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IMAGE ENHANCEMENT OF CT SCAN AND MRI IMAGES FOR TUMOR

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Abstract

Digital image processing based texture feature selection algorithm for tumor characterization and enhancement of chest images for Computed Tomography (CT scan) are presented in this paper .Our problem focuses on the high performance classification by optimization of feature set by various selection algorithms like sequential forward search (SFS), sequential backward search algorithm (SBS) and sequential forward floating search algorithm (SFFS). Here the focus is on statistical texture features obtained from the computed tomography abdominal images taken by the radiologist. Symlet Wavelet is used for feature extraction. Wavelet transform decomposes the data in such a way that any hidden information in image can be retrieved. As there is a great need for fast processing of large volume of data especially for real time applications and for giving instant response to the users, these applications are multimedia information retrieval, data mining, medical image data etc. I have tried my best to reduce the feature set size as it is very necessary to limit the number of features or to have optimization of feature set. Feature selection is prerequisite and feature extraction is another important aspect where texture can be described as statistical property of pixel gray level and then a design of compact classifier is required for improved classification of the selected problem (Liver Tumor, Brain Tumor), based on the classification of tumor as malignant tumor and benign tumor. Most and least significant features are identified on the basis of classification performance of the classifier and then unwanted features may be removed from the set of feature to get a feature subset, which is small in size. In this paper I have tried to characterize the hepatic, hepatoma, hemangeoma, hepatic masses using Symlet Wavelet. As the optimal classification performance is obtained so the cost of classifier is reduced. After comparing the performance of this technique to that of other approaches it is found to be superior and convenient for medical diagnosis.

Keywords: *Feature extraction, Feature selection, tumor classification, Symlet Wavelet*

INTRODUCTION

Image enhancement, noise removal and feature extraction at different depth level is essential task for medical image processing. Feature selection is the problem of selecting a subset of "d" feature form a set of "D" feature based on some optimization criterion. The primary purpose of feature selection is to design a more compact classifier with as little performance degradation performance as possible. The features removed should be useless, redundant or of the least possible use. Recently, interest in feature selection has been on the increase for several reasons. Firstly new applications dealing with vast amounts of data have been developed, such as data mining, multimedia information retrieval and medical data processing. since the fast processing of a large volume of data is critical in these applications for the purpose of real time processing or to provide a quick response to the users, limiting the number of feature is a very important requirement feature selection is a pre requisite while using multiple set of feature, as this is required for the subsequent processes involving classification or clustering.

A number of approaches to the texture classification problem has been developed over the years a major class of future extractors relies on the assumptions that texture can be defined by local statistical properties of pixel gray levels, from the image histogram, first order statistics can be derived and used as texture feature. Haralick, et al1,2 proposed a class of quickly computable texture feature computed for spatial gray level dependence matrix (SGLDM) which seems to have general applicability to many kind of image data others textures feature that can be applied to real world texture as the fractal features3, gray level difference(GLD) statistics4. Laws texture energy measures and the gray level run length statistics6,7 several multi channels textures analysis schemes have developed. S G mallat8 identified the important concepts of multi – resolution analysis which is the corner stone of modern wavelet theories, while Daubechies9 established a solid mathematical footing to shape and define the field. Typically, the wavelet transforms maps an image on a low resolution image and a series of detail images the low resolution image is obtained by iteratively blurring the image, the detail image contain the information lost during this the energy or mean deviation of the detail images are the most commonly used features for texture classification and segmentation problems10,11,12.Wavelet tram is very good in noise removal13,14.

Yu Len Huang, et al15 used auto covariance feature to classify the tumour using multi layer perceptran natural network. Artificial natural network (ANN) are used to diagnose hepatic masses. Matake, et al16proved that the ANN can provide useful output second opinion to improve radiologist diagnostic performance in the differential diagnosis of hepatic masses seen on contrast – enhanced CT.

METHODOLOGY

This data used in this work have been collected from Swati MRI and CT Scan Ghaziabad. The area of interest is captured by SOMATOM Emotion Due CT scanner with 8mm slices at 8mm intervals with 0mm interslice thickness .70mAs technique has been used with 110 KVP, for field of vision (foV) 280 and image matrix of (256× 256). The image is in DICOM format. They are converted to BMP format which is an acceptable format for medical image processing. The images are enhanced, filtered and inherent features are extracted by Symlet Wavelet transform. The usefulness of transformations is that they project a function onto a new set of basis functions. If one or more basis functions represent a feature, and all the other basis functions are orthogonal to it, then one can quickly determine if a feature exists in a signal by projecting signal function onto the new basis.

A. Symlet wavelet

We have used Symlet Wavelet made by I. Daubechies. It is quite effective in boundaries of image in texture. The wavelet decomposition function decomposes the image into different level of intensities, which makes able to compute the inherent texture in medical images.

Daubechies proposes modifications of her wavelet such that their symmetry can be increased while retaining simplicity. The idea consists of reusing the function m0 introduced in the dbN5 considering the $|m_0(\omega)|^2$ as function ω of $z = e^{i\omega}$. Then we can factor ω in several different ways in the form of $\omega(z) = U(z)\overline{U(\frac{1}{z})}$. The roots of ω with modulus not equal to 1 go in pairs. If one is, z_1, $\frac{1}{z_1}$ is also a root. By selecting U such that the modulus of all its root is strictly less than 1, we build Daubechies wavelets dbN. The U filter is minimum phase filter. By making another choice, we obtain more symmetrical filters; these are symlets. symlets are compactly supported wavelets with least asymmetry and highest number of vanishing moments for a given support width. Associated scaling filters are near linear-phase filters having support width 2N-1 and filters length 2N.

Daubechies introduced scaling function $\phi(x) = \sqrt{2}\sum_n h_n \phi(2x - n)$ for wavelet dbN (h_n are the coefficients associated to a „standard" multiresolution analysis and the corresponding orthonormal basis). However, more symmetric wavelet filters make easier to deal with the boundaries of the image9,10 . Symmetric filters are linear phase filters. More precisely, a filter with filter coefficients a_n is called linear phase if the phase of the function $a(\xi) = \sum_n a_n e^{-in\xi}$ is a linear function of ξ, i.e., if for some $l \in Z$, $a(\xi) = e^{-il\xi}|a(\xi)|$ This means that a_n are symmetric around l, $a_n = a_{2l-n}$. The phase introduced by I. Daubechies for symlet wavelet is given below

$$\hat{\Phi}^1(\xi) = m_0(\xi/2)\,\overline{m_0(\xi/4)}\,m_0(\xi/8)\,\overline{m_0(\xi/16)}\,.......$$

$$= \prod_{j=1}^{\infty} [m_0(2^{-2j-1}\xi)\,\overline{m_0(2^{-2j-2}\xi)}],$$

where $m_0(\xi) = \frac{1}{\sqrt{2}}\sum_n h_n e^{-in\xi}$. The phase $\hat{\Phi}^1$ of the symlet wavelet is closer to linear phase than that of dbN[9], $\hat{\Phi}(\xi) = \prod_{j=1}^{\infty} m_0(2^{-j}\xi)$

B. Filtering scheme

Multiresolution analysis provides a systematic way to generate a wavelet transform. A 1-D multiresolution analysis involves a sequence of nested subspace $\{V_j, J \in Z\}$ with $V_j \subset V_{j-1}$, and its orthogonal complements $\{W_j, J \in Z\}$. Constructing a 2-D multiresolution analysis, on the other hand, involves a tensor product of two 1-D multiresolution analysis11,12 . A 2-D subspace is given by

$$
\begin{aligned}
V_{j-1}^2 &= V_{j-1} \otimes V_{j-1} \\
&= (V_j \otimes W_j) \otimes (V_j \otimes W_j) \\
&= V_j \otimes V_j \otimes [(V_j \otimes W_j) \otimes (W_j \otimes V_j) \otimes (W_j \otimes W_j)] \\
&= V_j^2 \otimes W_j^2
\end{aligned}
$$

where the superscript 2 denotes two dimensions. A 2-D subspace at level j-1 is the sum of subspace at level j and its complement, where as the 2-D complement subspaces W_j^2 consists of three operands: $V_j \otimes W_j$, $W_j \otimes V_j$, and $W_j \otimes W_j$. As such, a 2-D multiresolution analysis can be expressed in terms of a sequence of nested subspaces $\{V_j^2, j \in Z\}$ and its complements $\{W_j^2, j \in Z\}$.

The scaling function and wavelets can be expressed as

$$\Phi(x, y) = \Phi(x)\Phi(y) \quad \text{......} (1)$$

$$
\begin{aligned}
\Psi^h(x, y) &= \Phi(x)\Psi(y), \\
\Psi^v(x, y) &= \Psi(x)\Phi(y), \quad \text{......}(2) \\
\Psi^d(x, y) &= \Psi(x)\Psi(y).
\end{aligned}
$$

where h = horizontal, v = vertical, d = diagonal .

X^h, X^v, X^d in equation (2)are horizontal, vertical and diagonal components respectively in the image which gives different features.

FEATURE EXTRACTION ALGORITHM

Image contains a large amount of data, much of which is redundant. Therefore, a major component in analyzing image involves data reduction, which is accomplished by intelligently modifying the image from the lowest level of pixel data into higher-level representations. Form this higher level representation, useful information is gathered by a process called feature called feature extraction. The exact use of these features application dependent. Feature vector is one method to represent an image, or part of image, by carrying out measurements on a set of features the feature vector is an n-dimensional vector that contains these measurements. While selecting this measurement in a computer image application, an important factor is the robustness of a feature. A feature is robust if it provides consistent results across the entire application domain. A feature should be RST – invariant where RST means rotation, size and translation. In the first step, Symlet wavelet transform is applied on the tumour region to get horizontal, vertical and diagonal details of the image.

The original image 4 is represented by set of sub images at several scales.

{Lid, Dm}i=1,2,3,n=1..d which is a multi scale representation of depth d and scale n of the image each wavelet coefficient Dm (bi,bj) € R and the co-occurrence matrix is defined for an image with a countable number of gray levels, the co occurrence matrix Cni dΘ can be defined for each detail image. The element (j, k) of the co-occurrence matrix Cni dΘ is defined as the joint probability that a wavelet coefficient Dni = j co-occurs with a coefficient Dni = k on a distance d in the direction Θ. Usually small values for d are used since most relevant correlation between pixels exists on small distance.

In the second step, From these three detail image three SGLDM or co-occurrence matrices C11dΘ is defined as the joint probability that a wavelet coefficient Cni = j co-occurrence with a coefficient Cni = k on a distance d in the direction Θ. Usually , small values for d are used since most relevant correlation between pixels exists on small distance,

In the third step, 14 second order statistical feature as given17,18,19,20 are extracted from each of the three co-occurrence matrices. Hence, 42 features are extracted.

FEATURE SELECTION ALGORITHMS

The feature selection problem involves the selection of a subset of “d” features form a total of “D” features, based on a given optimization criterion. The D feature are denoted uniquely by distinct numbers from 1 to D, so that the total set of D feature can be written as S={1,2,3…d}. X Denotes the subset of selected features and Y denotes the set of remaining features, so S= XU Y at any thing. J(X) denotes a function elevating the performance of X. J depends on the particular application. Here, J(X) denotes the classification performance of tumor region as benign or malignant using the set of feature in X.

SEQUENTIAL FORWARD SEARCH (SFS) ALGORITHM

1. X=Φ;
2. J={J/1≤ i ≤ D};

3. Repeat

Choose the most significant feature y in Y such that J (XU{Y}) gives maximal classification performance.

Move y to X.
Until J(X) gives optimal classification performance
4. End

SEQUENTIAL BACKWARD SEARCH (SBS) ALGORITHM

1. Y=Φ;
2. X=={i/≤ i ≤ D};
3. Repeat
Choose the least significant feature x in X such that J(X-{x}) gives maximal classification performance. Move x to Y until J(X) gives optimal classification performance.
4. End

SEQUENTIAL FORWARD FLOATING SEARCH (SFFS) ALGORITHM

1. X=Φ;
2. J={iJ/1≤ i ≤ D;
3. K=0 // initialization
4. While (K<d)

{Find the most significant feature y in Y and add to X. find the least significant feature x in X. While (J (J (X_K –{X})>J (X_{K-1})) {

X_{K-1} = X_K- {x};

K-1;

find the least significant x.

}

}

EXPERIMENTAL RESULTS

Image acquired were in digital imaging and communication in medicine (DICOM) format. They were collected from 20 hepatocellular carcinoma patients (malignant), 20cholangio carcinoma patients (malignant), 20 hemangioma (benign) patients and 20 hepato adenoma (benign) patients. Form these patients, 120 hepatocellar carcinoma slices (images), 120 cholangio carcinoma slices (image), 120 hemangioma slices (image) and 120 hepato adenoma slices images) have been considered for this work. The system was implemented using MATLAB and Labview. Figure1 is original chest ct image, figure 2 and figure3 are enhanced image by gradient and Symlet wavelet filter. Figure 5 is a ct scan of a patient with a liver tumour. The liver is located along the left upper of the image and is light gray in colour. The white tubular structures are the normal liver blood vessels. The liver tumour is dark and located on the edge of the liver and extends toward a blood vessel. The same experiment is repeated with images of different patients in which the probability of tumor is estimated. Several experiments were repeated with different images i.e. bran images, lungs images as shown in figure6 and figure7. The input data set is divided into different disjoint groups of training set and testing set to conduct the experiment. Data set size has been tabulated in table1. To prove the validity while testing, care must be taken so that the slices collected from a patient are not added in the training set.

From the tumour region, Identification by radiologist, 42 texture features have been extracted after applying Symlet wavelet filter.

Fig.1:Original chest images

Fig.2a: Structure detected

Fig.2a: 3D profilometry

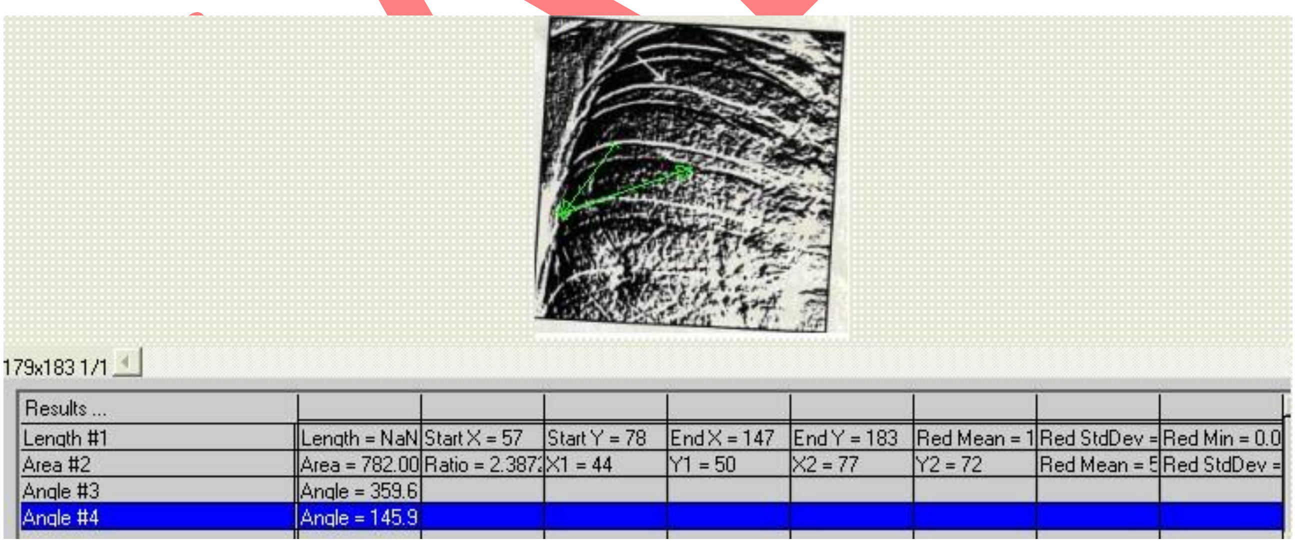

Fig.3: Enhanced and analyzedchest images by gradient and Symlet wavelet filter

Fig.4 Liver tumor detected

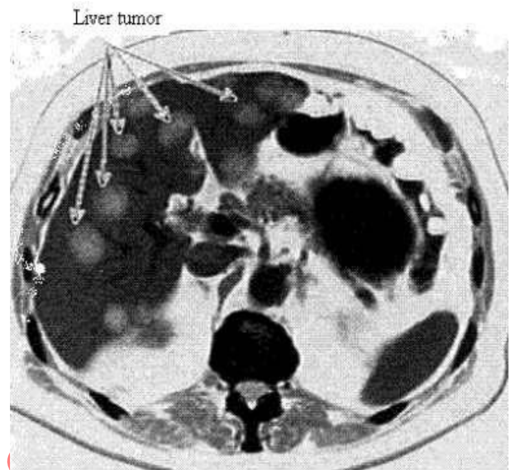

Fig.5.Liver tumors from enhanced image by Symlet wavelet

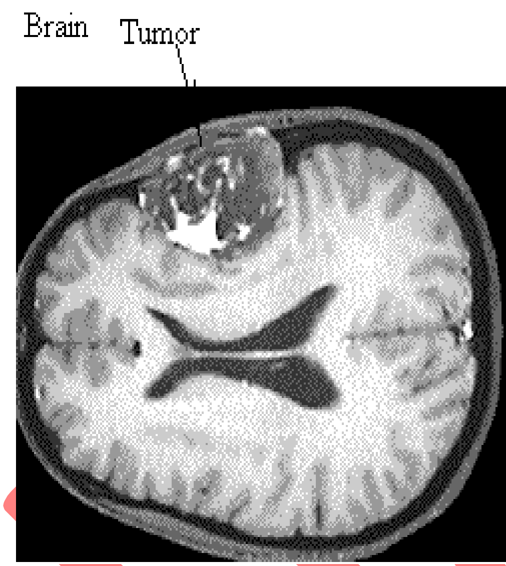

Fig.6: Brain tumor from enhanced image

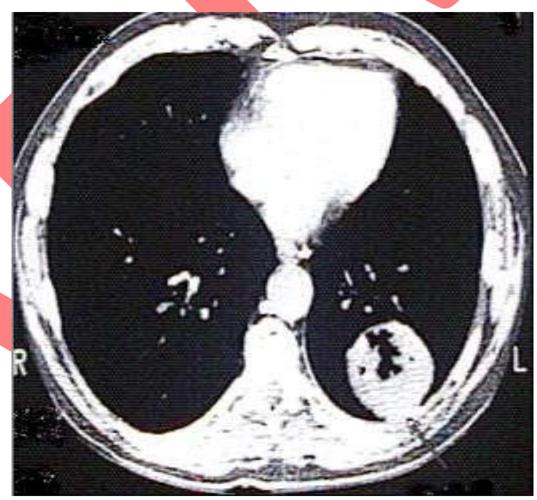

Fig.7: Lungs tumor from enhanced image by Symlet Wavelet

Table-1 INPUT DATA SET USED FOR CONDUCTING EXPERIMENT

Disease name	**Patient number of**	**slices number set of**	**Training set number of**	**testing set**
Benign Tumor	40	120	60	60
Malignant Tumor	40	120	60	60

The features are optimized by the SFS, SBS and SFFS techniques.

CONCLUSION

A novel method for filtering and feature extraction for medical image is proposed in this paper. A computer based system for the detection of tumor has been constructed using the minimal feature set, angular second moment, contrast, entropy and homogeneity. Since wavelet transform provides multiresolution, Symlet Wavelet transform is best for texture and other inherent features detection. The results above shows it is best for chest image enhancement, liver tumor, brain tumor, lungs tumor detection for both at the development stage and at developed stage. Of course the tool is helpful for the radiologist and powerful method to detect an unidentified diseases.

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