International Journal of Data Mining Techniques and Applications
Volume 5, Issue 1, June 2016, Page No.83-86
ISSN: 2278-2419

Discrete Wavelet Transform Based Brain Tumor Detection using Haar Algorithm

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Abstract - A brain tumour is an abnormal growth of cells that are spontaneously grows in uncontrolled manner. We can divide tumors in according to how exponentially they developed i.e. growth rate, with lower-grade tumors often being begin and higher-grade tumors being malignant. Based on interpolation of low frequency sub band images obtained by discrete wavelet transform (DWT) and the input image, the brain tumor detection is obtained by using Haar wavelet transform. Database image is also decomposed by using Haar wavelet transform by two levels and this database image is compared with the input image by using Mutual information principle. Both input image and database image is decomposed into different sub bands by using DWT. Interpolation of low frequency sub bands as well as input image is done. The proposed technique that first one is data base image and another is the input image in which both are decomposed into several bands by using wavelet transform and their coefficients are stored into matrix form with the help of MATLAB and these coefficients are compared with the help of mutual information principle. Corrected interpolated high frequency sub-bands and interpolated input image are combined by using inverse DWT (IDWT), finally. Hence, we get a brain tumour detected output image.

Key words: Brain tumour, glioma grade, clustering, dimension reduction, discrete wavelet transform, magnetic resonance spectroscopy, unsupervised learning.

I. INTRODUCTION

Magnetic resonance imaging (MRI) is a widely-used modality that facilitates the diagnosis and prognosis of brain tumours. Standard MRI sequences are routinely used to differentiate among various brain tumour types based on qualitative visual analyses of the represented soft tissue contrast. Indeed, more than 120 classes of brain tumours are known, which are categorised into four grades depending on the level of malignancy by the world health organisation (WHO) . The grading from low to high (I-IV) represents malignancy levels from biologically least aggressive to most aggressive brain tumours as shown by histological criteria, e.g., invasiveness, vascularity, and tumour growth rate . Gliomas are the most common primary brain tumour and pre-treatment assessment of grade is required; however, the sole use of standard MRI sequences may be insufficient for an accurate diagnosis.

II. DISCRETE WAVELET TRANSFORM

The Wavelet Series is nothing but a sampled version of CWT and its computation may consume significant amount of time and resources which is depending on the resolution required for the signal. The Discrete Wavelet Transform (DWT) is based on sub-band coding is found to yield a fast computation of Wavelet Transform due to which It is easy to implement and reduces the computation time and resources required.Short history about DWT.The foundations of DWT go back to1976 when techniques to decompose discrete time signals were devised which is Similar as work was done in speech signal coding which was named as sub-band coding. In 1983,a technique similar to sub-band coding was developed which was named pyramidal coding .Later many improvements were made to these coding schemes which resulted in efficient multi-resolution analysis schemes.On other hand In CWT, the signals are analyzed using a set of basic functions which relate simple scaling and translation contains only scaling function and translation function. In such case of DWT we obtain at image-scale representation of the digital signal is obtained using digital filtering techniques. The DWT is applied on image is very simple procedure as suppose ω be the image is having ω(j+1,m,n) as j+1 is scaling function m is row vector and n is the columns vector. is applied to the high pass filter h**ψ(-n)** and also to low pass filter h**(-n)**the filter is applied across the column as „n indicates the column and which divides the total signal into two filters as low pass and high pass filter.

Decomposition of an image using DWT

The decomposition of image by using wavelet transform. Image is decomposed into four different frequency bands namely HH, HL, LH, LL which contains diagonal contents, vertical contents, horizontal contents and approximate contents. Fig . Shows reverse operation which is taken placed in this figure original image is obtained from combining four decomposed parts by using IDWT.

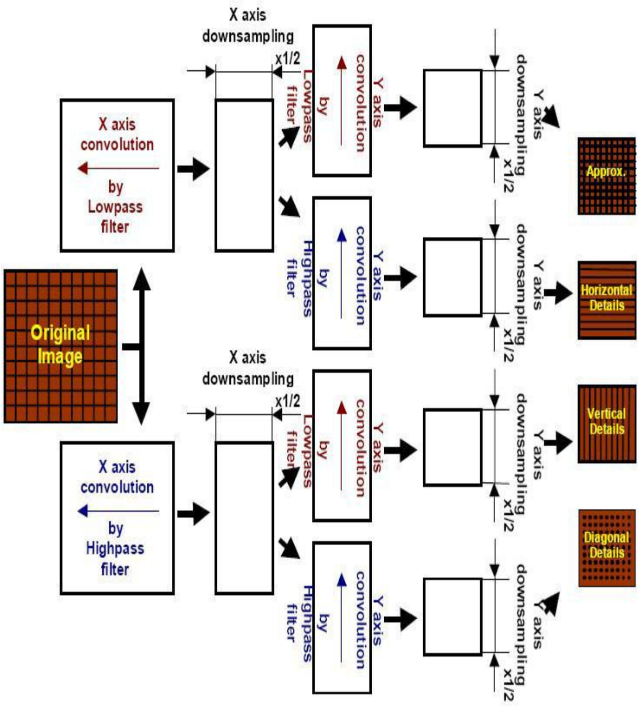

Figure.1: Equivalent image decomposition by using DWT

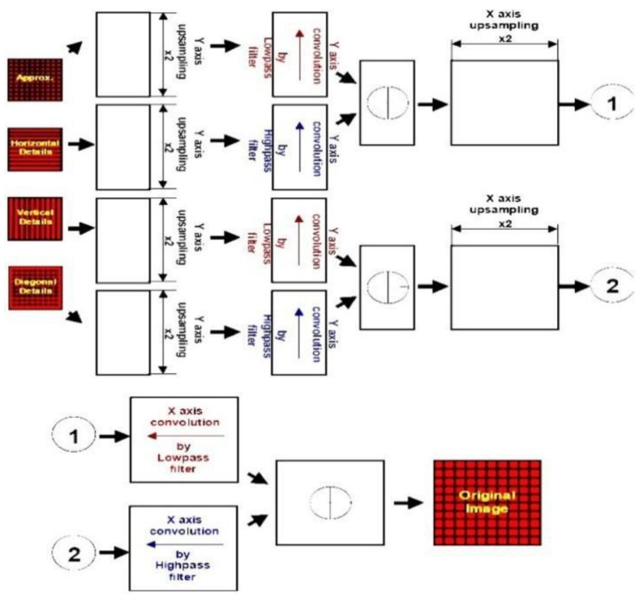

Figure.2:Equivalent Scheme of Wavelet reconstruction Algorithm

III. DWT AND FILTER BANK

Multi-Resolution Analysis Using Filter Bank

Filters are widely used signal processing functions to remove noise in signals. By using iteration of filters with rescaling, wavelets can be realized. The resolution of the signal is considered by using two terms i.e. measure of the amount of detail information in the signal is determined by the filtering operations and the scaling is determined by up-sampling and down-sampling.

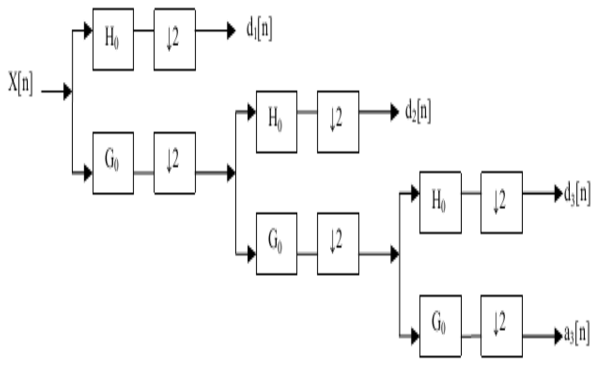

Figure.3:Three-level wavelet decomposition tree

The DWT is obtained by successive low pass and high pass filtering of the discrete time-domain signal as shown in fig. 3.This is called as Mallat algorithm or Mallat-tree decomposition of signal. Its significance is in the manner of which it connects the continuous- time multi resolution to discrete-time filters. In the figure3. The sequence x[n] is applied to wavelet decomposition tree where n is an integer.G0 is low pass filter reduces approximation a[n] and H0 is high pass filter produces detailed information i.e. d[n]. The time resolution becomes good at high frequencies, while the frequency resolution becomes good at lowfrequencies.Unless and until the desired level of resolution is reached the filtering and decimation process is carried out. The length ofthe signal determines maximum number of levels. The DWT of the original signal is then obtained by concatenating all the coefficients, a[n] and d[n], starting from the last level of decomposition

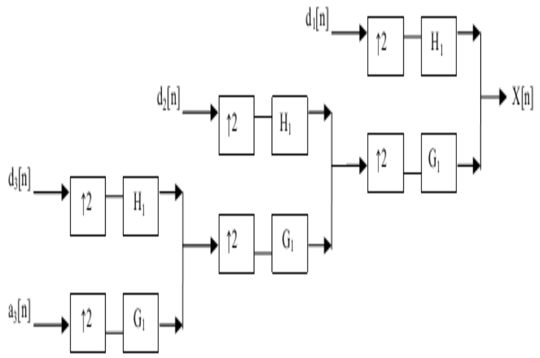

Fig.4:Three-level wavelet reconstruction tree

Shows three-level wavelet reconstruction tree There construction is the reverse process of decomposition. The approximation and detail coefficients at every level are up sampled by two, passed through the low pass and high pass synthesis filters and then added. This process is continued through the same number of levels as in the decomposition process to obtain the original signal. The Mallat algorithm works equally well if the analysis filters, G0 and H0, are exchanged with the synthesis filters, G1 and H1.

IV. EXISTING SYSTEM

MR data were obtained at St. George's University of London using a 1.5-Tesla scanner (GE Healthcare, Milwaukee, WI, USA), which was equipped with 22 gradients and a quadrature head coil. Written informed consent was obtained from all participants in accordance with local ethics procedures. Either biopsy or resected tumour tissue samples obtained as part of the patients' clinical diagnosis or treatment were used to provide a histological diagnosis of the tumour type and grade as the overall gold standard (ground truth). In total SV MRS were obtained including 24 Grade II (GII) tumours (2oligodendroglioma, 3 oligo astrocytoma, 3 fibrillary astrocytoma, 4 gemistocytic astrocytoma and 12 diffuse astrocytoma) and 31 Grade IV (GIV, glioblastomamultiforme). A further 79 MR spectra were obtained from three normal controls using multiple voxel MRS with the same acquisition parameters (i.e., which had compatible TR/TE) as the SV MRS All SV MRS data were acquired at short Echo Time (TE) using the GE developed point-resolved spectroscopic sequence (PRESS) protocol (Repetition Time (TR) = 2000ms, Echo time (TE) = 30ms, 2048 data points with 2500Hz bandwidth). An expert panel (including spectroscopists, pathologists and radiologists) validated the brain tissue types included in this study as part of the TUMOUR project, with a histo pathological diagnosis of the central nervous system (CNS) tumours according to WHO criteria. Individual voxels were placed to encompass predominantly viable tumour tissue as much as possible and avoid areas of pure necrosis. Apo disation in the time domain was performed using a half Hann window followed by a fast Fourier transform and automatic phasing according to .Each spectrum was referenced to both N-acetyl Aspirate (NAA at 2ppm and a search region) and Choline (Cho at 3.21ppm and a search region) for chemical shift alignment, and then truncated to the chemical shift range of 4.0 to 0.2ppm. In addition, the phased real part of the spectra

International Journal of Data Mining Techniques and Applications
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were used for further analysis . Each whole spectrum consisted of data points representing the majority of metabolic information.

V. DATA CLUSTERING

To quantitatively validate and compare the efficacy of our DWT based feature extraction method to previous studies, we applied agglomerative hierarchical clustering algorithms to the feature extraction outputs. Compared to widely used *k*-means clustering, hierarchical clustering requires no initialization settings, and thus can avoid possible local minima that could trap the *k*-means algorithm. For hierarchical clustering a dissimilarity measure was specified (the Euclidean distance) between disjoint groups of observations according to pairwise dissimilarities between the observations in the two groups.

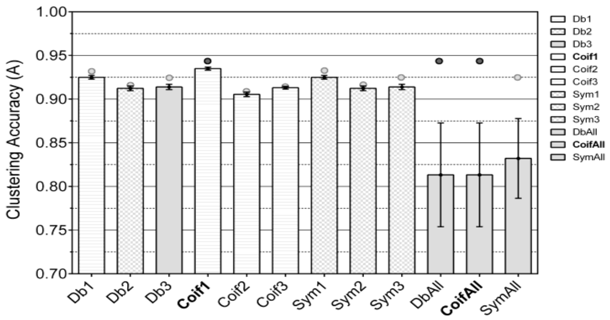
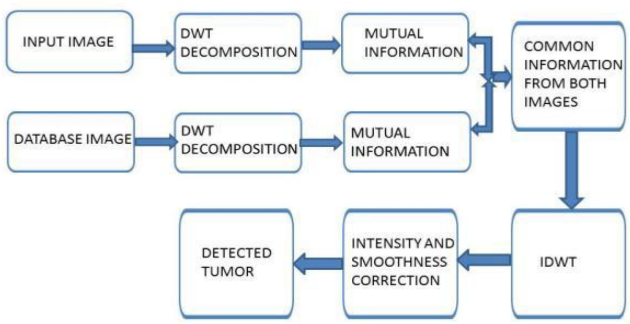


Figure 5: Comparison between different wavelet basis functions

VI. PROPOSED SYSTEM

BLOCK DIAGRAM



PREPROCESSING STEPS

PREPROSING

In the preprocessing stage defected input image and database image are to be taken and on which resize into 320×320pixels.and noise is also removed from both the images. The images should be of same modalities i.e M.R images. We can also go with various modalities such as PETThe input image of size 320×320 is decomposed by using the Haar wavelet into four frequency bands an Low-Low, Low-High, High-Low, High-High.

DECOMPOSTION USING HAAR WAVELET

As the decomposition level goes on increasing the resolution of an image get changed. The LL part contains most of information and due to which we choose only LL part for further processing. in which the low-low coefficients are processed with sub band coding .Similarly the database image is also decomposed by using Haar wavelet into four sub bands namely LL, LH, HL, HH. The decomposition of database image is shown in figure 8. These LL parts are contains most of information and used for mains processing stage in which filtering is carried out on the same and contrast enhancement and brightness enhancement is carried out. This is carried out with the help of MATLAB in which it shows the decomposition of both images with precise value and due which we get better results. The decomposition is carried out in the pyramid structure, of size as follows:

Pyramid level 1 size of 320×320
Pyramid level 2 size 160×160
Pyramid level 3 size of 80×80
Pyramid level 4 size 40×40

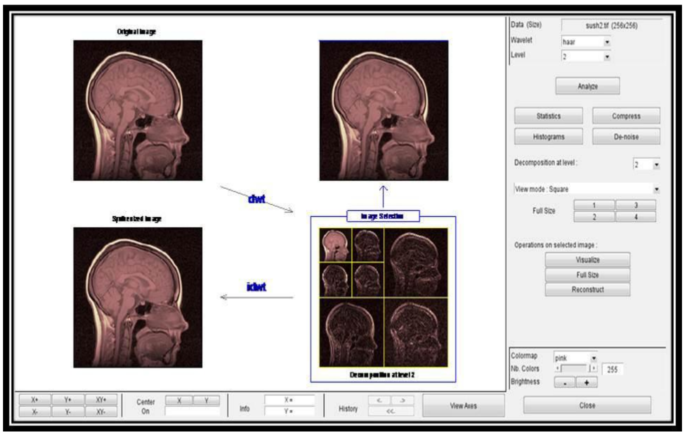


Figure 6: Decompostion Using Haar Wavelet.

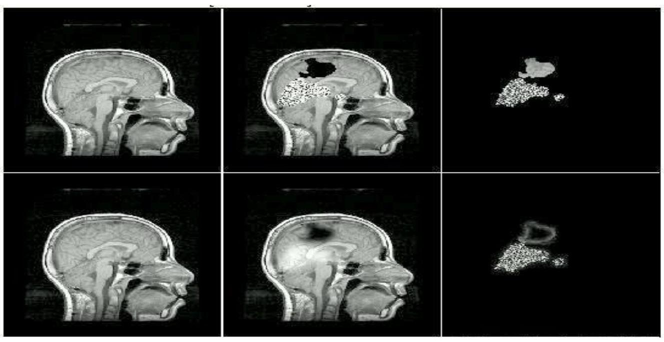
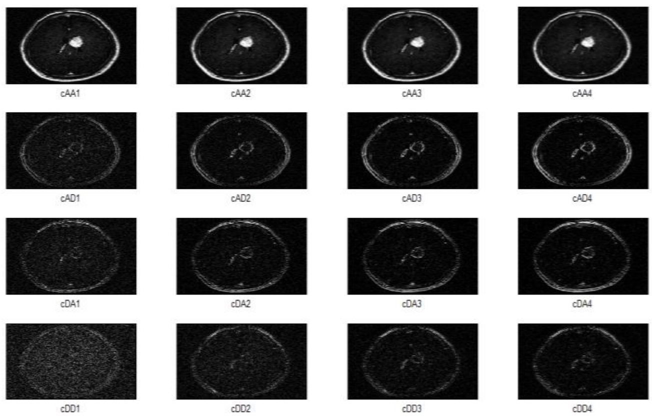


Fig. detected tumor by using proposed method. Images from top left corner (a) database image (b) defected image (C) detected tumor using proposed method.(d) Database image (e) defected image (f) detected tumor using proposed method.

VII. RESULT

Input Image and Wavelet Compression



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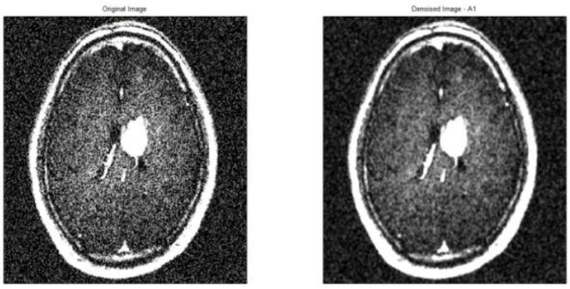
IDWT AND DENOISED IMAGE



TUMOR BOUNDARY

VIII. CONCLUSION

In this Report, I proposed the wavelet based brain tumor detection is the technique in which the tumor is detected by using the database and input image which is infected by the tumor and which is decomposed using Haar wavelet and then the uncommon partis taken into consideration which is nothing but detected tumor. This algorithm is also suitable for the detection of mammograms from the breast cancer detection. As far as this technique is concern is very helpful in brain tumor detection and crack of bones and mammogram detection in which database image is get compared with the help of mutual information matrix with the input image and resultant image is nothing but the defected breast cancer image from which we can further get treatment.

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