Wavelet based Brain Tumor Detection using Mutual Information

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***Abstract* :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.Both input image and database image is decomposed into different subbands by using DWT. Interpolation of low frequency subbands as well as input image is done. Database image is also decomposed by using Haar wavelet transform by two level and this database image is compared with the input image by using Mutual information principle. Same information present in both of images is used for image registration which is discarded and remaining information is considered that is nothing but Brain tumor.**

Keywords:Image registration, DWT, Mutual information, Brain tumor.

I. INTRODUCTION

A brain tumor is abnormal growth of cells that are spontaneously grows in uncontrolled manner. We can divide tumorsin according to how exponentially they developed I.e growth rate, with lower-grade tumors often being benign and higher-grade tumors being malignant. When normal cells grow old and they are damaged and can be repaired. As born in new cell can occur in the cellular DNA and due to disrupt of regulatory processes and the cells that may normally get died and goes to survive and rapidly grows in multiple number.due to which cells get multiply and due to which other brain are get damaged and increase in numerous amount and cells is contain the DNA which is abnormal and these gathered cells form a mass is called as brain tumor.

Image registration is the process of overlaying two or more images of the same image taken at random times and from different viewpoints and/or by using different sensors. It geometrically aligns two images the referenced and sensed images. Image registration is a crucial step in all image analysis tasks in which the final information is gained from the combination of various data sources like in image fusion of image and change detection in image and image restoration by multi-channel. Image registration is required in remote sensing Multi spectral classification, environmental monitoring change detection also image mosaicing and weather forecasting and creating super-resolution images. The patients tumor growth and treatment verification andcomparison of the patient's data with anatomical atlases), and in computer vision (target localization, automatic quality control)[1],Discrete Wavelet Transform (DWT) is one of the recent wavelet transforms used in image processing.Low-low(LL),Low-high(LH),High-low(HL), and High-high(HH) are the different sub-band images obtained from the decomposition of image using DWT. Haar Wavelet Transform is another recent wavelet transform which has been used in several image processing use down-sampling like DWT. Therefore the sub-bands will have the same size as that of the input image.At the end, by using inverse DWT (IDWT) corrected interpolated low frequency sub bands and interpolated input image are combined to achieve a high resolution output image. The proposed technique that first one is database 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 tumor detected output image.

II.STEPS INVOLVED IN BRAIN TUMOR DETECTION

Step 1. Input image of dimensions 320×320 is taken and read by using MATLAB.
Step 2. Then that image is decomposed by DWT (Discrete Wavelet Transform) into four sub bands namely Low-low (LL), Low-high (LH), High-low (HL), and High-high (HH).
Step 3. For further processing lower sub band low-low(LL) is for mutual information matrix. Lower band is taken because of it contains the approximate information and lot of information is contains in the LL band.
Step 4. Same steps are carried out on the database image onto which decomposed image using DWT into four parts and LL part is taken into consideration and further processing.
Step 5. The mutual information matrix is calculated by taking the uncommon content in both mutual information matrix of the input image and database image.
Step 6. From uncommon information the IDWT is calculated and the resultant image is the detected tumor which is having low sharpness and brightness.
Step 7. The brightness and sharpness and intensity is corrected at the last to obtain the tumor.
Step 8: obtained resultant image is the detected tumor from input image.

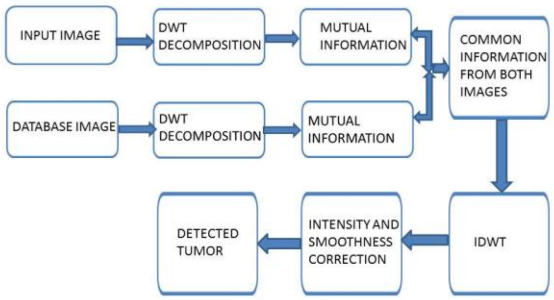

Fig 1.Block diagram of brain tumor detection algorithm

III. WAVELET DECOMPOSION OF IMAGE

The transform of a signal is just another form of representing thesignal.It can not modify the information content available in the signal so signal is as it is but only its form is get changed due to its representation but not information.The Wavelet transform gives a time–frequency and frequency – time representation of signal. The wavelet transform is developed to overcome the short coming of the Short Time Fourier Transform (STFT) from which it can be also be used to analyze non-stationary signals. The main difference between STFT is STFT gives a constant resolution at all frequencies and the Wavelet Transform is working on multi-resolution technique by means of which different frequencies are analyzed with different resolutions.A wave is nothing but an oscillating function of time or space and it is periodic in nature. While in contrastwavelets are localized waves.They have their energy concentrated in time or space and are suited to analysis of transient signals[3]. The Fourier Transform and STFT both use waves to analyze signals on the other hand the Wavelet Transform uses wavelets of finite energy.The wavelet analysis and STFT analysisis similar function used to analysis of different signals.The signal to be analyzed is multiplied with a wavelet function just as it is multiplied with a window function in STFTand then the transform is computed for each segment generated. In the Wavelet Transformwidth of the wavelet function changes with eachspectral component unlike STFT. The Wavelet Transform gives good resolution at higher frequencies and gives lower resolution at low frequencies and lastly the Wavelet Transform gives good frequency resolution and poor time resolution.

1. DESCRETE 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 to 1976 when techniques to decompose discrete time signals were devised which isSimilar 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 [4].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 basis functions which relate simple scaling and translation contains only scaling function and translation function. In such case of DWT we obtain a time-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_{ϕ} be the image is having $\omega_{\phi}(j+1,m,n)$ as j+1 is scaling function m is row vector and n is the columns vector.is applied to the high pass filterh_{ψ}**(-n)** and also to low pass filter h_{ϕ}**(-n)**the filter is applied across the column as ‘n’ indicates the columnand which divides the total signal into two filters as low pass and high pass filter. Due to which its halves due to use of two filters bandwidth gets half as shown in fig 1. Then sub-sampling is carried out on image by using down sampling by 2 due to which alternate samples get removed from an image. First sub sampling is carried out on image and then carried out on image as shown in fig.2 these sub samples are get forwarded to row filter. There are two high pass filter and two low pass filter of scaling and wavelet coefficient. Due to two times subsampling we get 1/4 times resolution and get 4 resultant image having diagonal, vertical, horizontal and approximate components. The equations (1) and (2) show the decomposition of image into four sub bands.suppose s(n1,n2)is image where n1 is the row indices and n2 is column indices. And N1,N2 is size of image. The reconstruction of original image is obtain by equation (3) as shown the inverse DWT operation performed on image.

$$\omega\phi(j0,m,n)=\frac{1}{\sqrt{N1\,N2}}\sum_{n1=0}^{N1-1}\sum_{n2=0}^{N2-1}s(n1,n2)\phi_{j0,k1,k2}(\mathrm{n1},\mathrm{n2}) \tag{1}$$

$$\omega_{\psi}^{i}(j0,m,n)=\frac{1}{\sqrt{N1\,N2}}\sum_{n1=0}^{N1-1}\sum_{n2=0}^{N2-1}s(n1,n2)\psi_{j2,k1,k2}^{i}(n1,n2) \tag{2}$$

i= {H,V,D}

$$s(n1,n2) = \frac{1}{\sqrt{N1\,N2}} \sum_{k1} \sum_{k2} \omega\phi(j0,k1,k2)\phi_{j0,k1,k2}(n1,n2) + \frac{1}{\sqrt{N1\,N2}} \sum_{i=H,V,D} \sum_{j=0}^{\infty} \sum_{k1} \sum_{k2} \omega_{\psi}(i,k1,k2) \quad (3)$$

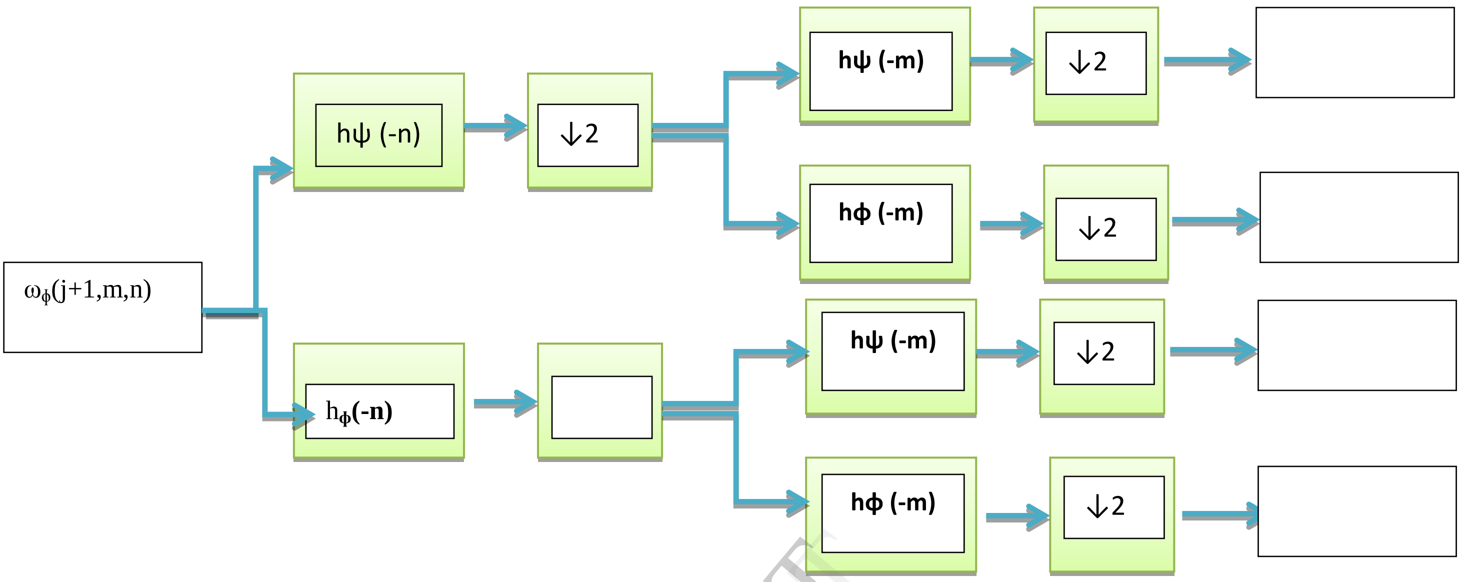

Fig 2. Decomposition of an image using DWT

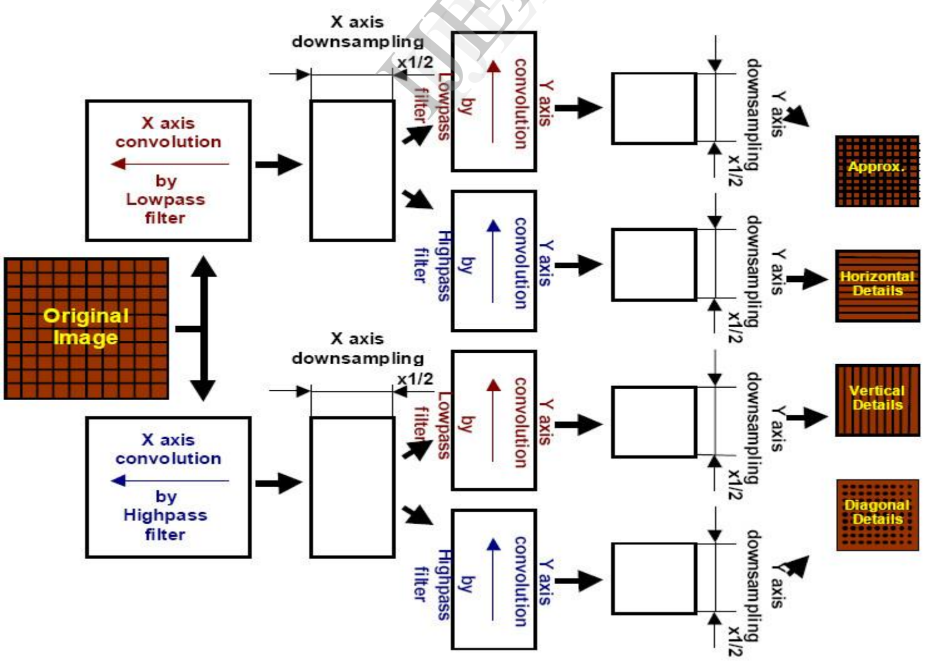

Fig 3. Equivalent image decomposition by using DWT

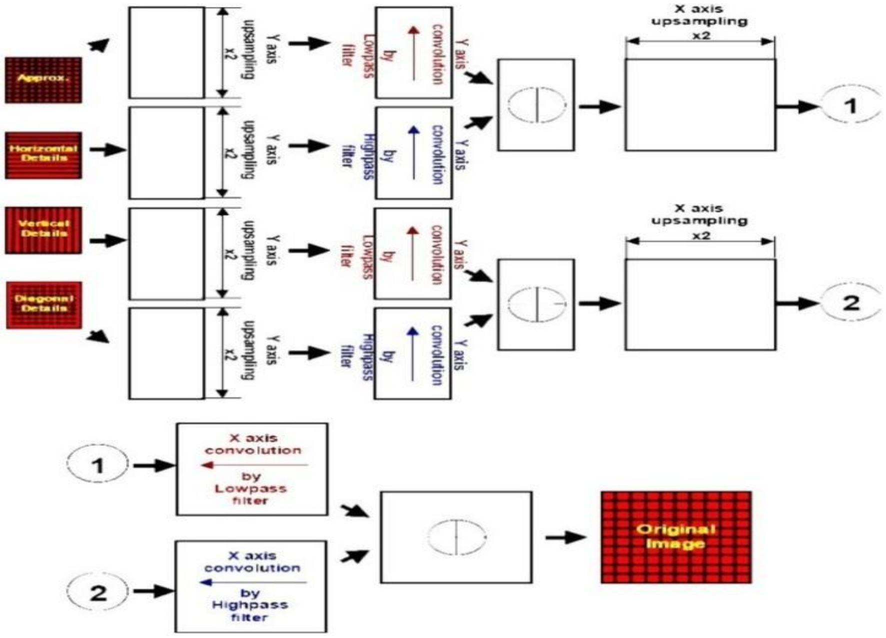

Fig.4Equivalent Scheme of Wavelet reconstruction Algorithm

The fig.3 shows 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 4. Shows reverse operation which is taken placed in Fig. 3. In this figure original image is obtained from combining four decomposed parts by using IDWT.

2. DWT AND FILTER BANK

2.1 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.

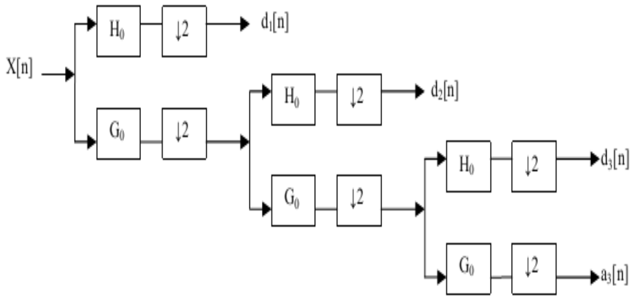

Fig. 5 Three-level wavelet decomposition tree

The DWT is obtained by successive low pass and high pass filtering of the discrete time-domain signal as shown in fig. 4. This is called asMallat algorithm or Mallat-tree decomposition of signal. Its significance is in the manner of which it connects the continuous- time mutiresolution to discrete-time filters. In the figure4. The sequence x[n] is applied to wavelet decomposition tree where n is an integer.G_0 is low pass filter produces approximation a[n] and H_0 is high pass filter produces detailed information i.e. d[n]. At each decomposition level, the half band filters produce signals spanning only half the frequency band. This doubles the frequency resolution as the uncertainty in frequency is reduced by half[3]. According to Nyquist's criteria if the original signal hasa highest frequency of **ω** and it needs a sampling frequency of 2ω radians, then it produces highest frequency of **ω**/2 radians. Now it can be sampled at a frequency of **ω**radians thus discarding half the samples with no loss of information. The down sampling by 2 halves the time resolution as the entire signal is now represented by only half the number of samples. Thus, while the half band low pass filtering removes half of the frequencies and thus halves the resolution, the decimation by 2 doubles the scale [3]. The time resolution becomes good at high frequencies, while the frequency resolution becomes good at low frequencies.Unless and until the desired level of resolution is reachedthe filtering and decimation process is carried out. The length of the signaldetermines 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 [3]

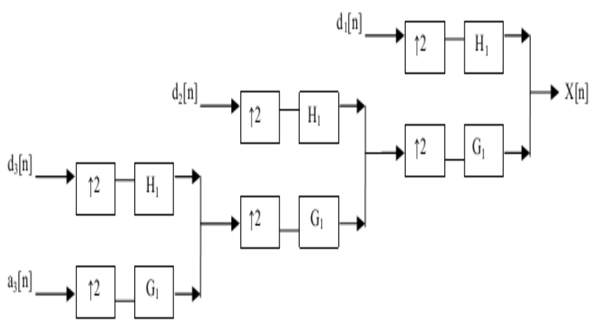

Fig. 6 Three-level wavelet reconstruction tree

Fig.6shows three-level wavelet reconstruction tree. The reconstruction 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 obtainthe original signal. TheMallat algorithm works equally well if the analysis filters, G_0 and H0, are exchanged with the synthesis filters, G1 and H1.[3]

2.2 CONDITIONS FOR PERFECT RECONSTRUCTION

In Wavelet Transform applications, it is need to be get the original signal bysynthesizing of wavelet coefficients. Perfect reconstruction is achieved by the analysis and synthesis filters which satisfy following certain conditions aslet $G_0(z)$ and $G_1(z)$ are low pass analysis and synthesis filters,and $H_0(z)$ and $H_1(z)$ the high pass analysis and synthesis filters.Then the filters have to satisfy the following two conditions as given in equation 1 and 2

$$G_0(-z)\ G_1(z) + H_0(-z) . H_1(z) = 0 \tag{4}$$

$$G_0(-z)\ G_1(z) + H_0(z) . H_1(z) = 2z^{-d} \tag{5}$$

The first equation implies that the reconstruction is aliasing-free and the second equation shows that the amplitude distortion has amplitude of one.The perfect reconstruction condition does not change if we switch the analysis and synthesis filters i.e. reversible.There are number of filters which satisfy two conditions as above mentioned. But not all of them give accurate Wavelet Transforms, especially when the filter coefficients are quantized [3]. The accuracy of the Wavelet Transform can be determined after reconstruction by calculating the Signal to Noise Ratio (SNR) of the signal. Some applications like pattern recognition do not need reconstruction, and in such applications, the above conditions need not apply [3].

IV. USE OF ENTROPY AND MUTUAL INFORMATION

1.ENTROPY

Measure of information of a message is termed as entropy. It is actually concern with communication. How much amount of information is transmitted and amount of information is received. Hartley prosed theory of entropy. In which he proposed measure of information of a message that formsthe basis of many present-day measures. He consider message of a string of symbol. Each symbol is represented as *s* different possibilities if there are *n* number of symbols then total amount of possible combinations are of message are s^n. He sought to define an information measure that increases with message length. The measure s^ncomplies, but the amount of information would increase exponentially with the length of the message and that is not realistic. Hartley wanted a measure H that increases linearly withn, i.e. H = Kn, where K is a constant depending on the number of symbols *s*. then he also consider message of n1 and n2 length from s1 and s2 number of symbols. If possible messages are equal i.e $s1^{n1}=s2^{n2}$. Then amount of information is also equal. Due to these restrictions he proposed

$$H = n \log s = \log s^n \tag{6}$$

Entropy measure depends on the number of possible outcomes:as the largerthe number of possible messages, the larger the amountof information message. If thereis only a single message possible, there is no information (log 1 = 0) obtained, because you already knew we wouldreceive that message. Drawbacks of Hartley's entropy are overcome by Shannon's entropy measure as he consider e1,e2,e3………e_m And having probabilities are p1,p2,p3…………p_m.

Shannon's entropy is formulated as

$$H = \sum_i \text{pi} \log 1/\text{pi} (7)$$

$$H= -\sum_i pi \log pi (8)$$

As we apply Shannon's entropy if event is more likely occurs then equation becomes

$$H= - \sum 1/s^n \log 1/s^n = \sum 1/s^n \log s^n = \log sn \tag{9}$$

Which is same as Hartley entropy shown in (9)

Shannon's entropy is used on the image. In which probabilities are not going to be taken into consideration but the uses distribution of grey level of image is used. Distribution of Probability of these grey level is is calculated by counting total number of times each grey level is occurred divided by total number of time it occurs. An image consisting single intensity is having low less entropy and having less information and the and high entropy is obtained by the more number of times intensity occurs and gives more amount of information.

2.MUTUAL INFORMATION

The research that eventually led to the introduction ofmutual information as a registration measure dates back tothe early 1990's. Woods et al. [5, 6] first introduced a registrationmeasure for multimodality images based on theassumption that regions of similar tissue (and hence similargrey values) in one image would correspond to regionsin the other image that also consist of similar grey values(though probably different values to those of the firstimage). Ideally, the ratio of the grey values for all correspondingpoints in a certain region in either image varieslittle. Consequently, the average variance of this ratio forall regions is minimized to achieve registration.

Basically mutual information of two images A and B is expressed in terms of I, can be formulated as

$$I(A,B)=H(B) - H(B \mid A) \tag{10}$$

Where H(B) is entropy calculated on the basis of distribution of grey level of image. And $H(B \mid A)$ is the conditional entropy based on conditional probabilities $p(a \mid b)$ which is the chance of grey value b in image B given that the corresponding voxel in A has grey value a.When interpreting entropy as a measure of uncertainty, equation (5) translates to "the amount of uncertainty about image B minus the uncertainty about B when A is known". Simply we can say that mutual information is nothing but amount of uncertainty about B decreases with A is known i.e amount of information A contains about B as A and B can be interchanged so I(A,B) is amount of information contained in B about A, so called mutual information.

The second definition is closely related to joint entropy. It is shown in equation (10)

$$I(A,B) = H(A)+H(B) - H(A,B) \qquad (11)$$

In this definition contains the term −H(A,B) is thatmaximizing mutual information is related to minimizingjoint entropy. It is fact that joint histogramof two images' grey values disperses with misregistrationand that joint entropy is a measure of dispersion.Mutual information and joint entropy are computedfor the overlaying part of the many images and resultsare obtained are sensitive to the size also contents of overlap.A problem that can occur when using joint entropyon its own, is that low values (normally associated with ahigh degree of alignment) can be found for complete misregistrations.

Mutual information has following properties:

1. Symmetry property

Basically in result part it consist of detection of tumor from an defected image. Following are parts of detection of tumor

Figure.7 Database image

Figure 8. defected image.

$$I(A,B) = I(B,A)$$

2. $I(A,A) = H(A)$

The informationin image A contains about itself is equal to the information (entropy) of image A.

3. $I(A,B) \leq H(A)$,
   $I(A,B) \leq H(B)$

The information the images contain about each other can never be greater than the information in the images themselves.

4. $I(A,B) \geq 0$

The uncertainty about A cannot be increased by learning about B.

5. $I(A,B) = 0$ if and only if A and B are independent.

When A and B are not in any way related, no knowledgeis gained about one image when the other is given.

V.RESULTS AND DISCUSSION

1.PREPROSING

In the preprocessing stagedefected input image(figure 8) and database image(figure 7) 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 PET

2. DECOMPOSTION USING HAAR WAVELET

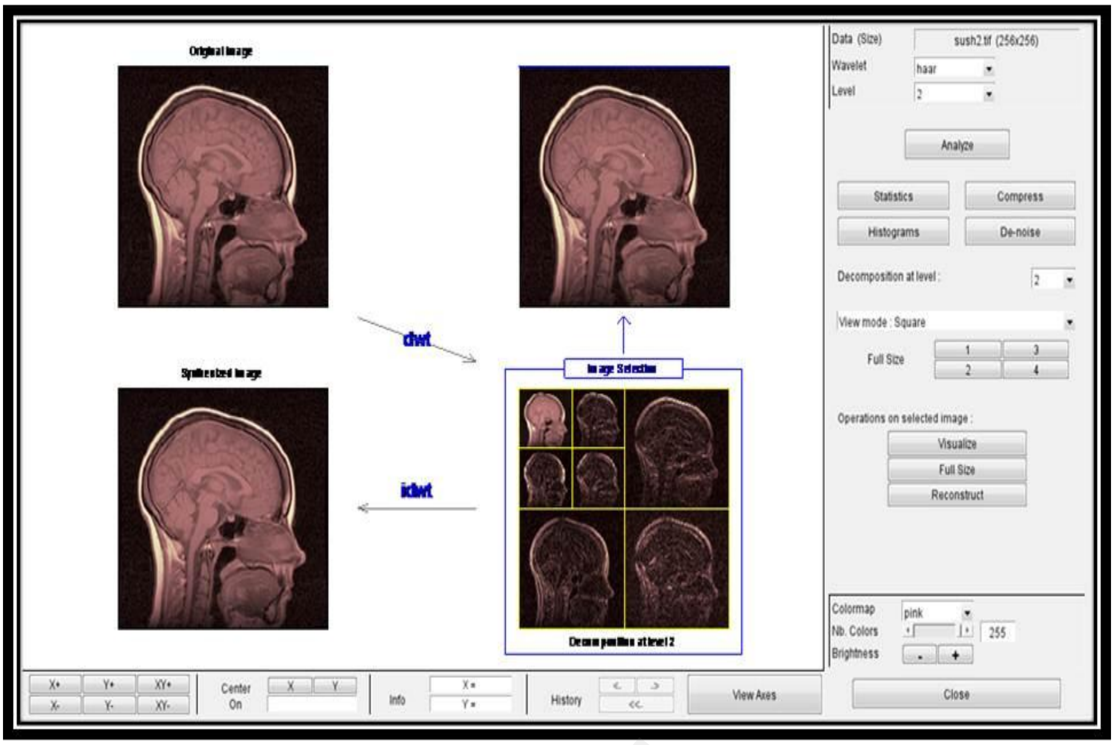

figure.9 Wavelet decompostion using Haar wavelet

The inputimage of size 320×320 is decomposed by using the Haar wavelet into four frequency bands an Low-Low, Low-High, High-Low, High-High. Which is and operation is carried out only on LL part as it contains the approximate contents rather other part contains Vertical contents , horizontal contents and diagonal contents. 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 9. 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

The decomposition of an image is carried out at each level is exactly 1/4 times the original image. Same decomposition is carried put at each level with the 1/4 times resolution change at each level so as we are having 320×320 as original image after one level of decomposition it becomes 160×160. Likewise after each level its resolution gets changes to 1/4 times and after 4 levels it becomes to 40×40 pixels.

3. DETECTION OF TUMOR:

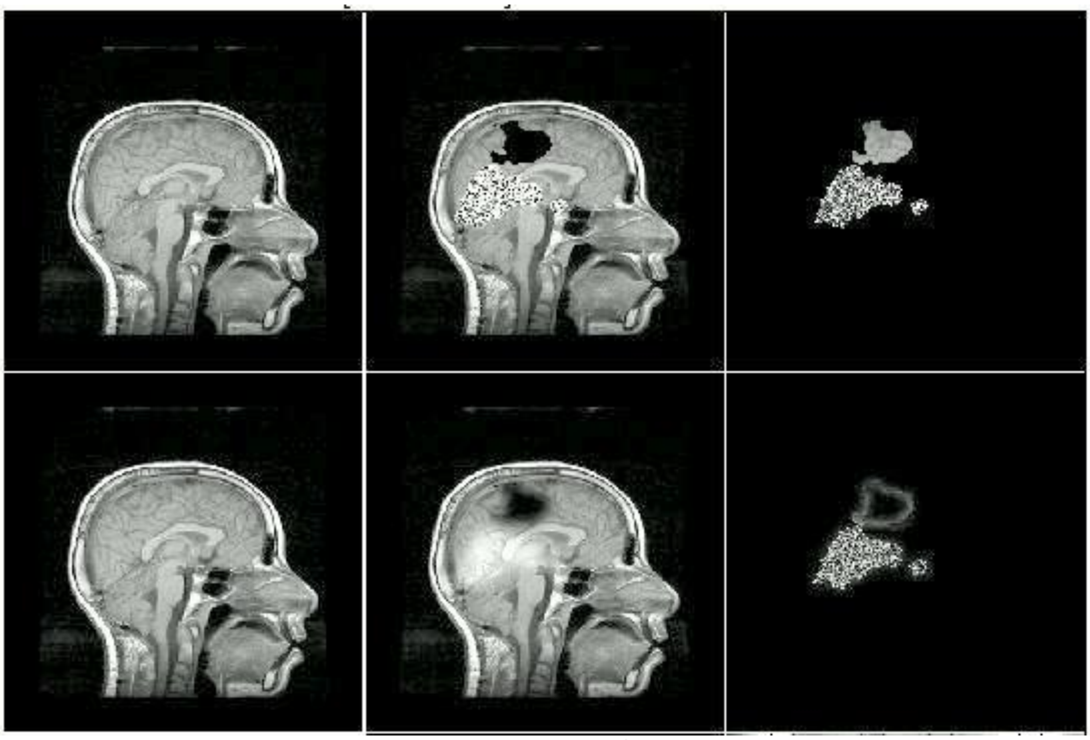

Fig.10 detected tumor by using proposed method. Images from top left corner (a) database image (b) defected image (C) detected tumor using proposed method. (d) Database image (e) defected image (f) detected tumor using proposed method

In the detection stage, it is last stage of the algorithm in which input image and database image is decomposed using Haar wavelet and these are form the mutual information matrix in which the common data available in image is not consider and uncommon data is the detected tumor. As discussed above there are 4 levels of pyramid and which are 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

At each levels there are total 5 outer iterations are used to detect the outer changes in an image and 40 inner iterations it shows that there are 120 total iterations used for the outer and inner smoothness and correction and detection of change in each of pixel. The mean square error is also calculated from each level of pyramid. The mean square error shows the error from an image when it get reconstructed from taking inverse transform. When MSE is greater then reconstruction is poor and gets error in the resultant image. For this algorithm the various values of MSE are calculated as shown in table 1. This implies that the MSE is very low for this algorithm.

Pyramid level	Size of image	MSE
Level 1	320×320	0.0650
Level 2	160×160	0.0462
Level 3	80×80	0.04283
Level 4	40×40	0.0391

Table 1. MSE calculation

From this algorithm we can also find out the recovery tumor after treatment by keeping the MR image of patient before treatment as database image and by taking input image as image taken after the treatment as we can easily find out the difference between two images so one can check whether goes in positive direction or to change the treatment and recovery ratio of the patient.Thus we can go with detection of mammograms and also detection of crack in bones, and many more .due to this technique we can go with the smallest details of image to b get detected as decomposing Image into several parts and several levels and several iterations. The final output is shown in figure 10.(c) and 10.(f), in which the detected tumor is clearly shown. As this is carried out with the help of this algorithm. In which to mutual information matrix are calculated for input image and database image. And finally the uncommon part of both input image and database image are taken into consideration and final output is shown in results which is uncommon part from these input image and database image.

VI. CONCLUSION

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 part is 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 mammogramdetection 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

REFERENCES

[1] Josien P. W. Pluim, J. B. Antoine Maintz and Max A. Viergever,"Mutual information based registration of medical images: a survey"Ieee Transactions On Medical Imaging, Vol. Xx, No. Y, Month 2003
[2] DarshanaMistry,Asim Banerjee "Descrete wavelet transform ushingmatlab" IJCETVolume 4, Issue 2, March – April (2013), pp. 252-259
[3] DeepikaSripath "Efficient Implementations of Discrete WaveletTransforms Using FPGAs" Electronic Theses, Treatises andDissertations. Paper 1599.
[4] Tullimilli.ch.padminiM.V.Sudhkar"Image Resolution Enhancement ByUsing Different Wavelet Decompositions"International Journal of Research in Advent Technology,Volume 1, Issue 4, November 2013
[5] G.Shruthi1 ,Radha Krishna A.N."Image Reconstruction Using Discrete Wavelet Transform" IOSR Journal of VLSI and Signal Processing (IOSR-JVSP)Volume2,Issue4(May.–Jun.2013),PP14-20
[6] Rajesh C. Patil, Dr. A. S. Bhalchandra, "Brain Tumour Extraction from MRI Images Using MATLAB", International Journal of Electronics, Communication & Soft Computing Science and Engineering, Volume 2, Issue 1
[7] Monica Subashini.M, Sarat Kumar Sahoo, "Brain MR Image Segmentation for Tumor Detection using Artificial Neural Networks", International Journal of Engineering and Technology, vol. 5, no. 2 Apr-May 2013
[8] R. P. Woods, S. R. Cherry, and J. C. Mazziotta, "Rapid automatedalgorithm for aligning and reslicing PET images," Journal of Computer Assisted Tomography, vol. 16, no. 4, pp. 620– 633, 1992.
[9] R. P. Woods, J. C. Mazziotta, and S. R. Cherry, "MRI-PETregistration with automated algorithm," Journal of ComputerAssisted Tomography, vol. 17, no. 4, pp. 536–546, 1993.2010
[10] W. Gonzalez, "Digital Image Processing", 2nd ed. Prentice Hall, Year of Publication 2008, Page no 378
[11] Mohamed LamineToure, "Advanced Algorithm for Brain Segmentation using Fuzzy to Localize Cancer and Epilepsy Region", International Conference on Electronics and Information Engineering (ICEIE 2010),Vol. no 2
[12] SenthilPeriaswamyHanyFarid"Medical Image Registration with Partial Data"Siemens Medical Solutions USA,Inc.,Malvern,PA1935DartmouthCollege,Hanover,NH 03755,USA