagnosis, brain MRI analysis, neuroimaging

Keywords
3D MRI, ANN, DWT Features, SPM, VBM

1. INTRODUCTION
Alzheimer's disease (AD) is the most common neurodegenerative illness, accounting for 60–70% of age-related dementia cases [1]. In 2000, approximately 24 million people over the age of 60 were diagnosed with dementia worldwide, and this number is expected to reach over 81 million by 2040 [2]. MRI is widely used in AD studies as it can non-invasively quantify gray and white matter integrity with high reproducibility [3]. Madhubanti Maitra, Amitava Chatterjee [4] employed an improved version of orthogonal discrete wavelet transform (DWT) for feature extraction, called Slantlet transform, which can especially be useful to provide improved time localization with simultaneous achievement of shorter supports for the filters. The features hence derived are used to train a neural network based binary classifier, which can automatically infer whether the image is that of a normal brain or a pathological brain, suffering from Alzheimer's disease. An excellent classification ratio of 100% could be achieved. Sadik Kara, Fatma Dirgenali [5] has employed discrete wave transform (DWT), performed Principal component analysis (PCA) for data reduction and ANN in order to distinguish between atherosclerosis and healthy subjects. The overall results show that 97.9% correct classification. Soo-Yeon Ji, Kevin Ward and Kayvan Naja [6] successfully showed that their optimization algorithm improves the fMRI signal activity for both healthy and dyslexia subjects. In addition, they found that DWT based features can identify the difference between healthy and dyslexia subjects. El-Sayed Ahmed et al [7] proposed hybrid technique consisting of three stages, namely, feature extraction, dimensionality reduction, and classification. Obtained the features related to MRI images using discrete wavelet transformation (DWT), reduced using principal component analysis (PCA). The first classifier based on feed forward back propagation artificial neural network (FP-ANN) and the second classifier is based on k nearest neighbor (k-NN). The classifiers have been used to classify subjects as normal or abnormal MRI human images. A classification with a success of 97% and 98% has been obtained by FP-ANN and k-NN, respectively. Ulacl Bagcl, Li Bai [8] reported experience using different types of wavelets and different SVM kernel functions for classification of Magnetic Resonance Images to identify those showing symptoms of Alzheimer's disease. Developed a novel computational framework for extracting discriminative Gabor wavelet features from the images for classification using Support Vector Machines with various kernel functions. Showed that Gabor wavelets perform better than Daubechies wavelets in classification. Obtained classification with accuracies of 74% and 67% using Daubechies wavelet and Haar wavelet respectively. Torabi M.et al [9] categorized the features of interest in features of the spatial domain (FSD's) and Features of the frequency domain (FFD's) which are based on the first four statistic moments of the wavelet transform. Extracted features have been classified by a multi-layer perceptron artificial neural network (ANN), achieved 79% and 100% accuracy among test

set and training set respectively. Aibinu et al [10] explained of Inverse Discrete Fourier Transform (IDFT) in the form of Inverse Fourier Transform (IFFT) is one of the standard methods of reconstructing Magnetic Resonance Imaging (MRI) from uniformly sampled K-space data. AmirEhsan Lashkari [11] used DFT for preprocessing of 2D MR images, especially for noise reduction.

2. METHOD

Selected subjects from Normal MCI and AD categories. MRI preprocessing was done using statistical parametric mapping software (SPM5; Welcome Department of Cognitive Neurology, Institute of Neurology, London,UK. http://www.fil.ion.ucl.ac.uk/spm/) website accessed on 21 November 2010) with the VBM tool Updated version VBM5.1 toolbox Published by Christian Gaser on May 13, 2009. Jena script http://dbm.neuro.uni-jena.de/vbm.html; in MATLAB. Image by image VBM image segmentation is carried out. VBM calculates the bias-corrected whole brain image in normalized space (wm*). Feature extraction scheme using DWT: The proposed system uses the discrete wavelet transform (DWT) coefficients as feature vector. The wavelet is a powerful mathematical tool for feature extraction, and has been used to extract the wavelet coefficient from MR images. Wavelets are localized basis functions, which are scaled and shifted versions of some fixed mother wavelets. The main advantage of wavelets is that they provide localized frequency information about the function of a signal, which is particularly beneficial for classification [12]. A review of basic fundamental of wavelet decomposition is introduced as follows. The continuous wavelet transform of a signal x (t), square-integrable function, and relative to a real-valued wavelet, Ψ(t) is defined as [1]:

$$W_{\psi}(a,b) = \int_{-\infty}^{\infty} x(t) * \Psi_{a,b}(t)\, dx$$

Where,

$$\Psi_{a,b}(t) = \frac{1}{\sqrt{|a|}} \Psi\left((t-a)/b\right)$$

and the wavelet Ψa,b is computed from the mother wavelet Ψ by translation and dilation; a is the dilation factor and b is the translation parameter (both being real positive numbers).Under some mild assumptions, the mother wavelet Ψ satisfies the constraint of having zero mean [13],[14]. Eq. (1) can be discretized by restraining a and b to a discrete lattice (a = 2b,a ∈ R+, b ∈ R) to give the discrete wavelet transform. There are several different kinds of wavelets which have gained popularity throughout the development of wavelet analysis. One important discrete wavelet is the Haar wavelet. The Haar wavelet is one of the simplest wavelets. Basically, it is one period of a square wave. Because of its simplicity, it is often the wavelet to be chosen. The discrete wavelet transform is a linear transformation that operates on a data vector whose length is an integer power of two, transforming it into a numerically different vector of the same length. It is a tool that separates data into different frequency components, and then studies each component with resolution matched to its scale. To compute the wavelet features in the first stage, the wavelet coefficients are calculated for the LL sub-band using Haar wavelet function.

$$\mathrm{DWT}_{x(n)} = \begin{cases} d_{j,k} = \sum x(n) h_j^*(n-2jk), \\ a_{j,k} = \sum x(n) g_j^*(n-2jk). \end{cases}$$

The coefficients d j, k refer to the detail components in signal x(n) and correspond to the wavelet function, whereas a j,k refer to the approximation components in the signal. The functions h(n) and g(n) in the equation represent the coefficients of the high-pass and low-pass filters, respectively, whilst parameters j and k refer to wavelet scale and translation factors. The main feature of DWT is multiscale representation of function. The original image is a process along the x and y direction by h(n) and g(n) filters which, is the row representation of the original image. As a result of this transform there are 4 sub-band (LL, LH, HH, HL) images at each scale. Sub-band image LL is used only for DWT calculation at the next scale. To compute the wavelet features, using MIPAV (Medical Image Processing and Visualization) the 3D MRI is compressed to 2D using spatial filtering and slice averaging, the wavelet coefficients are first calculated for the LL sub-band using Haar wavelet function. Secondly wavelet coefficients are also calculated for the LL sub-band using Daubechies wavelet function.

**Data used in preparation of this article were obtained from the Alzheimer's disease Neuroimaging Initiative (ADNI) database (www.loni.ucla.edu/ADNI). As such, the investigators within the ADNI contributed to the design and implementation of ADNI and/or provided data but did not participate in analysis or writing of this report. A complete listing of ADNI investigators can be found at: http://loni.ucla.edu//ADNI//Collaboration//ADNI_Authorship_list.pdf*

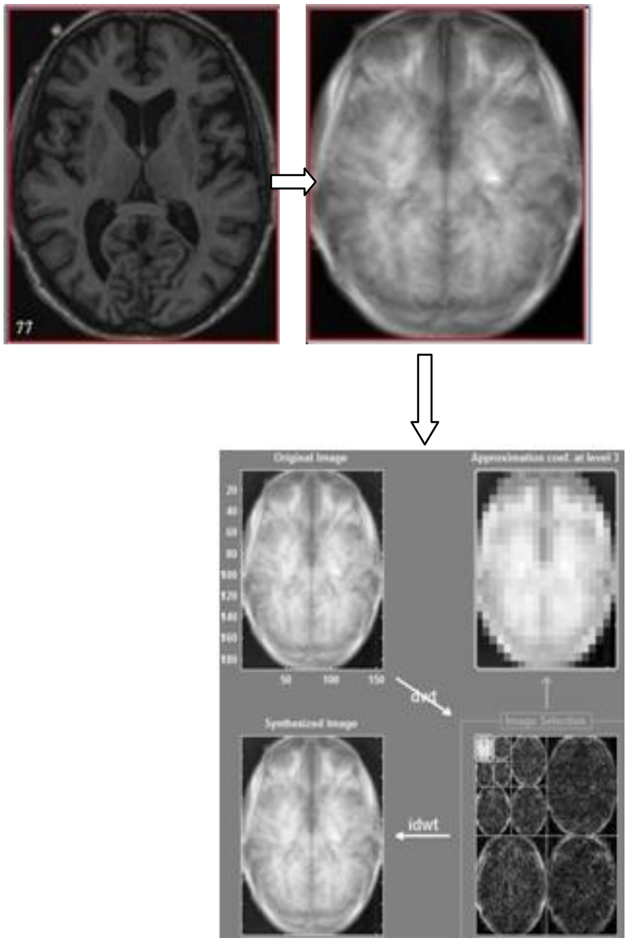

Fig.2 a: normalized 3D MRI b:Spatial filtered slice aveaveraged 2D MRI c: DWT with Haar level 3

2.1 Feature Selection and ANN Design

In ANN applications, feature selection is an important step in the process. First few DWT coefficients are selected as features in the current study. ANN is a machine approach designed on the model of biological brain system way of working. In biological systems, learning occurs when the synaptic connections are set up. This set up improves by the experiences of people. This is the same for ANN. Learning emerges through examples in training. In training, input and output data is processed. Using this data, the algorithm repeatedly adjusts the weights until convergence is achieved. This mathematical system is a transfer function. This processing unit combines, transforms and induces numeric results of the signals it took from the input or the former neurons. These process units corresponds neurons and interconnected in one. Besides learning, these networks have the ability of memorization and connect the information. Although, there are many types of artificial neural network, some of them are more common. The most widely used back propagation neural network known as ANN. This type of artificial neural network gives very good results in forecasting and classification process. Artificial neural network is used in many areas such as recognition and classification of biological signals, voice recognition, and fingerprint recognition, automatic vehicle control, auditing and modeling.[14]

2.2 Feedforward Neural Network

Neural networks are widely used in pattern classification since they do not need any information about the probability distribution and the a priori probabilities of different classes. The training vectors were presented to the FNN, which is trained in batch mode. The network configuration is supposed as NI x NH x NO, i.e., a two-layer network with NI input neurons, NH neurons in the hidden layer, and NO output indicating the brain is normal or MCI or AD. Each neuron in the input layer is fed directly to the hidden layer neurons via a series of weights. The sum of the products of the weights and the inputs is calculated in each node. The calculated values are fed directly to the output layer neurons via a series of weights. As in hidden layer, the sum of the products of the weights and the hidden layer neuron outputs is calculated in each node in the output layer. If the error between calculated output value and the desired value is more than the error ratio, then the training (changing the weights and calculating the new output by using the new weights) process begins. This training process can be finished by obtaining the desired error rate for all input combinations.ANN training is carried out in Matlab. Supervised neural networks are trained to produce desired outputs in response to sample inputs. Training algorithms used are gradient descent (GD) method and the Levenberg-Marquardt algorithm (LM). Various activation functions are tried to find the combination suitable for problem in hand. Finally a modified logsig, symmetrical sigmoid and purely liner are chosen respectively at three layers. During the training phase, the network is presented with sets of pairs (input and desired output) for training and testing sets. The network is iteratively updated till obtaining desired error rate. Tab. I and Fig.3 give all the details of FFNN used.

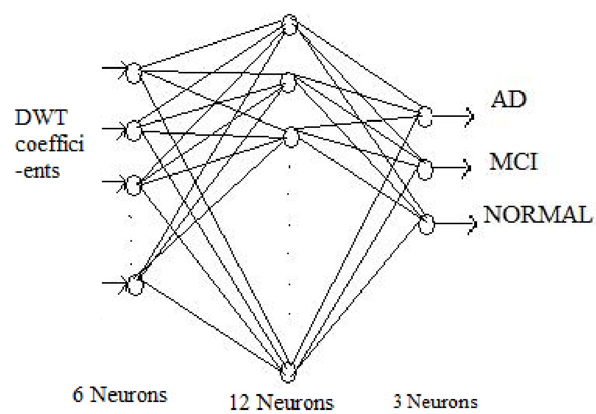

Fig.3 :Feedforward neural network architecture used

3. RESULTS

Experiments were repeated using Haar wavelet coefficients as well as Daubechies wavelet coefficients. Daubechies wavelet found to produce better classification. After 1000 iterations, the system is reached to the minimum error rate and the training process was stopped. The experimental results are given in Tab.II , which are obtained using Daubechies wavelet. The training performance of the diagnosing system is 100% whereas testing performance is 74% with Daubechies, 67% with Haar wavelet.

Tab. I: ANN architecture used in MATLAB

Network topology	Feedforward backpropagation
Trainning function	TRAINLM
Transfer function	SYMSIG-SYMSIG-PURELIN SYMSIG=a= (1- exp(-2*n))./ (1 + exp(-2*n));
Learning function	LEARNGDM
Performance	MSE
Learning rate	0.001
No. Of layers	3
Layer1	6 neurons
Layer 2	12 neurons
Layer 3	3 neurons
Epoches	1000

Tab.II: Result of test input

Test I/P	Expected Output			Actual Output		
AD1	0	0	**1**	0.90458	-3.3786	**3.474**
AD2	0	0	**1**	-0.0492	0.019288	**1.0299**
AD3	0	0	**1**	-0.35805	0.1704	**1.1876**
AD4	0	0	**1**	0.11537	-0.09938	**0.98401**
AD5	0	0	**1**	0.068369	-1.9585	**2.8901**
MCI1	0	**1**	0	1.1018	**-0.14325**	0.041472
MCI2	0	**1**	0	-2.0723	**1.6969**	1.3753
MCI3	0	**1**	0	0.029017	**-1.1192**	2.0902
MCI4	0	**1**	0	-5.6114	**6.2715**	0.3399
MCI5	0	**1**	0	1.9013	**-0.37929**	-0.52198
NOR1	**1**	0	0	**7.8742**	-9.5602	2.686
NOR2	**1**	0	0	**1.4235**	0.24997	-0.67349
NOR3	**1**	0	0	**1.8105**	-0.71596	-0.0945
NOR4	**1**	0	0	**5.5774**	-6.8585	2.2811
NOR5	**1**	0	0	**0.2408**	0.71017	0.049024

4. CONCLUSION

In conclusion, we have developed a medical decision support system with normal and MCI and AD classes based on artificial neural networks. For this purpose, the 3D MR images acquired from ADNI database. Discrete wavelet transform were performed for extracting the features of these images using mother wavelets Haar and Daubechies . The selected feature vectors were fed into the multi-layered ANN as input. After training the network, testing images were classified and as a result. This proposed diagnosing system can be used for helping to make a decision on disease as a support tool for radiologists.

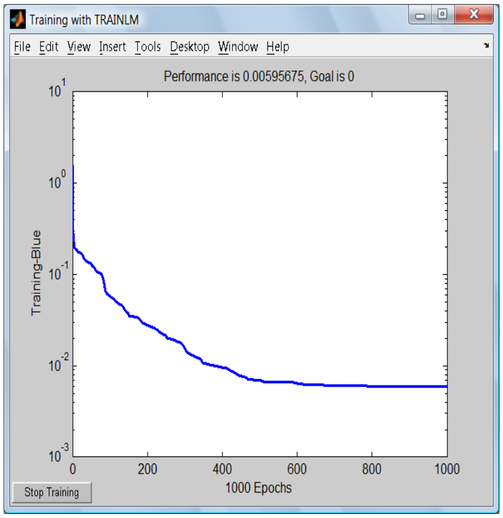

Fig.4 :FFNN training curve

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