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Textural Analysis and Diagonsis Image Fusion Classification of Medical Images using Various Transforms

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ABSTRACT

Background: Textural classification of tumor images is done based on histogram equalization and texture analysis techniques of wavelet, Ridgelet and Curvelet transforms. For low quality medical CT images, a general framework based on conventional histogram equalization for image feature enhancement is presented. CT images are taken (brain tumor images) and they are transformed using various transforms such as Wavelet, Curvelet and Ridgelet transforms. The transformed image is given to the feature extraction module, processed to get various features such as Energy, Entropy, Homogeneity, Contrast, Mean, Variance, Standard Deviation, by using these features, the efficiency of various multi resolution image transforms are found. The main objective is to Develop an imaging system for classification of tumour tissues in medical images obtained. The discriminating powers of these transforms are helpful for classification of tumor types such as Glioma, Menin and Metastatic are pondered upon. Analyzing the best multi-resolution transform method and the method which gives the better resolution between similar type of diseased images and dissimilar types of images. The tumor images (glioma, meningioma, metastatic) of the CT scan is taken. Tumor varies for different persons. So two persons per tumor had been taken and three types of transforms (Haar Wavelet, Daubachies Wavelet, Curvelet transform and Ridgelet transform) are applied. From the results Wavelet is sporadic. Ridgelet gives near approximate values.curvelet gives approximate values and is the best multiresolution method.

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INTRODUCTION

Problem Identification:

Tumor is the major disease in human. Here the brain tumor is taken. There are various types of brain tumor the classification of these types is a tedious task. So tumor classification method is used to classify the brain tumors.

Proposed work (textural classification of tumor tissues):

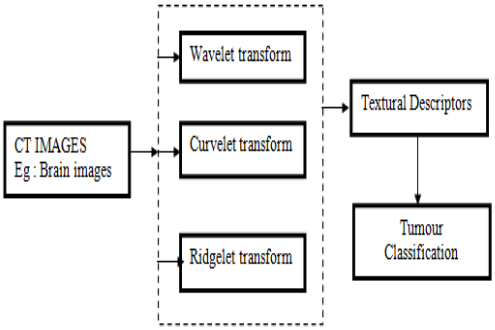

Fig. 1: Block diagram

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The block diagram gives an overview of the, initially CT images are taken (brain tumor images) and they are transformed using various transforms such Wavelet, Curvelet & Ridgelet transforms. Then it is given to the feature extraction module, processed to get various features such Energy, Entropy, Contrast, Mean, Homogeneity,Standard deviation etc., with the help of the features the three transforms were compared and the best tansform method for tumor classification is identified.

Feature extraction:

The feature from images is extracted and then compared, so a new step called feature extraction is needed.

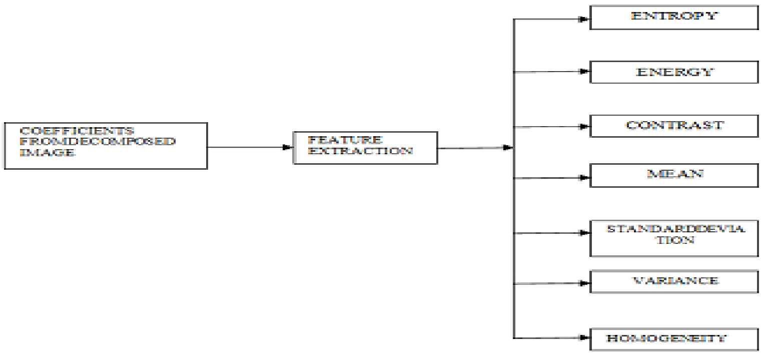

Fig. 2: Block Diagram for Feature Extraction.

Ct Images:

Computed tomography (CT) or Computed axial tomography (CAT), can be used for medical imaging and industrial imaging methods employing tomography created by computer processing. CT produces a volume of data that can be manipulated, through a process known as "windowing", in order to demonstrate various bodily structures based on their ability to block the X-ray beam.

Brain tumor:

A brain tumor is an intracranial solid neoplasm a tumor (defined as an abnormal growth of cells) within the brain or the central spinal canal. Types –meningioma,glioma,metastatic

Histogram equalisation:

The histogram equalization is an approach to enhance a given image.

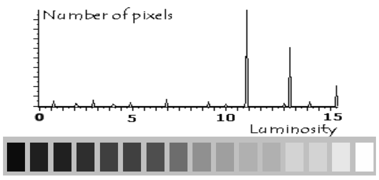

Fig. 3: Histogram Of Image With 256 Grey Level

MATERIALS AND METHODS

MATLAB:

MATLAB desktop is the main MATLAB application window. Desktop contains five sub windows: command window, the workspace window Browser, the current directory window and one or more figure windows.

Wavelet Transform:

A Wavelet is a mathematical function that can decompose a signal or an image with a series of averaging and differencing calculations.

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RIDGELET transform:

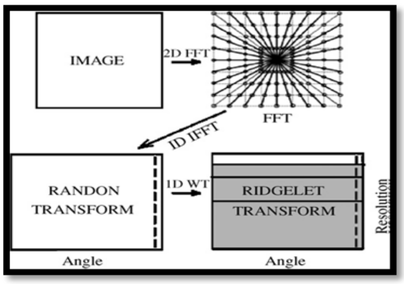


Fig. 4: Ridgelet Flow Graph

The Ridgelet transform two steps: a calculation of a discrete radon transform and an application of a 1D Wavelet transform. The radon transform two steps: a calculation of the 2D fast Fourier transform of the image and an application of a 1D inverse Fourier transform on each of the 32 radial directions of the radon projection. A 1D Haar Wavelet was applied to each of the radial directions, for three levels of resolution. The following texture descriptors were then calculated for each radial direction

Curvelet transform:

Curvelet transform is used to find the singularities in a curve with another curve. Detecting and enhancing the boundaries between different structures is very important in image processing, especially in medical imaging
1. Sub-band Decomposition: The image is first decomposed into log2M (M is the size of the image) Wavelet sub-bands and then Curvelet Sub-bands are formed by performing partial reconstruction from these Wavelet sub-bands at various levels.
2. Smooth Partitioning: Each sub band is smoothly windowed in to ‘squares’ of an appropriate scale.
3. Renormalization: Each resulting square is renormalized to unit scale.
4. Ridgelet Analysis: Ridgelet transform is performed on each square resulting from the previous stage.

Textural features:

ENERGY: It measures the number of repeated pairs

Energy=$\sum_i^M \sum_j^N \mathrm{P}^2\ [i,j\ ]$ (1)

ENTROPY: It measures the randomness of a gray-level distribution.

Entropy=-$\sum_i^M \sum_j^N \mathrm{P}[i,j\ ]\log \mathrm{P}[i,j\ ]$ (2)

CONTRAST: It measures the local Contrast of an image.

Contrast =$\sum_i^M \sum_j^N (i-j)\ \ \mathrm{P}[i,j]$ (3)

HOMOGENEITY: It measures the local Homogeneity of a pixel pair

Homogeneity= $\sum_i^M \sum_j^N \mathrm{P}[i,j\ ]/(1+|\ i-j\ \ |)$ (4)

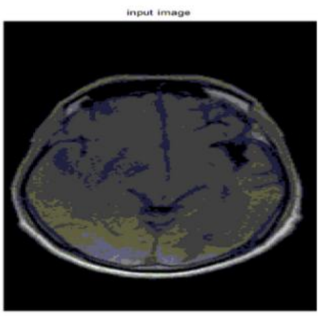
MEAN: It provides the Mean of the gray levels in the image.

Mean = 1/2 $\sum_i^M \sum_j^N (i\ \mathrm{P}[i,j] + j\ \mathrm{P}[i,j])$ (5)

STANDARD DEVIATION(SD): The Standard Deviation is the root Mean square (RMS) Deviation of the values from their arithmetic Mean.

SD= [1/ (M*N)$\sum_i^M \sum_j^N (\mathrm{P}[i,j\ ] - \mu)$] (6)

Simulation Results And Discussion: Input Images:



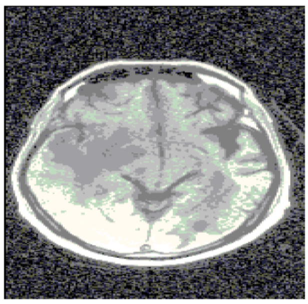


Fig. 5: Input Image Figure 6: General Histogram Equalization of Input Image.

The Figure 5 is the input image used. It is the CT image of a tumor affected brain. It is a gray scale image having the pixel value ranging from 0 to 255.

GENERAL HISTOGRAM EQUALISATION The figure 6 is the General histogram equalization of the input image. General histogram equalization is done for improving the features of images. The images when processed it may become low contrast. When the low contrast image is subjected to General histogram equalization it makes it a high contrast image and compensates it.

Haar wavelet output images:

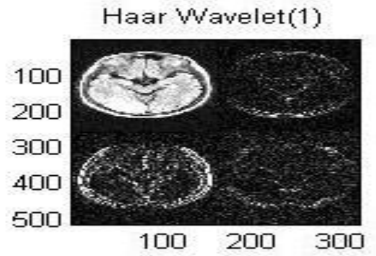


Fig. 7: Level Decomposition

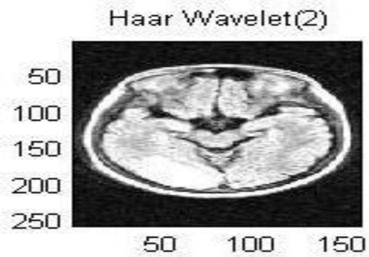


Fig. 8: Haar Transformed Image

The figure 7 shows the three level decomposition by Haar transform of the input image. The top left of the figure7 gives the approximation coefficients, top right shows the horizontal detail coefficients , bottom left gives the vertical detail coefficients and the bottom right gives the diagonal detail coefficients that are recommended for a texture feature extraction.The figure 8 shows the Haar transformed image of the original input image.

Curvelet output images:

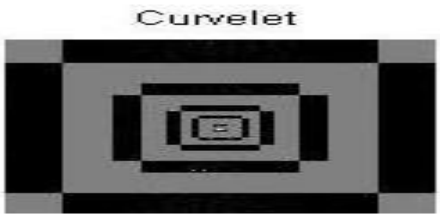


Fig. 9: Curvelet Transformed Image.

The figure 9 shows the curvelet transformed image of the input image. Curvelets are supported by a generic ‘wedge’the shaded area provides an example of such a ‘wedge’. Radial direction and resolution level based on each radial ‘wedge’ (16 angles) number of resolutions and number of angles at the coarsest level are used for feature extraction and tumor classification.

Ridgelet output image:

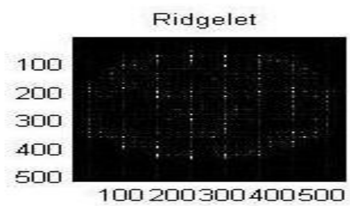


Fig. 10: Ridgelet Output Image

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The figure 10 shows the Ridgelet transformed image of the input image.. Ridgelet transformed image figure 10 is a calculation of a discrete radon transform and an application of a 1D wavelet transform. Radial direction and residual level are present in the figure 10 which is useful in texture feature extraction.

Results:

The tumor images (glioma, meningioma, metastatic) of the CT scan is taken. Tumor varies for different persons. So two persons per tumor had been taken and three types of transforms(Haar Wavelet, Daubachies Wavelet, Curvelet transform and Ridgelet transform) are applied. From the results Wavelet is sporadic .Ridgelet gives near approximate values .Curvelet gives approximate values and classifies the type of brain tumor effectively.Curvelet is the best multi-resolution transform method, because the curvelet gives the better resolution between similar type of diseased images and dissimilar type of images

Table 1: Feature extracted from image of type 1.

FEATURES	HAAR WAVELET	DB WAVELET	RIDGELET	CURVELET
Energy	61762229	43280068	4.04E+08	1.12E+05
Entropy	-2.90E+06	-2.31E+06	2.7219e+006i	1.76E+05
Contrast	4.81E+09	4.13E+09	5.57E+10	3.04E+10
Homogeneity	2.93E+04	2.43E+04	3.17E+04	4.78E+06
Mean	148222621	126161662	8.92E+08	2.20E+08
Std	34.5452	28.694	3.76E+01	0.2433
Variance	3.99E+21	2.46E+21	3.44E+23	2.78E+21

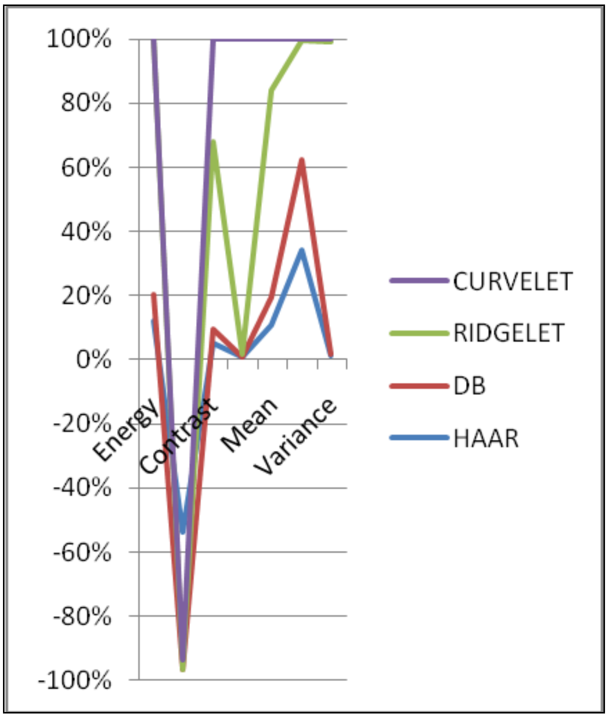

Fig. 11: Curve of Feature Extracted From Image of Type 1.

Table 2 FEATURE EXTRACTED FROM IMAGE OF TYPE 1

FEATURES	HAAR WAVELET	DB WAVELET	RIGELET	CURVELET
Energy	38073354	18668020	1.34E+08	1.12E+05
Entropy	-1.99E+06	-1.19E+06	1.6379e+1	1.74E+05
Contrast	3.17E+09	2.27E+09	2.11E+10	3.03E+10
Homogeneity	2.10E+04	1.47E+04	2.42E+04	4.46E+03
Mean	106607716	73801716	5.48E+08	2.20E+08
Std	28.6766	20.0679	21.6248	0.2436
Variance	1.45E+21	25269139	7.80E+22	2.76E+21

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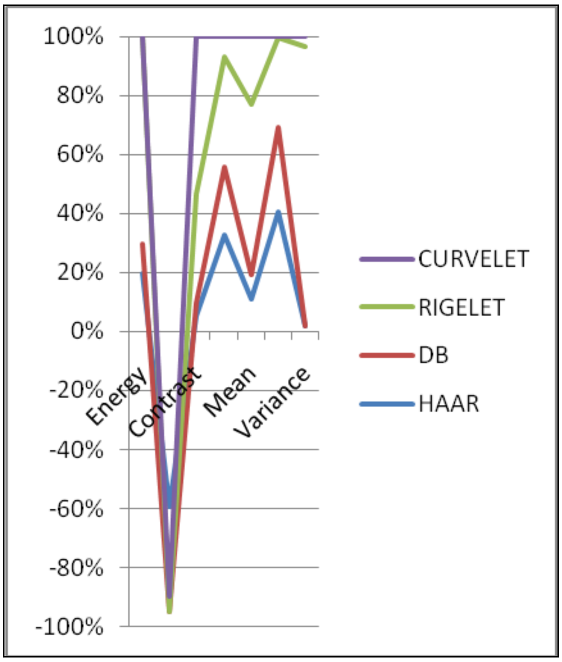

Fig. 12: Curve of Feature Extracted from Image of Type 1.

Table 3: Feature extracted from image of type 2.

FEATURES	HAAR WAVELET	DB WAVELET	RIGELET	CURVELET
Energy	61305805	29980023	4.30E+08	1.11E+05
Entropy	-2.88E+06	-1.78E+06	2.8309e+06i	1.72E+05
Contrast	4.79E+09	3.50E+09	5.68E+10	3.00E+10
Homogeneity	2.96E+04	2.07E+04	3.51E+04	4.47E+03
Mean	146450905	103436567	9.26E+08	2.18E+08
Std	34.4303	23.994	38.7718	0.2448
Variance	3.88E+21	1.35E+21	3.86E+23	2.70E+21

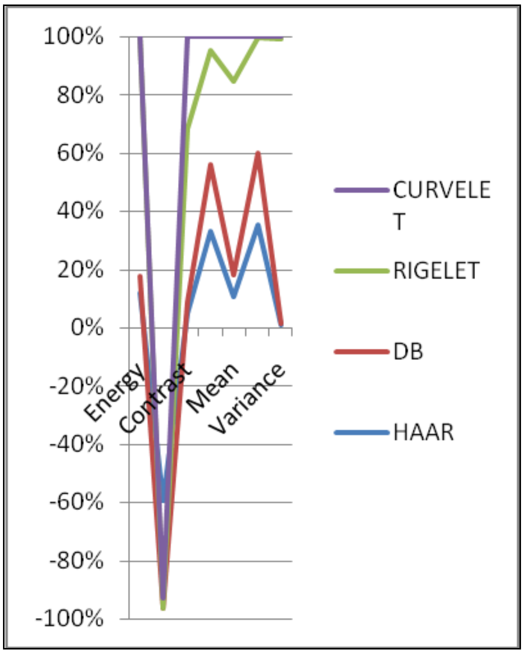

Fig. 13: Curve of feature extracted from image of type 2

Table 4: Feature extracted from image of type 2.

FEATURES	HAAR WAVELET	DB WAVELET	RIGELET	CURVELET
Energy	50635929	22809547	4.31E+08	1.11E+05
Entropy	-2.54E+06	-1.48E+06	2.8172e+06i	1.72E+05
Contrast	4.33E+09	3.04E+09	5.66E+10	3.01E+10
Homogeneity	2.58E+04	1.75E+04	3.59E+04	4.46E+03
Mean	132996674	90052417	9.35E+08	2.18E+08
Std	31.3173	20.9513	38.8095	0.2447
Variance	2.90E+21	8.89E+20	3.92E+23	2.71E+21

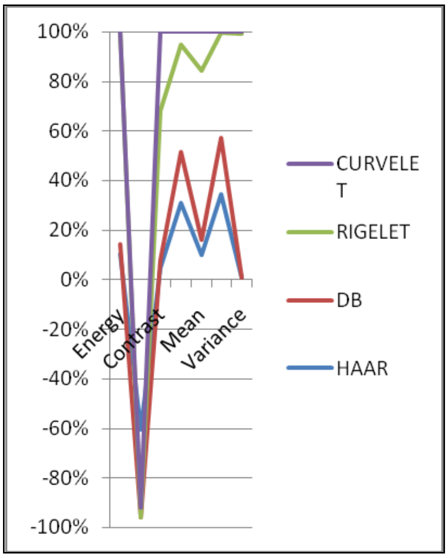

Fig. 14: Curve of feature extracted from image of type 2

Table 5: Feature extracted from image of type 3.

FEATURES	HAAR WAVELET	DB WAVELET	RIGELET	CURVELET
Energy	106087073	79013267	3.26E+08	1.14E+05
Entropy	-6.12E+06	-5.09E+06	3.7995e+006i	2.09E+05
Contrast	1.43E+10	1.41E+10	9.24E+10	3.29E+10
Homogeneity	5.68E+04	4.73E+04	4.78E+04	4.55E+03
Mean	316124747	278458752	1.25E+09	2.35E+08
Std	34.4928	29.5347	33.0566	0.2306
Variance	3.83E+22	2.58E+22	9.45E+23	3.38E+21

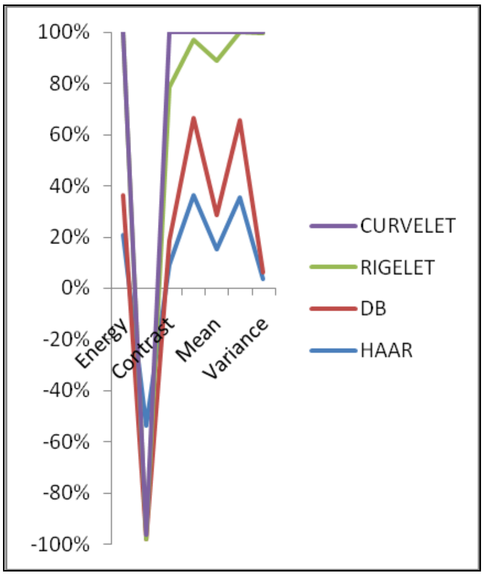

Fig. 15: Curve of feature extracted from image of type 3.

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Table 6: Feature extracted from image of type 3.

FEATURES	HAAR WAVELET	DB WAVELET	RIGELET	CURVELET
Energy	95380518	45594556	3.41E+08	1.13E+05
Entropy	-5.66E+06	-3.48E+06	3.9033e+06i	2.03E+05
Contrast	1.35E+10	1.04E+10	9.54E+10	3.21E+10
Homogeneity	5.14E+04	3.52E+04	5.09E+04	4.54E+03
Mean	295393814	204151655	1.27E+09	2.31E+08
Std	33.138	23.0778	33.8003	0.2334
Variance	3.13E+22	1.03E+22	1.01E+24	3.22E+21

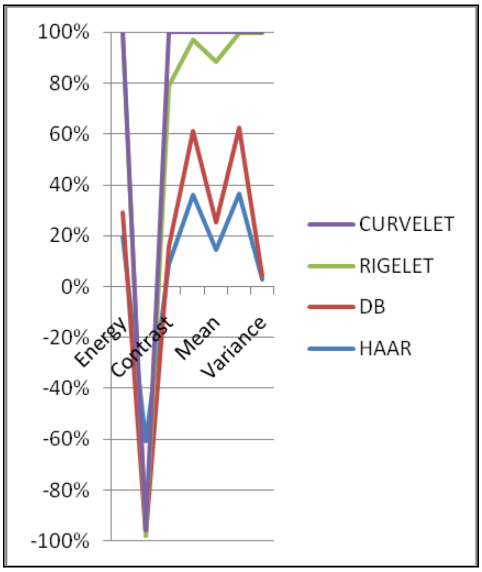

Fig. 16: Curve of feature extracted from image of type 3

Conclusion:

Thus the images are taken from the CT scanning machine, is afterwards given to the various transform such as Haar Wavelet, Daubachies Wavelet, Curvelet transform and Ridgelet transform. After the coefficients are taken ,then it is given to the Feature Extraction of the block ,then the features are extracted such as Energy, Entropy, Contrast, Homogeneity, Mean, Standard Deviation and Variance. The features extracted are used for brain tumor classification. The extracted values of images of each type are ranged for each transform with the help of the tabulations from 1 to 6 .From figure 11 to 16 graph it is concluded that wavelet is sporadic, the ranges are random. There are high deviations in the ranges and the differences in the ranges of type1, type2, type3 tumor cannot be identified. Even though the Ridgelet gives approximate values, there is a chance of imitating images and it can be misinterpreted. So it cannot be used for medical images in which even a small error leads to a big loss. The curvelet gives 100 percent appropriate values of images, images cannot be imitated and it accurately classifies the type of brain tumor. After this it can be told that the Curvelet is the best multi-resolution transform method, because the Curvelet gives the better resolution between similar type of diseased images and dissimilar type of images.

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