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Application of Contourlet Transform in Brain Tumor Classification

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Abstract

In this paper, contourlet transformation has been used for Brain Tumor classification along with Probabilistic neural network. The other methods like wavelet and support vector machine based classification resulted in a limited precision, since it cannot work accurately for a large data due to training complexity. Computerized Tomography and Magnetic Resonance Images are based on human inspection for tumor classification and detection. These methods are not effective and are also non reproducible if amount of data is large. Also, the directional features of wavelet and other transforms are not taken from all directions except horizontal,vertical and diagonal. Neural Networks based classificatioin shows good results in medical fields which are combined here with contourlet transform. Decision is based on two steps (i) Image reduction and Feature extraction using contourlet transform (ii) Classification using probabilistic Neural Network(PNN). Various Features extracted from different brain images are tabulated which shows 100% recognition rate and also fast results, when compared to other classifiers.

Index Terms— *Brain tumor image classification, Probabilistic, Neural Networks, Contourlet Transform, Dimensionality Reduction, Feature Extraction.*

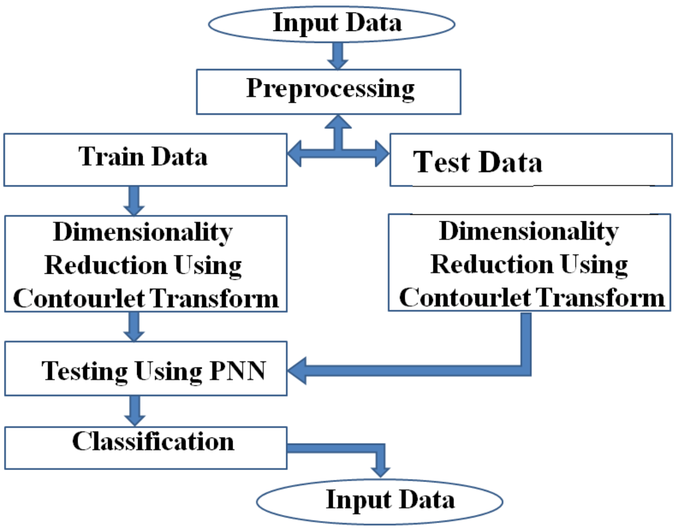
INTRODUCTION

A brain tumor or intracranial neoplasm occurs when abnormal cells form within the brain. There are two main types of tumors: malignant or cancerous tumors and benign tumors. Cancerous tumors can be divided into primary tumors that started within the brain and those that spread from somewhere else known as brain metastasis tumors.. All types of brain tumors may produce symptoms that vary depending on the part of the brain involved.

Visibility of signs and symptoms of brain tumors mainly depends on two factors: the tumor size (volume) and tumor location. The moment of symptom onset, when symptoms become apparent either to the person or people around them, is an important milestone in the course of the diagnosis and treatment of the tumor. The symptom onset – in the timeline of the development of the neoplasm – depends in many cases, on the nature of the tumor but in many cases is also related to the change of the neoplasm from benign to more malignant.

The diagnosis methods includes Biopsy, Neurologicexam, Angiogram and various scans. In biopsy the surgeon obtains cells in two ways, either it can be taken directly from tumor or in case of critical tumor locations they use images includes Computed Tomography (CT) scan, Magnetic Resonance Imaging (MRl) scan, to learn as much as possible about the tumor. In this paper, using the potential of Probabilistic Neural Network (PNN), a computer aided brain tumor classification method is proposed. The feed-forward neural network is used to identify the type of brain tumor suffered by patient with refer to the brain image tumor from the MRl and CT scan as inputs for the network.

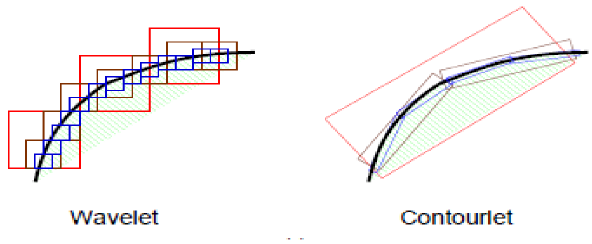
Extract the features and reduce the dimensions of the images are the main function of any classifier. Even small size images are having large dimensionality which leads to very large memory occupation, complexity and computational time. Classification based on wavelet shows high performance with LH and HL sub-bands than LL bands which contain more information. The performance of any classifier mainly depends on high discriminatory features of the images. In the proposed method we used contourlet transform for both dimensionality reduction and feature extraction. The flowchart for the given method is given below.



CONTOURLET TRANSFORM

Contourlets is proposed by Do and vetterli which captures edges and smooth contour at any orientation .It filters the noise in image in a better way. This technique is derived directly from discrete domain rather than extending from continuous domain. Contourlet Transform can capture the intrinsic geometrical structure of an image. Contourlet possesses the important properties of directionality and anisotropy which wavelets do not possess and so it outperforms wavelet in image processing applications.

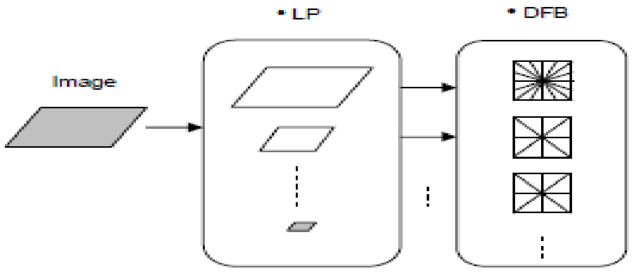
Contourlet transform is a multi resolution and multidirectional transformation technique which is used in image analysis for capturing contours and fine details in images. The subband decomposition and the directional transform are the two major steps in this transform. The Contourlet transform uses a double filter bank structure to get the smooth contours of images. In this double filter bank, the Laplacian pyramid (LP) is first used to capture the point discontinuities, and then a directional filter bank (DFB) is used to form those point discontinuities into linear structures.



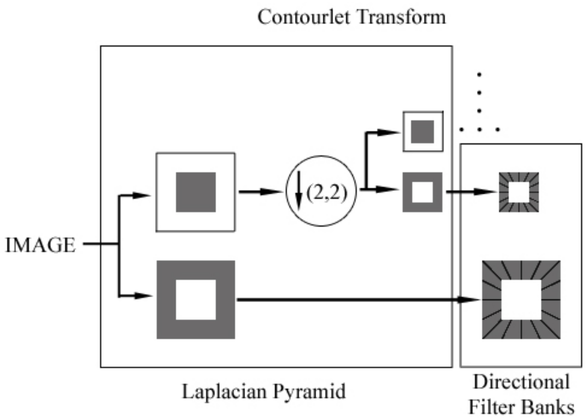
The contourlet transform is composed of basis functions with different directions in multiple scales with flexible aspect ratios. This frame work forms a basis with small redundancy unlike other transforms. The basis element of the transforms oriented at various directions much more than few directions that are offered by other separable transform technique. The contourlet transform is a discrete extension of the curvelet transform that aims to capture curves instead of points, and provides for directionality [6].

The image is decomposed using the transform and a low pass image and many band pass images are obtained. When using the low pass band large volume of data can be embedded with high robustness and in high frequency bands the mean square error is less, so security will be high. The low frequency subimages gather most energy and consequently they suffer little impact caused by image processing.

The fundamental difference of contourlets with other multiscale directional systems is that the contourlet transform takes different and flexible number of directions at each scale, while achieving nearly critical sampling. In addition, the iterated filter banks, used in this method makes it computationally efficient; specifically, it requires O(N) operations for an N-pixel image.



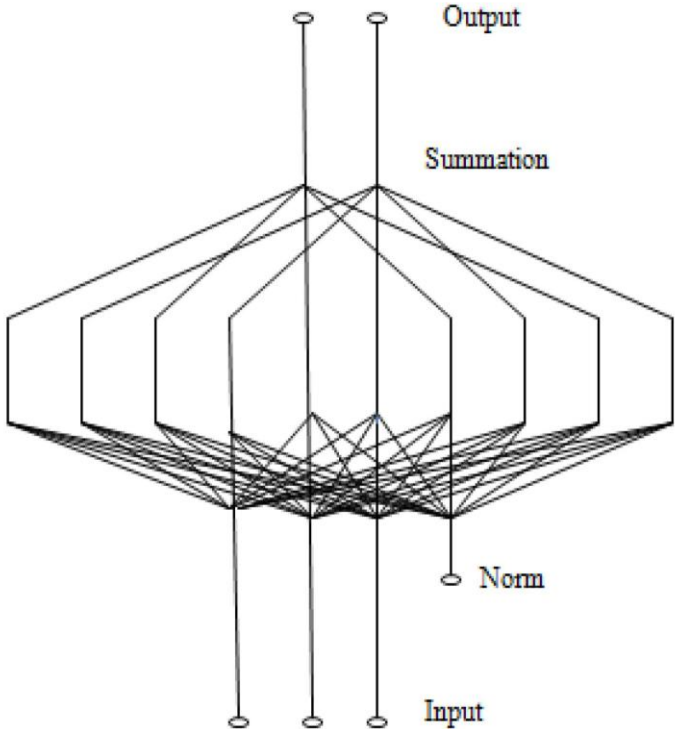
The structural design of contourlet via laplacian pyramid and directional filter is as follow:



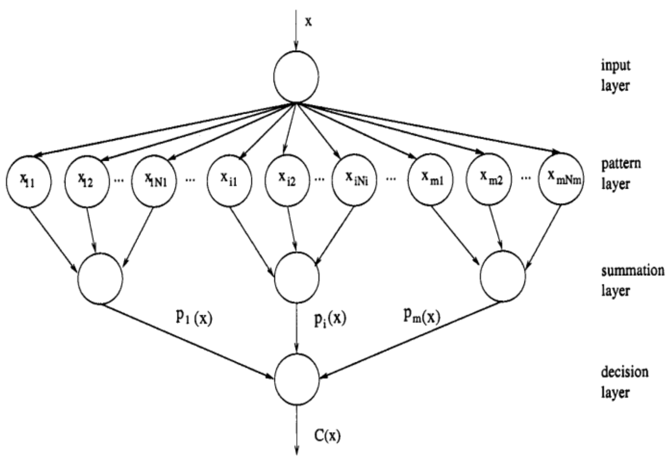
There are six different features are going to be extracted from the image. Those features include Energy, Entropy, contrast, Inverse difference, correlation and Homogeneity. Based on these features the training and test data will be compared using PNN.

PROBABILISTIC NEURAL NETWORK

Probabilistic Neural Network is a type of neural network using a kernel-based approximation to form an estimate of the p.d.f's of categories in a pattern classification. The basic structure of a probabilistic neural network is shown in figure. The fundamental architecture of PNN is composed of many interconnected processing units or neurons organized in successive layers. The pattern layer has a neural based implementation of a Bayes classifier, where the class dependent Probability Oensity Functions (POF) uses Parzen Estimator for approximation. The Parzen estimator determines the POF after minimizing the expected risk in classifying the training set incorrectly. Using the Parzen estimator, the classification gets closer to the true underlying class density functions as the number of training samples increases,



PNN is often used in classification problems. After giving the input, the distance from the input vector to the training input vectors is calculated by the first layer. This produces a vector where its elements indicate how close the input is to the training input. The contribution for each class of inputs is summed up by the second layer and produces its net output as a vector of probabilities[10]. Finally, the output of the second layer picks the maximum of these probabilities and forms a complete transfer function, and produces a 1 (positive identification) for that class and a 0 (negative identification) for non-targeted classes.



The training of the probabilistic neural network is much simpler Compared to the feed forward back propagation network. Since the probabilistic networks classify on the basis of Bayesian theory, it is essential to classify the input vectors into one of the two classes in a Bayesian optimal manner. This theory provides a cost function to comprise the fact that it may be worse to misclassify a vector that is actually a member of class A than it is to misclassify a vector that belongs to class B[9] .The Bayes rule classifies an input vector belonging to classA as,

$$P_A\, C_A\, f_A(x) > P_B\, C_B\, f_B(x)$$

Where,

P_A - Priori probability of occurrence of patterns in class A

C_A - Cost associated with classifying vectors

$f_A(x)$ - Probability density function of class A

The PDF estimated using the Bayesian theory should be

positive and integratable over all x and the result must be 1. The probabilistic neural net uses the following equation to estimate the probability density function given by,

$$fA(x) = \frac{1}{(2\pi)^{n/2}} \frac{1}{\sigma^n} \frac{1}{mn} \sum_{i=1}^{m} \exp\left(\frac{-2(x - xA)(x - xAi)}{\sigma 2}\right)$$

Where

x_{Ai} - ith training pattern from class A

n - Dimension of the input vectors

σ- Smoothing parameter (corresponds to standard deviations of Guassian distribution)

The function f_A (x) acts as an estimator as long as the parent density is smooth and continuous. If the number of data points used for the estimation increases f_A (x) approaches the parent density function. The function $f_A(x)$ is a sum of guassian distributions.

RESULTS

The six features extracted from normal, benign and malignant brain images using contourlets are tabulated here with maximum accuracy. Along with the in- built functions, code has been developed for extra features like inverse difference and Homogeneity. Matlab 7.9 version is used for simulations and proposed method evaluation. Before doing simulation size of the brain tumor images are reduced. The extracted features obtained from different type of images are given below.

Table 1: Texture Features Obtained From Lh&Hl Sub Bands Of A Normal Mr Image

SUB BANDS	ENERGY	CONTRAST	CORRELATION	HOMOGENEITY	INVERSE DIFFERENCE	ENTROPY
LH1	0.6125	2.3253	0.0253	0.6438	0.0004	1.3642
HL1	0.5023	39.5643	-0.0321	0.5381	0.0003	2.0205
LH2	0.5214	115.0564	0.2127	0.5735	0.0003	2.0103
HL2	0.4825	450.5231	0.0002	0.5723	0.0002	1.9382
LH3	0.0004	0.9426	0.0002	0.0004	0.0002	0.0021
HL3	0.0004	1.6251	0.0002	0.0002	0.0001	0.0030
LH4	0.0006	1.6359	0.0001	0.0007	0.00001	0.0031
HL4	0.0004	6.5926	-0.0002	0.0003	0.0003	0.0034
LH5	0.0003	3.0103	0.0003	0.0002	0.0005	0.0027
HL5	0.0002	6.6126	0.0001	0.0003	0.0004	0.0023

These reduced size images are used as inputs to the Contourlet Transform and it gives maximum features per image as output. The sub bands of LH and HL for five directions are taken for consideration and tabulated here.

The feature vectors of the brain tumor images obtained at the output of the contourlet Transform are given to the Probabilistic Neural Network for classification. Probabilistic Neural network (PNN) gives fast and accurate classification of Brain tumor images. The disadvantages of wavelet and SVM in case of accuracy and time requirement are rectified by using contourlet transform

Table 2: Texture Features Obtained From Lh&Hl Sub Bands Of A Benign Mr Image

SUB BAN DS	ENERG Y	CONT RAST	CORRE LATION	HOM OGEN EITY	INVERS E DIFFER ENCE	ENTROP Y
LH1	0.3216	17.3745	0.2253	0.5271	0.0001	2.4965
HL1	0.2436	71.2389	0.1328	0.4725	0.0002	3.0181
LH2	0.3101	292.196 5	0.5482	0.3587	0.0000	2.5692
HL2	0.0004	0.8864	0.0000	0.0008	0.00013	2.4113
LH3	0.0002	2.9426	0.0002	0.0007	0.0001	0.0037
HL3	0.0003	1.6251	0.0000	0.0006	0.0004	0.0048
LH4	0.0002	2.6359	0.0003	0.0004	0.00007	0.0052
HL4	0.0001	4.3244	0.0002	0.0006	0.00032	0.0049
LH5	0.0002	8.8654	0.0003	0.0004	0.0001	0.0055
HL5	0.0001	8.7342	0.0001	0.0001	0.0000	0.0042

Table 3: Texture Features Obtained From Lh&Hl Sub Bands Of A Malignant Mr Image

SUB BAN DS	ENERG Y	CONT RAST	CORRE LATION	HOM OGEN EITY	INVERS E DIFFER ENCE	ENTROP Y
LH1	0.3156	10.6538	0.4923	0.6554	0.0002	2.7431
HL1	0.2397	13.3671	-0.0953	0.5832	0.0001	3.0986
LH2	0.3035	311.164	0.3752	0.4662	0.0000	3.3265
HL2	0.9542	482.886	-0.0604	0.6419	0.00017	2.3211
LH3	0.0002	2.6821	0.0002	0.0004	0.0003	0.0042
HL3	0.0001	3.5642	-0.0001	0.0004	0.0002	0.0041
LH4	0.0001	6.9352	0.0002	0.0007	0.00006	0.0051
HL4	0.0000	0.9342	0.0001	0.0000	0.00019	0.0049
LH5	0.0001	7.8543	0.0000	0.0002	0.0001	0.0039
HL5	0.0000	1.5429	0.0003	0.0000	0.0000	0.0004

The extracted features from the test image and the database images are compared using Neural Network. Based on the output, the test image will be classified under anyone of the class. The training of neural network is done using contourlet transform for all the classes of around 90 brain tumor images obtained from MRI scan or CT scan.
When compared to the previous transforms , our method provides the result accurately with 100% recognition rate.

CONCLUSION

In this paper, a Brain Tumor images are analysed using four level decomposition. So totally 24 sub bands are obtained, and from each subband six features are extracted.So totally 144 features are extracted and are used for classification. For training of neural network, 90x144 features are extracted and compared with the test image. This new method is a combination of contourlet Transform and Probabilistic Neural Network. By using these algorithms an efficient Brain Tumor Classification method was constructed with maximum recognition rate of 100%. The ability of the proposed method shows optimal feature extraction and efficient Brain Tumor classification.
The ability of our proposed Brain Tumor Classification method is demonstrated on the basis of obtained and collected results on Brain Tumor image database. For generalization, the proposed method should achieve 100% Recognition rate on other Brain Tumor image databases and also on other combinations of training and test samples. In the proposed method only 4 classes of Brain tumors are considered, but this method can be extended to more classes of Brain tumors.

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