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Image Classification and Clustering using Wavelet Based Radial Basis Neural Network

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ABSTRACT

Accurate image segmentation and classification, is essential for medical diagnosis of scans. Of late, magnetic resonance (MR) images have become the commonest tool of clinical investigation. In this study we address to clarify brain tumor images into normal, non-cancerous (benign) brain tumor and cancerous (malignant) brain tumor by collecting the complete history of the patients in terms of their food habit, life style and the severity of the age. The proposed method follows three steps, (1) wavelet decomposition, (2) texture feature extraction and (3) classification. Discrete Wavelet Transform is first employed using Daubechies wavelet (db4), for decomposing the MR image into different levels of approximate and detailed coefficients and then the gray level co-occurrence matrix is formed, from which the texture statistics such as energy, contrast, correlation, homogeneity and entropy are obtained. The results of co-occurrence matrices are then fed into a radial basis neural network for further classification and clustering for tumor detection. The proposed method will be applied on real MR images, and on all types cancer images and the accuracy of classification using radial basis neural network will be rigorously evaluated and the physician can diagnose and design the better therapies.

Keywords: Wavelet Decomposition, Co-Occurrence Matrix, Gray Level Spatial Dependence Matrix (GLSDM)

I. Methodology

Proposed method of brain tumor classification is outlined in figure 1.

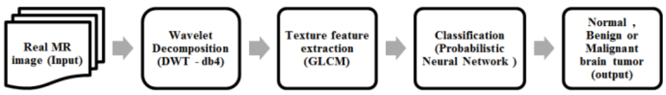

Figure 1. Brain tumor classification process

II. Feature Extraction

The wavelet is a powerful mathematical tool for feature extraction, and has been used to extract the wavelet coefficients from MR images. The Discrete Wavelet Transform is an implementation of the WT using the dyadic scales and positions. The basic fundamental principle of DWT is introduced as follows:

Suppose x (t) is a square-integrable function, then the continuous WT of x (t) relative to a given wavelet Ψ (t) is defined as,

$$W_{\Psi(a,b)} = \int_{-\infty}^{\infty} x(t)\Psi_{a,b}(t)dt \quad (1)$$

Where, the wavelet $\Psi_{a,b}(t)$ is calculated from the mother wavelet Ψ (t) by dilation and translation factor a and b respectively, which are real positive numbers.

$$\Psi_{a,b}(t) = \frac{1}{\sqrt{a}}\Psi\left(\frac{t-a}{b}\right) \quad (2)$$

Equation (1) can be discretized by restraining a and b to a discrete lattice ($a=2^b$ and a > 0) to give the discrete wavelet transform, which can be expressed as,

$$a_{j,k}(n) = DS\left[\sum_n x(n)g_j^*(n-2^j k)\right] \quad (3)$$

$$d_{j,k}(n) = DS\left[\sum_n x(n)g_j^*(n-2^j k)\right] \quad (4)$$

Where, the coefficients $a_{j,k}$and$d_{j,k}$ refer to the approximate and detail components, respectively. The functions g (n) and h (n) denote the coefficients of the low-pass and high-pass filter, respectively. The subscripts j and k represent the wavelet scale and translation factors, respectively. The DS operator is used for down sampling.Two dimensional DWT results in four sub bands LL (low-low), LH (low-high), HL (high-low), HH (high-high) at each scale. Sub band LL, is the approximation component of the image, which is used for next two dimensional DWT. Whereas, LH, HL, HH are the detailed components of the image along the horizontal, vertical and diagonal axis, as shown in the figure 2.

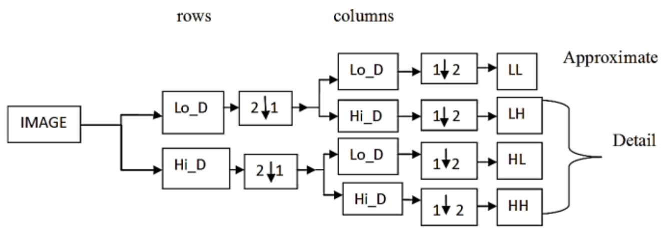

Figure 2. 2D Discrete Wavelet Transform

Lo_D – Low Pass Filter
Ho_D – High Pass Filter

$\boxed{2\downarrow}$ - Down sampling columns: keeps the even columns.

$\boxed{1\downarrow}$ - Down sampling rows: keeps the even rows.

Based on the literature study, Daubechies wavelet is considered as the best among the other wavelets for image application and LH, HL sub-bands had higher performance compared to the features from LL sub band. Hence in this method, a five level decomposition using daubechies wavelet was computed and the features were extracted from LH and HL sub bands using DWT.

III. Texture Analysis

The statistical features from MR images are obtained using Gray Level Co-Occurrence Matrix (GLCM), which is also known as Gray Level Spatial Dependence Matrix (GLSDM). GLCM, introduced by Haralick is a statistical approach that can well describe the spatial relationship between pixels of different gray levels.

GLCM is a two dimensional histogram in which $(i, j)^{th}$ element is the frequency of event i that occurs with j. It is a function of distance d=1, angle θ (at 0° (horizontal), 45° (along the positive diagonal), 90° (vertical) and 135° (along the negative diagonal) and gray scales i and j, thereby, calculates how often a pixel with intensity i, occurs in relation with another pixel j at a certain distance d and orientationθ. In this method, Gray level co-occurrence matrix was formed and the statistical texture features such as contrast, correlation, energy, homogeneity and entropy were obtained for the LH and HL sub bands of the 4^{th} and 5^{th} level of wavelet decomposition.

Contrast: Measures the local variation in the gray level co-occurrence matrix, which can be calculated as,

$$\sum_{i,j} |i-j|^2 P_{d,\theta}(i,j) \tag{5}$$

Correlation: Measures the degree of correlation a pixel has to its neighbor over the whole image. Its range is [-1 1].

$$\sum_{i,j} \frac{(i-\mu i)(j-\mu j) P_{d,\theta}(i,j)}{\sigma_i \sigma_j} \tag{6}$$

Energy: Uniformity (or) Angular Second Moment, returns the sum of squared elements in the gray level co-occurrence matrix. Its range is [0 1].

$$\sum_{i,j} (P_{d,\theta}(i,j))^2 \tag{7}$$

Homogeneity: or the Inverse Differential Moment, returns a value that measuresthe closeness of the distribution of elements in gray level co-occurrence matrix to the gray level co-occurrence matrix diagonal. Its range is [0 1].

$$\sum_{i,j} \frac{P_{d,\theta}(i,j)}{1+|i-j|} \tag{8}$$

Entropy: or Disorder

$$\sum_{i,j} P_{d,\theta}(i,j) log_2[(P_{d,\theta}(i,j)] \tag{9}$$

These statistical features are given as inputs to the radial basis neural network for further classification.

IV. Classification

Radial Basis Neural Network (RBNN) is a Radial Basis Neural Network, which provides a general solution to pattern classification problems by following an approach developed in statistics, called Bayesian classifiers. It is employed to implement an automatic MR image classification of brain tumors into normal, benign and malignant.

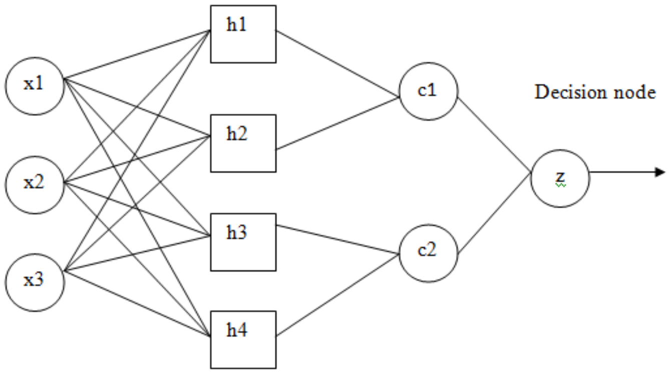

Figure 3. Radial basis neural network Architecture

A RBNN is predominantly a classifier since it can map any input pattern to a number of classifications. The main advantages that discriminate RBNN are, its Fast training process, an inherently parallel structure, guaranteed to converge to an optimal classifier as the size of the representative training set increases and training samples can be added or removed without extensive retraining. Accordingly, a RBNN learns more quickly than many neural networks model and have had success on a variety of applications [5]. Based on these facts and advantages, RBNN can be viewed as a supervised neural network that is capable of using it in system classification and pattern recognition.

The probability can be estimated using the formula,

$$f_q(X)=\frac{1}{(2\pi)^{p}/_{2}\sigma^{p}}\frac{1}{N_q}\sum_{i=1}^{N_q} exp\left[\frac{-(X-X_i^q)^T(X-X_i^q)}{2\sigma^2}\right] \quad 10$$

P denotes the dimension of the pattern vector X.
$N_q$is the samples number of category q
$X_i^q$is the i-th pattern sample from category q and
$\sigma$is the smoothing factor or the width of the Gaussian function.

In this paper, the RBNN has three layers: the Input layer, Radial Basis Layer and the Competitive Layer. Radial Basis Layer evaluates vector distances between input vector and row weight vectors in weight matrix. These distances are scaled by Radial Basis Function nonlinearly.

V. Expected Results and outcome

This study may be an efficient method of classifying MR brain images into normal, benign and malignant tumor, using a radial basis neural network. The proposed approach is expected to result in classifying MR images. Most of the existing methods can detect and classify MR brain images only into normal and abnormal [2]. Whereas, the proposed method, with the help of the texture statistics obtained from LH and HL sub bands, is able to classify brain tumor into benign and malignant. The percentage of accuracy of classification using RBNNis found to be nearly 100 %, when the spread value is set to 1. Based on the experimental results, RBNN is considered to have major advantages over conventional neural networks, because RBNN learns from the training data instantaneously. This speed of learning gives the RBNN the capability of adapting its learning in real time.

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