Brain Tumor Detection using Hybrid Model of DCT DWT and Thresholding

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Abstract: - Brain tumor is an unwanted growth of a network of fibre in brain. If not treated on time then it continued to grow with fast rate. The deep effect of tumor is so much on brain that it can affect the functioning of brain to work properly. Detection of tumor in brain using magnetic resonance imaging is widely accepted technique in worldwide. In the present research a new segmentation techniques is proposed for the detection of brain tumor in MR images.

Discrete Cosine Transform (DCT) and Discrete Wavelet Transform (DWT) are used for reducing the desired number of binary digits or bits to represent the digital image by eliminating the repeated data present in the original image. DCT gives best result for lossy compression techniques and have high peak signal to noise ratio. While DWT have average PSNR value but compression is good. So both DWT and DCT will be used for extraction the features from the digital input image.

Principal Component Analysis (PCA) is used to reduce the present dimensions or attributes present within the dataset. Actually dataset contains large number of dependent variables so benefit of PCA is that it refines the dataset by keeping attributes which have significant effects of the dataset.

In the proposed model the combined effect of discrete wavelet transform and discrete cosine transform is used to find the features of the digital image. Then principal component analysis is used to minimize the dimensions of image. Then fuzzy c means algorithm is used to perform segmentation of the output image. Proposed technique is compared with other brain tumor segmentation techniques to show the significance of new one.

Keywords: - Image processing, thresholding, DCT, DWT, PCA.

INTRODUCTION

Segmentation of medical images in comparison to natural images of different scenes has the main advantage that structural and intensity attributes are well known up to a natural biological variability. Most common is pixel dependent statistical classification utilizing multi parameter digital images. These processes depend on the attributes of individual voxels and do not grab the global shape and as well as boundary information. More often, lesions or say tumors were considered as outliers of a mixture of Gaussian model for the global intensity distribution assuming that lesion voxels or pixels are distinctly different from normal tissue characteristics. The benign tumor is easier to identify than the malignant tumor. Also the first stage tumor may be malignant of benign but after first stage it will change to dangerous malignant tumor which is life threatening.

MRI (Magnetic Resonance Imaging) is a scan based digital imaging technique is utillized for detection of brain tumor. This technique is not limited for detecting tumor inside the brain but is able to scan the whole internal structure of human body to detect any tumor. This technique has a special advantage of "not using ionized radiation" as done in X-Rays, which has many harmful effects. Instead it uses magnetic field and radio waves to form images of internal body structure it helps us to investigate the anatomy and physiology of human body with fine minor details for proper diagnosis. With the advancement in technologies of image processing, we are able to refine the images up to such clarity that we can easily diagnose brain tumor. Segmentation is one such technique of digital image processing which help us to segment or partition the digital image into multiple segments of pixels - basically talking about super pixels of images.

I. LITERATURE SURVEY

T. Menaka Devi et al. [1] explained the technique of classifying MR brain digital images into normal or abnormal which were affected by tumor. It further abnormality segmented the input digital image. This paper proposed a DWT in beginning step to extract the digital image attributes from the given input image. To reduce the dimensions of the feature image PCA was employed. Reduced extracted feature image was given to kernel support vector machine (KSVM) for processing. Discrete wavelet transforms (DWT) with Fejer–Korovkin filters which was used in the proposed method gives better results in terms of classification accuracy. For segmentation of the tumour, thresholding technique was used. In the proposed method an automated threshold approach used which gave better results in terms of PSNR. Gaussian Radial Basis (GRB) kernel was used for the classification method proposed and yields maximum accuracy of 98% compared to linear kernel (LIN). From the analysis, compared with the existing methods GRB kernel method was effective.

C. Hemasundara Rao et al. [2] presented an automated technique to detect and segment the brain tumor regions. The proposed technique consists of three main steps: initial segmentation, modeling of energy functions and optimizes the energy function. To make our segmentation more reliable authors used the information present in the T1 and FLAIR MRI digital images. Conditional random field (CRF) based framework was utilized to combined the information present in T1 and FLAIR in probabilistic domain. Main advantage of CRF based framework was that one could model complex shapes easily and incorporate the observations in energy function. Here Label-0 corresponds to tumor class and label-1 corresponds to non tumor class. For modeling the energy function in CRF requires initial labeling. Proposed technique was tested on data collected from 10 cases (8 with tumores and 2 normal), contains 200 slices. In the first step of algorithm it classified slices into normal and abnormal (having tumor) classes. Authors got 92.3% sensitivity and 96 % specivity at the detection stage. For quantitative evaluation of segmentation used Dice coefficient as a parameter. Algorithm got average accuracy of 89% but maximum is 98% as compared with 79% and maximum is 86% of MRF based segmentation method.

L. Zhao et al. [3] proposed a novel and simple fully convolutional network (FCN) which had better in competitive performance and as well as faster runtime than other state-of-the art models. Using the database provided for the Brain Tumor Segmentation (BraTS) proposed algorithm was able to achieve dice scores of 0.83 in the whole tumor region, 0.75 in the core tumor region and 0.72 in the enhancing tumor region, while proposed method was about 18 times faster than the state of the art models. The proposed network used similar "contracting-expanding" paths with skip connections. But instead of using weight map for each pixel, which had a high memory footprint, empirically derived class weights were utilized. The proposed network segmented the whole test set, containing 74 3D images in about 976 seconds (excluding preprocessing), while Pereira network took about 300 minutes on a Quadro K4000 GPU under the same computational environment, which was about 18.4 times slower than the proposed model. For medical imaging, where a huge volume of data needs to be processed, time becomes a bottleneck. In that perspective, the proposed network proved to be very efficient.

S. Pereira et al. [4] proposed an automatic segmentation method which was based on Convolutional Neural Networks (CNN) with small 3×3 kernels. The utilization of tiny kernels for designing a deep architecture and had a good effect against overfitting with the known small number of weights in the mesh. Authors also investigated the utilization of intensity normalization as a pre-processing step, which though not common in CNN-based segmentation methods, proved together with data augmentation to be very effective for brain tumor segmentation in MRI images. Authors technique was implemented in the BRATS 2013 and obtained the first position for the complete, core, and enhanced regions in Dice Similarity Coefficient metric (0.88, 0.83, 0.77) for the Challenged data set. Also, this technique got the overall first position by the online evaluation platform.

D. Somwanshi et al. [5] had compared and analyzed various threshold-entropy based segmentation methods on the basis of simulation results. Entropy methods like shannon, Renvi, Vajda, Havrda-Charvat and Kapur were applied to the MRI images of brain tumor or any internal structure of our body, were analyzed and compared. An approach of threshold selection of images based on entropy methods were found highly effective in diagnosis of brain tumor.

The basic steps of algorithm are reproduced here for sake of convenience

(i) The co-occurrence matrix Cm1, m2 of the image to be segmented was computed first for each color channel.

(ii) The probability distribution Pm1, m2 was then calculated from its co-occurrence matrix as Pm1, m2 = Cm1, m2/MN.

(iii) The entropy was then calculated for each gray level image for each entropy definitions.

(iv) The numbers of minima points were then determined from the entropy function versus gray level (t) plot.

After performing the experimentation work it was observed that in detecting the tumor at its earlier stage the Havrda Charvat produced the best result in terms of preservation of color and to got an accurate picture. After then the Renyi Entropy gave its best while detecting the Tumor at stage 2. Other than these two entropies the other entropies detected the tumors at its last stage that was when the tumor becomes malignant.

II. PROPSED TECHNIQUES AND RESEARCH METHODOLOGY

1. Discrete Cosine Transform

DCT transforms the image into frequency domain. It produces image independent transformations to reduce the dimension of images. It explores the correlation and reduces the unique number of coefficient that is utilized to represent the information. DCT belongs to a family of 16 trigonometric transformations. First image is divided into N x N block. For each N x N block DCT transform matrix is calculated. Transform exploits and eliminates the correlation between the data.

$$D = TMT'$$

Here in equation, D is the N x N transformed DCT matrix, T s the transformation matrix and M is image block of size N x N. As human eye are more sensitive to low frequencies so quantization is done after transformation

2. Discrete Wavelet Transform

In 2D images, the DWT is performed to every dimension separately. There are 4 sub-band namely LL, LH, HH, and HL digital images at each scale. The sub-band LL is used for next 2D DWT. The LL subband can be regarded as the approximation component of the image, while the LH, HL, and HH subbands can be regarded as the detailed components of the image. With the increase of level of decomposition, coarser approximation component was achieved. So wavelets provide a simple hierarchical framework for interpreting the image information.

3. Principal Component Analysis

Dimensionality. It is required to reduce the number of features. PCA is an efficient tool to overcome the dimension of a data set consisting of a large number of interrelated variables while retaining most of the variations. This technique has three effects: it orthogonalizes the components of the input vectors so that uncorrelated with each other, it orders the resulting orthogonal components so that those with the strongest variation come first, and eradicates the components which have least variation in the data setExcessive features increase computation times and storage memory. It makes classification more complex which is known as the curse of.

4. Fuzzy CMeans Clustering Algorithm

Fuzzy c-means (FCM) algorithm is used in digital image segmentation as it has strong attributes for ambiguity and can produce more information than other hard digital image segmentation techniques. PCA is an iterative clustering technique that produces an effective partition by minimizing the weighted within class sum of squared error objective function known as JFCM. FCM produces a dataset which is grouped into different n clusters which have every datapoint in the dataset that maps to every cluster to some degree.

3. Proposed Technique

The hybrid algorithm includes fusion of DWT and DCT. The specific process is as follows:

(1) Perform DWT and DCT on original image.

(2) Use PCA for feature extraction on the resultant image and then CMeans for tumor detection.

(3) Perform the objective parameter evaluation for original and proposed images.

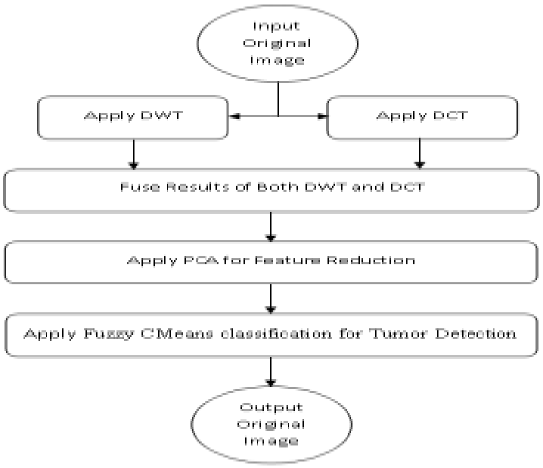


Fig. 3.1: Proposed Technique

4. Research Methodology

The following strategy will be followed to get the desired results.

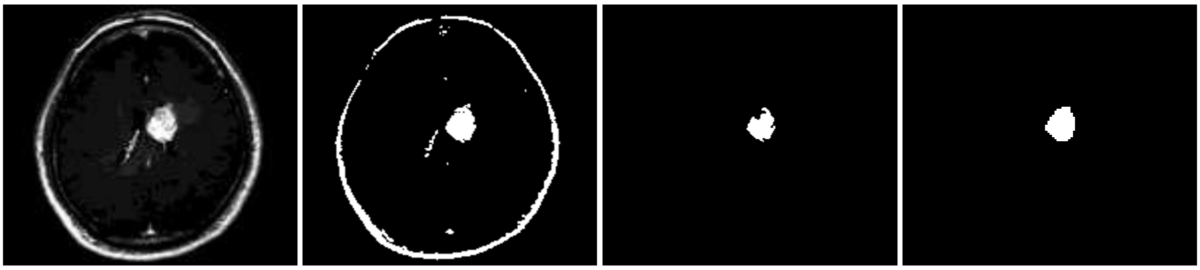
Step 1: *Combine or fuse the results of Discrete Wavelet Transform (DWT) and Discrete Cosine Transform (DCT) for feature extraction.*

Step 2: *Performing Principal Component Analysis (PCA) on the output of step 1 for feature reduction.*

Step 3: *Executing Fuzzy CMeans classification on the output of step 2 for segmenting tumors.*

Step 4: *Executing the combined methodology to detect tumors in the dataset.*

III. RESULTS



Original Filtered by DWT Filtered by DWT +DCT Filtered by Proposed

Fig. 4.1: Original and filtered Images of Tumor

Table 4.1: Objective parameter values of difference of different gray scale images of tumor

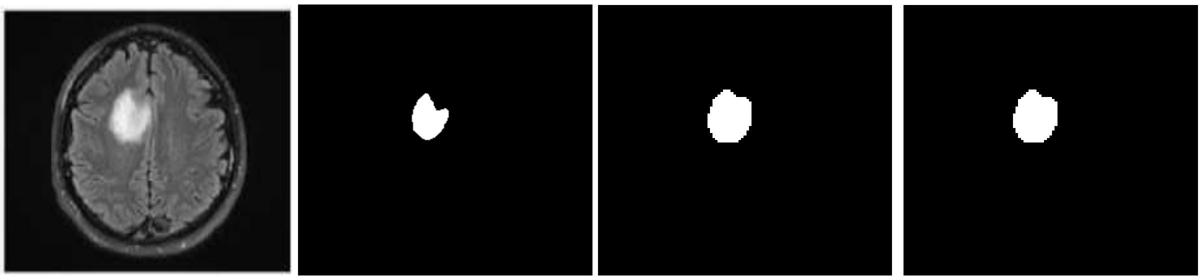
	DWT	DWT + DCT	Proposed
RMSE	.4653	.4127	.3281
PSNR	.28	.34	.38
Correlation	.0922	.1248	.1427
Contrast	.26	.29	.33
Entropy	1.25	2.14	2.31

Original Filtered by DWT Filtered by DWT +DCT Filtered by Proposed

Fig. 4.2: Original and filtered Images of Tumor

Table 4.2: Objective parameter values of difference of different gray scale images of tumor

	DWT	DWT + DCT	Proposed
RMSE	.7982	.7134	.5790
PSNR	.31	.39	.56
Correlation	.0873	.1185	.1742
Contrast	.25	.28	.31
Entropy	1.31	2.21	2.53

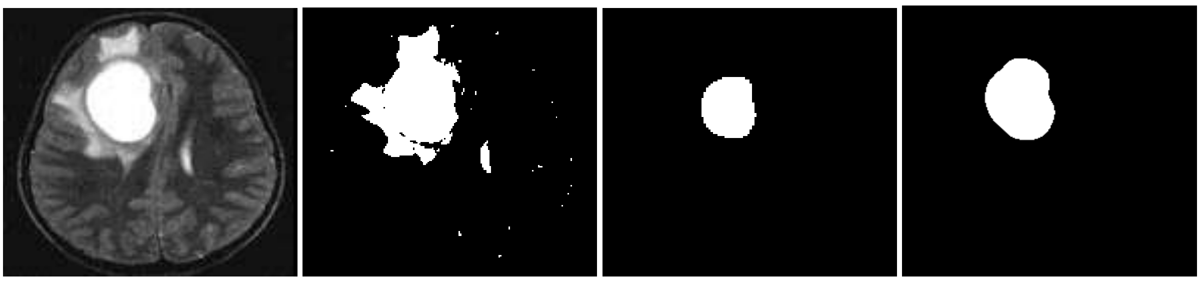


Original Filtered by DWT Filtered by DWT +DCT Filtered by Proposed

Fig. 4.3: Original and filtered Images of Tumor

Table 4.3: Objective parameter values of difference of different gray scale images of tumor

	DWT	DWT + DCT	Proposed
RMSE	.4318	.3854	.3285
PSNR	.35	.39	.41
Correlation	.1189	.1467	.1523
Contrast	.28	.36	.38
Entropy	2.36	2.61	2.87



Original Filtered by DWT Filtered by DWT +DCT Filtered by Proposed

Fig. 4.4: Original and filtered Images of Tumor

Table 4.4: Objective parameter values of difference of different gray scale images of tumor

	DWT	DWT + DCT	Proposed
RMSE	.8980	.8213	.7831
PSNR	.36	.39	.46
Correlation	.1298	.1498	.1587
Contrast	.33	.34	.36
Entropy	2.67	2.71	2.74

IV. CONCLUSIONS

From the results it is cleared that mean square difference is least and peak signal to noise ratio is maximum for proposed method which performs better in comparison to DWT and combined DWT-DCT technique for digital tumor images.

The outcomes of the proposed tumor detection method have refined sharp edges and also do not remove any import detail of tumor present in the segmented image. While the other techniques sometimes performed poorly in comparison to proposed method. So the proposed technique is better in comparison to other older techniques for detecting the tumor in digital images.

In the future work other techniques can be used to get even better results in comparison to the proposed technique. Other objective parameters like variance, skewness can also be taken in consideration so that more refined tumor detection is possible in the digital images.

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