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Contourlet Transform and PNN Based Brain Tumor Classification

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Abstract:
In this paper a new method is proposed for Brain Tumor classification using a Probabilistic neural network with contourlet transformation. The conventional methods like Computerized Tomography (CT) and Magnetic Resonance Images (MRI) are based on human inspection for tumor classification and detection. These methods are inefficient and are also non reproducible for large amount of data. Also, those methods include noise due to operator performance which creates serious inaccuracies in tumor classification. Neural Networks shows good results in medical diagnosis which is combined here with contourlet transform. Decision making is based on two steps (i) Image reduction and Feature extraction using contourlet transform (ii) Classification using probabilistic Neural Network(PNN). Performance evaluation on various brain tumor images shows fast and better recognition rate and also low computational requirements, when compared to previous classifiers.

Key words*: Brain tumor image classification, Probabilistic Neural Networks, Contourlet Transform, Dimensionality Reduction, Feature Extraction*

1. Introduction

A brain Tumor is an abnormal growth of cells within the brain or central spinal canal, either it may be cancerous (malignant) or non-cancerous (benign). Its threat level depends on the type of tumor, its size and its location. There are so many types of brain tumor which makes the decision tough[1]. Treatments of various types of brain tumor are mostly depending on types of brain tumor.

The conventional methods, which are present in diagnosis, are Biopsy, Human inspection, Expert opinion and etc. The biopsy method takes around ten to fifteen days of time to give a result about tumor.. In general, early stage brain tumor diagnose mainly includes CT scan, MRl scan, Nerve test, Biopsy etc [3].. 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.

Dimensionality Reduction and Feature Extraction are very important aspects in any classification system. Even small size images are having large dimensionality which leads to very large memory occupation, complexity and computational time. 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.

2. System Overview

The overall methodology of the proposed method is given as a flowchart below which includes PNN and the proposed transform

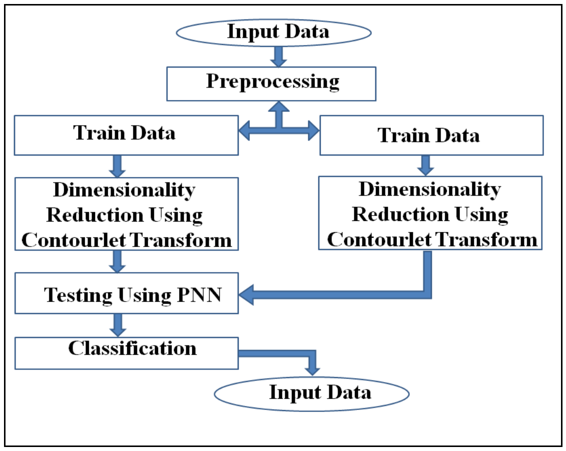

Figure 1: Flowchart of the system

The input data is preprocessed and then contourlet transform is applied to both the train and test data. The results of both the process are given as a input to PNN for comparison based on which classification will be done. The results are formed as a vector under which input is classified under a class based on the features extracted.

3. Contourlet transform

The disadvantage of two-dimensional wavelets is their limited ability to capture directional information. To avoid this deficiency, a new method has been proposed which takes multiscale and directional representations that can capture the intrinsic geometrical structures such as smooth contours in natural images.

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. At the first step, we used Laplacian pyramid (LP), and for the second one we used directional filter banks (DFB)[5].

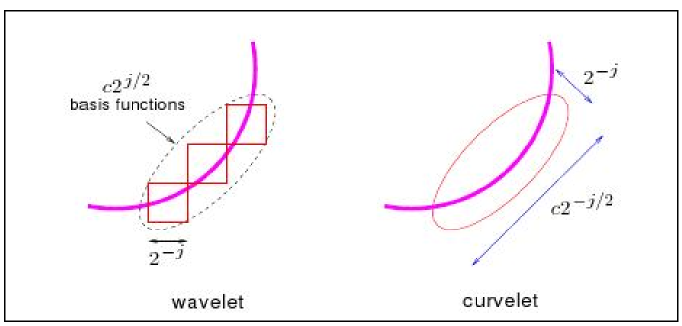

Figure 2: Comparison of wavelet and curvelet. Refer [6]

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 transformts 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.

Contourlets not only possess the main features of wavelets (namely, multiscale and time-frequency localization), but also offer a high degree of directionality and anisotropy. 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[6].

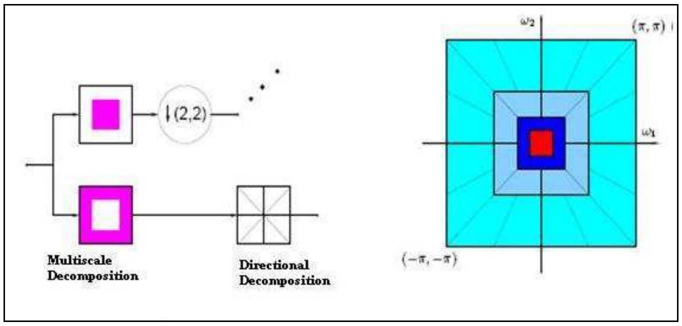

Figure 3: Decomposition using contourlet Refer [6]

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

- Components like LL (Low Low), LH (Low High), HL (High Low) and HH (High High) are the 4 frequency components of the input image.
- At each level, the laplacian pyramid produces a low pass output (LL) and a band pass output (LH, HL, HH).
- And then the band pass output is passed into directional filter bank, which results in contourlets coefficients. After that the low pass output is again passed through the laplacian pyramid to obtain more coefficients and this process is repeated until the fine details of the image are retrieved.
- Then the image is reformed by applying the inverse contourlet transform.

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.

4. Probabilistic Neural Network

Probabilistic Neural Network is a type of Radial Basis Function (RBF) network, which is mainly used for pattern classification. The basic architecture of a probabilistic neural network is shown in figures. An input layer, a pattern layer, and an output layer are the three layers contained in the fundamental architecture of PNN layers. A neural based implementation of a Bayes classifier has been explained by the pattern layer, where the Probability Oensity Functions (POF) dependent on the class uses Parzen Estimator for approximation. After minimizing the expected risk in classifying the training set incorrectly the Parzen estimator determines the POF. Using the Parzen estimator, if the number of training samples increases, the classification will be very nearer to the original underlying class density functions.

The feed forward back propagation network is complex when compare to the training of the probabilistic neural network which is much simpler. Since the probabilistic networks classification is based on the Bayesian theory, the input vectors should be essentially classify 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,

$P_A\, C_A\, f_A(x) > P_B\, C_B\, f_B(x)$ ……….. (1)

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

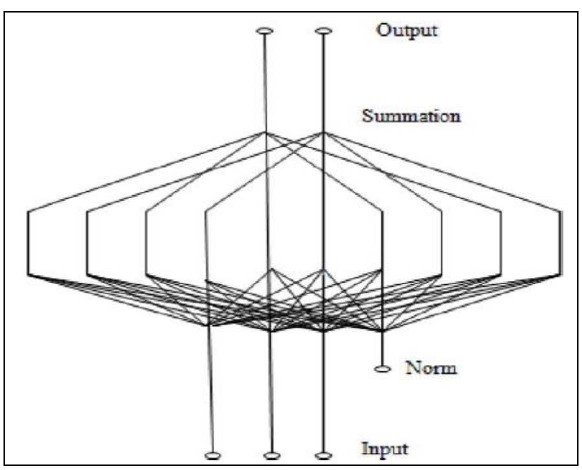

Figure 4: Layers of PNN.Refer [9]

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 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,

$$fA(x) = \frac{1}{(2\pi)^{n/2}} \frac{1}{\sigma^n} \frac{1}{mn}$$

$$\sum_{i=1}^{m} \exp \left(\frac{-2(x - xA)(x - xAi)}{\sigma 2} \right) \quad \text{……….(2)}$$

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)

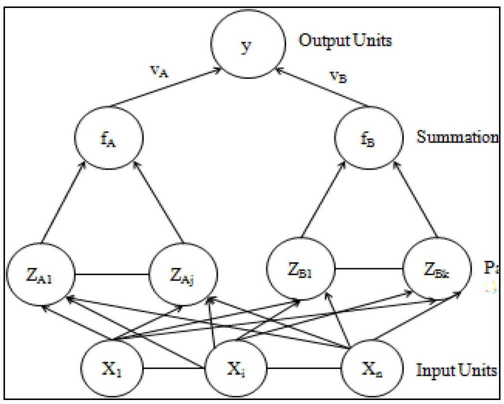

Figure 5: Architecture of PNN. Refer [10]

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.

5. Expected Results

So far, in this project Dimensionality reduction and feature extraction using contourlet transform has been implemented. There are four inbuilt features available in Matlab, along with that two extra features have been included namely inverse difference and entropy.
The proposed new method with contourlet transform was applied on Brain Tumor image database containing 4 classes and each class having 5 images of size 70 x 60 with different background conditions. For simulations and proposed method evaluation Matlab is used Brain tumor image database and its normalized version is taken for classification. Before doing simulation size of the brain tumor images are reduced to 4 x 4.
Contourlet transform takes the input from the reduced size images and it gives maximum features per image as output. For this database the graph drawn between recognition rate vs Image size and the graph drawn between recognition rate Vs number of features per sample (Sample dimension) will be drawn to show the efficiency.
From all of these figures it has been confirmed that Image size of around 4x4 with sample dimension of 6 is giving maximum recognition rate of 100%. The brain tumor images obtained at the output of the contourlet Transform are formed as a feature vector and are given to the Probabilistic Neural Network for classification. Based on the extracted features Probabilistic Neural network (PNN) gives fast and accurate classification of Brain tumor images.

6. Conclusion

In this paper, a modified and efficient method for Brain Tumor Classification is presented. This new method is a combination of contourlet Transform and Probabilistic Neural Network. By using these algorithms an effective Brain Tumor Classification method was constructed at the maximum recognition rate of 100%. The ability of the proposed method shows optimal feature extraction and efficient Brain Tumor classification.

Based on the obtained and collected results on Brain Tumor image, a database has been formed. The proposed Brain Tumor Classification method's ability is demonstrated by using this database. Not only for the given database,for generalization, the proposed method should achieve 100% Recognition rate even on other Brain Tumor image databases and also on other test and training samples combinations. In the proposed method only four classes of Brain tumors are considered, but this method can be extended to more classes of Brain tumors.

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