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AUTOMATED SEGMENTATION OF BRAIN MR IMAGES BY COMBINING CONTOURLET TRANSFORM AND K-MEANS CLUSTERING TECHNIQUES

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ABSTRACT

Segmentation is usually conceived as a compulsory phase for the analysis and classification to the field of medical imaging. The aim of the paper is to find a means for the segmentation of brain from MR images by technique of combining Contourlet Transform and K-Means Clustering in an automatic way. De-noising is always an exigent problem in magnetic resonance imaging and significant for clinical diagnosis and computerized analysis such as tissue classification and segmentation. In this paper Contourlet transform has been used for noise removal and enhancement for the image superiority. The proposed technique is exclusively based upon the information enclosed within the image. There is no need for human interventions and extra information about the system. This technique has been tested on different types of MR images, and conclusion had been concluded.

Keywords: *Image Segmentation, Silhouette, Laplacian Pyramids (LP), Directional Filter Banks (DFB), Means, SNR (Signal To Noise Ratio), MSE (Mean Squared Error).*

1. INTRODUCTION

Magnetic resonance imaging (MRI) is diagnostic technique which is considered as a powerful in the field of medical imaging. The human brain is concealed from direct view by the protective skull, which not only defends it from injury but also hinders the study of its function in both disease and health. The cells which supplies the brain in the arteries are tightly bound together thereby routine laboratory test are insufficient and inadequate to analyze the chemistry of brain. The medical imaging modalities like computed tomography and magnetic resonance imaging are two mechanisms that allow the researchers, radiologists and doctors to study the brain by looking at the brain non-invasively [1].

Magnetic Resonance Imaging (MRI) is a medical imaging approach which is used in radiology to explore and visualize the internal structure of the human body. MRI provides deep, rich and strong information about human soft tissues anatomy. It uses a magnetic field and radio waves to yield detailed images of the anatomy of an organ.

Image segmentation is the procedure of partitioning a digital image into non-overlapping regions, so that significant, important and meaningful information about the image can be recovered and various analysis can be carried out on that segmented image. There are three classes or groups of tissue of human brain that are Gray Matter (GM), White Matter (WM) and Cerebrospinal Fluid (CSF). Precise segmentation of these tissue groups is an essential, crucial and vital step for brain image processing.

A. K-means clustering

K-means clustering [2] also called hard clustering is an unsupervised method of clustering that has been effectively applied in fields such as geostatistics, agriculture, astronomy, computer vision, image segmentation, classifier designs and feature analysis. Different feature spaces can be designed by an image and the k-means algorithm group similar data points in the feature space into clusters for classifying an image. The dependency of k-means is a cost function which is minimized iteratively that is dependent on the distance of the pixel to the cluster centers in the feature domain for achieving clusters. By using memberships, k-

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means algorithm allots pixels to each group. K-means starts with an initial guess for the each cluster center. Convergence of the kmeans can be perceived by evaluating the changes in the membership function or the cluster center at two successive iteration steps.

B. Cluster Validity

Cluster Validity is the procedure of evaluating quantitatively the clustering algorithm's results. Using k-means algorithm we can acquire the partition of the given data set. Here clustering results validation is required because pre-defined number of cluster(s) from user are needed to k-means algorithm and different values of clusters corresponds to different partitions. Recently researchers proposed many methods to validate the cluster that are appropriate for k-means. One of them is proposed by Rousseeuw. Rousseeuw advanced cluster validity method [3], the silhouette validation technique.

C. Noise Model

MRI, Brain and Cancer images often composed of random noise that does not occur directly from tissues but comes from other sources in the Electronics instrumentation during acquisition. The noise of an image gives it a gray appearances and mainly the noise is evenly spread and more uniform. In such situation it is very hard to diagnosis the particular disease. Therefore it is necessary to get rid of noise from the image.

There are many types of noise like RF noise, Speckle noise, Gaussian noise, Rician noise and Salt & Pepper noise but salt & pepper noise frequently occurred in MR Images. Salt and pepper noise is a form of noise typically seen on images. It represents itself as randomly occurring white and black pixels. Salt and pepper noise is an impulse type of noise, which is also referred to as intensity spikes. This type of noise is caused generally due to errors in data transmission. For an 8-bit image, the typical values for pepper noise and salt noise are 0 and 255 respectively. The salt and pepper noise is generally caused by malfunctioning of pixel elements in the faulty memory locations, camera sensors, or timing errors in the digitization process [4], [5].

With this type of noise, one pixel is assigned either maximum or minimum intensity value. In case of impulse noise, this kind is considered to be most simple and most widely used. Other pixels can posses any value from allowed dynamic limit when we use random values impulse noise model. This type of noise is not easy to detect and separate as compared to simple salt and pepper noise. In our work, our main area of attention is separation of both these kind of noises from 8-bit gray scale images [6].

Let $x'(i,j)$ and $y'(i,j)$ be the pixel values at position (i,j) of the original and noisy image, respectively. Where p is the probability of impulse noise model. This can be described in this way.

$$x'(i,j) = \begin{cases} o(i,j) & 1-p \\ \eta'(i,j) & p \end{cases} \quad (1)$$

Where $\eta'(i,j)$ is the noisy pixel at position (i,j). The noisy pixel $\eta'(i,j)$ can get value between 0~255 for 8-bit grayscale image. Figure 3 shows the histogram representation of original image and noisy image with salt & pepper noise image.

The rest of the paper is managed as follows. First, Section 2 comprises a survey on related research that is most closely related to the present work and find out problems. Section 3 outlines the methodologies while Implementation and relevant results are represented in Section 4. Finally, conclusions and discussions are presented in Section 5.

2. RELATED WORK

Jian Zhu [7] proposed a method to find the numbers of clusters by analyzing k-means and genetic algorithm to select optimal clusters. This method shows some improved results but results are calculated by very small amount of data. This method is not applied on large and natural data to evaluate further results.

K. Mumtaz [8] proposed a density based improved k-means (Dbk-means) method. In this method, he first forms the small clusters from a given set and then merge small clusters into large clusters by applying clustering errors method through some criteria. This method is iterative and takes some long time for convergence.

Siddheswar Ray [9] proposed a method to determine the number of clusters in kmeans. In this method, all the objects are put in one single clusters first, then splitting that single clusters into two clusters then further splitting the cluster

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which have maximum number of points. This process continues unless this slitting process reaches to a maximum number defined prior. At the end, clusters are validated by Dunn's index. This is iterative method and time cost is high.

One of the main drawback of the k-means algorithm is that it needs the number of clusters as an input to the algorithm manually. As designed, the algorithm is not able to determine the appropriate number of clusters and depends upon the user to identify this in advance. The other drawback of k-means is that, it does not perform the process of segmentation with perfection in the presence of noise in the images.

We proposed the solution of these problems and developed a system which is capable to reduce the noise and made the k-means algorithm to perform the process of segmentation of brain MR images in an automatic and unsupervised way. We used contourlets transform technique for noise removal purpose, k-means for segmentation and silhouette validation method to validate clusters for the automatic segmentation of brain MR images. Major contributions of the proposed technique includes

- Contourlet Transform has been used to remove the noise from MR images.
- This method is fully automatic and completely unsupervised.
- No prior knowledge, information and assumptions are involved about the type, feature, model and contents of image.
- Proposed technique calculates optimal clusters and segments images automatically.

3. METHODOLOGY

The proposed system comprises of two major phases, which includes a multi-resolution based technique for noise removal and k-means technique for segmentation. Since uncertainty and ambiguity are main issues of noise corrupted images and can result in false segmentation therefore, multi-resolution based noise removal is performed on the input image as a preprocessing step and then k-means based technique is applied on the noise free image to segment different objects present in image data automatically.

Complete system design of the proposed method is given in figure 1 and details about the each major components are discussed in the following subsections one by one.

3.1 Preprocessing-Noise Removal

To achieve the best possible diagnose target, it is necessary and essential that medical image should be distinct, sharp and noise free. Though acquisition technologies of digital medical image are improvi ng tremendously now a day's, which gives images of high resolutio n and quality but noise is still a major issue of many images. Removing the noise accurately while maintaining the image quality at best is the key challenge to the study of image.

Noise is a very frequent matter in the MR images and it can be appeared in MR images at the time of image acquisition, transferring the image into the computer and converting the images between different computer formats. So for achieving the good results for segmentation and correct classification, it is very important and fundamental issue to remove noise from the images.

For the intention of this, the original image is corrupted by adding the noise and then contourlet transform is used to remove the noise and restoring an image (see figure 3). Latest research illustrates that, many problems in the field of image processing like classical multiresolution ideas are not much more enough and effective. For instance, Fourier's methods were not proper for all purposes then wavelets were introduced. W avelets accomplish the restrictions of Fourier. However, curving smoothness have been the issue of wavelets. For this purpose, new technique "Fast D iscrete Curvelet transform [10]" was developed to conquer the fundamental restriction of these conventional multiresolution fourier and wavelets techniques. Curvelet transform has bette r edge representation and directional facilities, but Curvelets provides a fixed transform and defined in the continuous domain.

3.1.1 Adaptive Thresholding

Traditionally, coefficients of noisy image are compared to a threshold value for the reduction of noise. Trial and error method is used to obtain the value of those coefficients. It is

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noted that threshold values depend on noise variance, noise level and the noise intensity at different frequencies doesn't line up because high-frequency coefficients have higher noise intensity and low frequency coefficients have lower noise intensity, so we consider adaptive threshold value.

Offering a compromise between soft and hard thresholding by changing the gradient of the slope is the main purpose of adaptive threshold. The idea behind this scheme [11] requires two thresholds, an upper threshold λ_2 and a lower threshold λ_1 where λ_2 is estimated to be twice the value of lower threshold λ_1. The main criterion of each scheme is depicted as follows. Suppose that λ denotes the threshold limit, X_w denotes the input transform coefficients and $\mathbf{Y}_t$ denotes the output transform coefficients after thresholding, and thresholding functions and following:

$$\mathrm{Y}_t = \left\{ \begin{array}{ll} 0 & if \mid X_w \mid \leq \lambda \\ sign\{X_w\} \frac{\lambda_1(\mid X_w \mid - \lambda)}{\lambda_1 - \lambda} & if \lambda < \mid X_w \mid \leq \lambda_1 \\ X_w & if \mid X_w \mid > \lambda_1 \end{array} \right\} \tag{1}$$

3.1.2 Contourlet Transform

Recently new multiscale and multidirectional technique Contourlets [12] is proposed by Do and Vetterli which captures edges and smooth contours at any orientation. It filters the noise in image in a better way. This technique is derived directly from discrete domain rather than extending from continuous domain. This scheme is implemented by using filter banks. This technique decouples the multiscale and directional decompositions. The multiscale and the directional decompositions are handled by a Laplacian pyramid [13][14] and a directional filter bank (DFB)[15] respectively. The point discontinuities are first captured by laplacian pyramid (LP) and then followed by a directional filter bank (DFB) to link the discontinuities into linear structures. The structural design of contourlet via laplacian pyramid and directional filter is as follow:

i. There are four frequency components of the input image like LL (Low Low), LH (Low High), HL (High Low) and HH (High High).
ii. At each level, the laplacian pyramid produces a low pass output (LL) and a band pass output (LH, HL, HH).
iii. And then the band pass output is passed into directional filter bank, which results in contourlets coefficients. After that the low pass output is again passed through the laplacian pyramid to obtain more coefficients and this process is repeated until the fine details of the image are retrieved. This process is shown in the figure 2.
iv. Then the image is reconstructed by applying the inverse contourlet transform (CT). The Algorithm1 describes the complete restoration process of brain MR image via Contourlet Transform(CT).

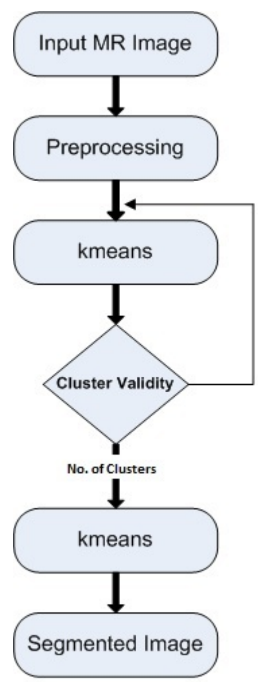

Figure 1: System Flow Diagram of Proposed Method

3.2 SEGMENTATION

The Segmentation process is performed to extract the abnormal (tumorous) portion of the brain from the brain MR image. This segmentation process make the segments of the brain MR image into two portions. One segment portion contains the brain tissues which are normal and the second segment portion contains the tumorous cells. The segment part which

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contains the abnormal cells is the desired region which is known as tumorous region.

After noise removal, K-Means clustering method was used to segment the image. This procedure illustrates the image using only the pixel intensity feature. To find the number of clusters accurately, K-Mean algorithm is iterated for a range of hypothesized numbers of clusters. Best choice for cluster is selected based on cluster validity measure. The silhouette validity method [3] generated amazingly some good results for some of the test images.

3.3 K-MEANS CLUSTERING

K-means clustering technique is used to partition the n data points into K classes [16][17]. K-means clustering algorithm initially sets centroids of each cluster. This algorithm maximize the inter cluster distance and minimizes the intra cluster distance. The cluster which has closest center value with an instance within a data set, keeps that instance in its group. Each cluster center C_j is modified by calculating the mean of its constituent instances. Minimizing an objective function is the aim of this algorithm and that function is as follows:

$$J = \sum_{j=1}^{k} \sum_{i=1}^{n} \left\| x_i^{(j)} - c_j \right\|^2 \qquad (2)$$

where $\left\| x_i^{(j)} - c_j \right\|^2$ is an Euclidian distance measure between a data point $x_i^{(j)}$ and the cluster centre c_j. The example of sum of distance calculated by eq. 2 is given in fig 4(b).

3.4 CLUSTER VALIDITY

The Silhouette validation method [3] calculates the silhouette width for each sample, average silhouette width for each cluster and overall average silhouette width for entire data set. By using this mechanism, each cluster could be represented by so-called silhouette, which is based on the evaluation of its compactness and separation. The average silhouette width could be applied for evaluation of clustering validity and also could be used to decide how good is the number of selected clusters, validity criteria is defined as

$$S(i) = \frac{\left(b(i) - a(i)\right)}{\max\{a(i), b(i)\}} \qquad (3)$$

where *a(i)* represents average dissimilarity of *i*-object to all other objects in the same cluster; *b(i)* represents minimum of average dissimilarity *of i*-object to all objects in other cluster (in the closest cluster).

It is followed from the formula that $-1 \le s(i) \le 1$. If silhouette have the value nearly close to 1, it can be concluded that sample is "well-clustered" and it was assigned to a very appropriate cluster. If silhouette have the value near about zero, it can be concluded that, that sample of data could be dispense to another closest cluster as well, and the sample of that data chunk lies evenly far away from both clusters. If silhouette have the value nearly close to –1, it can be concluded that, sample is "misclassified" and is merely somewhere in between the clusters. The overall average silhouette width for the entire plot is simply the average of the S(i) for all objects in the whole dataset.

The largest overall average silhouette indicates the best clustering (number of cluster). Therefore, the number of cluster with maximum overall average silhouette width is taken as the optimal number of the clusters. Graphically cluster validity is shown in figure 4(a).

4. EXPERIMENTAL RESULTS AND DISCUSSION

The proposed system was implemented by using the Matlab R2009a environment. We acquired some images from brain web [18] and internet. First, we performed contourlet transform for noise removal and de-noised results are compared with wavelet and curvelet transforms which are shown in Table1. After that, Kmeans clustering technique has been used for segmenting the brain MR images.

Figure 6 (6b), (6d), (6f), (6h), (6j),(6l) shows some results of our proposed technique when applied on different types of brain MR images like T1,T2 and PD weighted. The proposed system generates much better results than the schemes that have been used former which is manifest from our results. If the images are less contrast and gray matter, white matter and cerebrospinal fluid are overlapped in an image

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then nearly all preceding techniques do not perform segmentation accurately. However, our proposed mechanism shows excellent results on various types of MR images. Our proposed system can segment the gray matter, white matter and cerebrospinal fluid tissues for different MR images. We just showed results which are generated qualitatively in the form of visualization. As so far there is no any specific standard quantitative measure criteria for determining the quality of segmented medical image.

Algorithm 1: Restoration of MRI Images.

Input: Medical MRI image X'.

Output: Restored image Y'.

Begin

Step 1: Input medical MR image X'.

Step 2: Apply log transformation to the input image X'.

Step 3: Apply the Contourlet Transform on the log transformed image of step 2 up to n levels of Laplacians pyramidal decomposition and m directional decompositions at each level where n and m depend on the image size

Step 4: Perform thresholding of contourlet transformed image of Step 3. We have used semi soft threshold.

Step 5: By performing the inverse contourlet transform on the thresholded image of Step 4, the restored image Y' is obtained (output image).

Step 6: Compute the performance parameters, namely, **MSE, SNR, PSNR,** for the restored image Y' of Step 5.

End

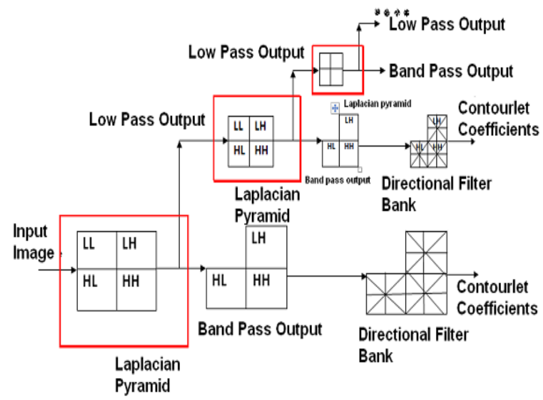
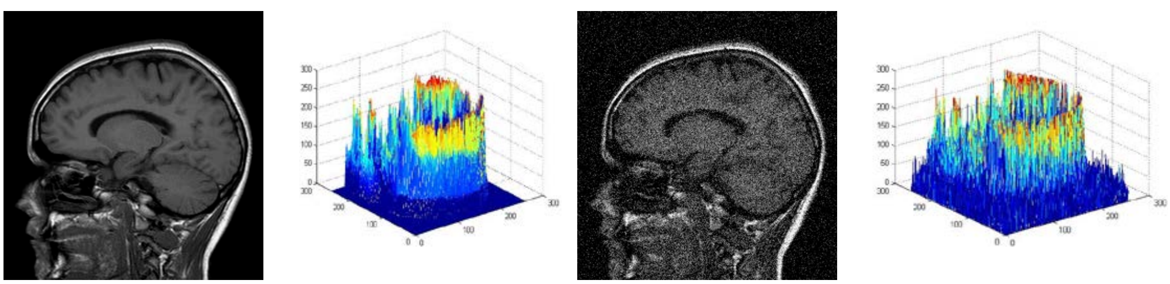


Figure 2: Illustration Of Contourlet Transform

(Adapted From [14])



(a). Original Image (c). Histogram of Original Image (b). Noisy Image (SNR = 3.55 dB) (d). Histogram of Noisy Image

Figure 3: (A) Original Image And (B) Noise Added Image With Salt & Pepper Noise

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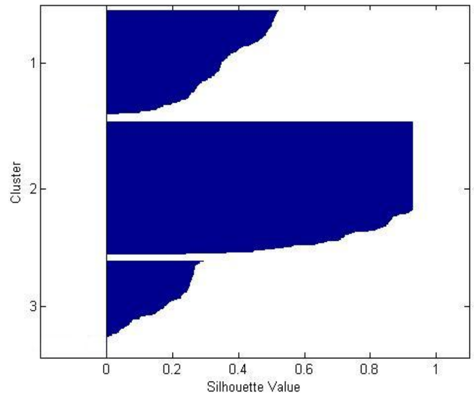
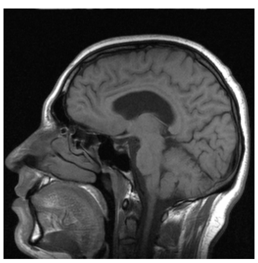


Figure 4(a): Cluster Validity by equation (3)

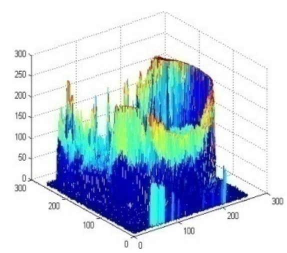
iter	phase	num	sum
1	1	512	3.79553e+006
2	1	17	3.76e+006
3	1	4	3.75416e+006
4	1	2	3.75273e+006
5	1	2	3.75205e+006
6	2	0	3.75205e+006

6 iterations, total sum of distances = 3.75205e+006

Figure 4(b): Total sum of distances by equation (2)

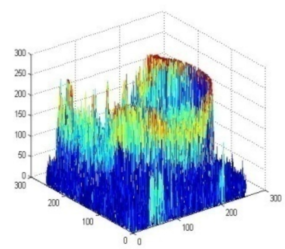


(a). Original



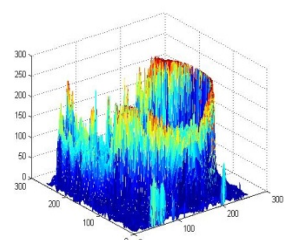
(b). Histogram of image a

(c). Noisy SNR=9.41 dB

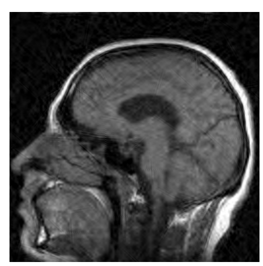


(d). Histogram of c

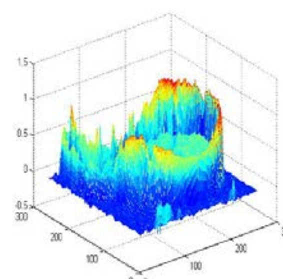
(e). De-noised from Wavelet



(1-e). Histogram of image e

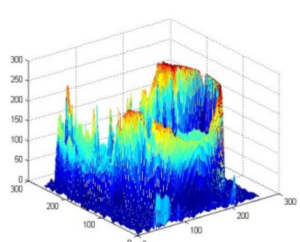


(f). De-noised from Curvelet



(1-f). Histogram of image f

(g). De-noised from Contourlet



(1-g). Histogram of image g

Wavelet restored image SNR = 15.41 dB

Curvelet restored image SNR = 16.02 dB

Contourlet restored image SNR = 16.38 dB

Figure 5: Images De-Noised with wavelet, curvelet and Contourlet transforms

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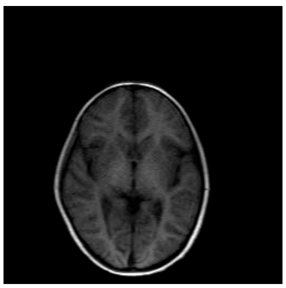
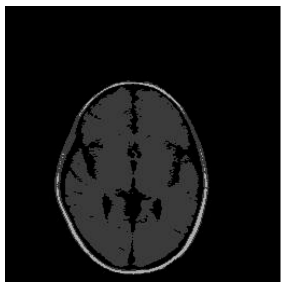
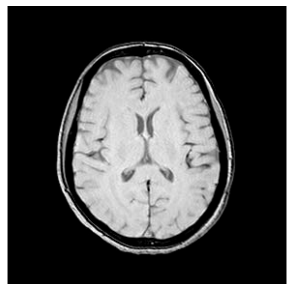
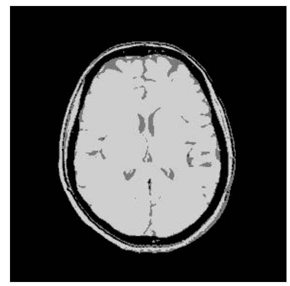
Table 1: Results Comparisons of Contourlet Transform with Wavelet and Curvelet Transforms

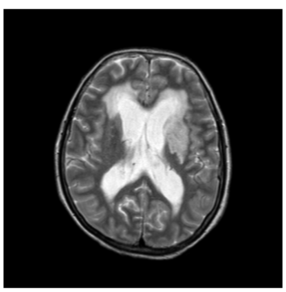
Transform	Noisy image SNR (dB)	Noisy image PSNR (dB)	Noisy image MSE	Restored image SNR (dB)	Restored image PSNR (dB)	Restored image MSE
Wavelet	9.54	27.74	21.8185	17.48	35.91	20.99
	8.48	26.23	23.7752	15.53	33.44	22.74
	3.52	23.67	26.6741	13.30	30.03	26.43
Curvelet	9.54	27.74	21.8185	17.59	36.11	19.34
	8.48	26.23	23.7752	15.95	33.98	21.11
	3.52	23.67	26.6741	14.21	31.12	23.51
Contourlet	9.54	27.74	21.8185	17.70	36.76	18.71
	8.48	26.23	23.7752	16.29	34.21	18.93
	3.52	23.67	26.6741	14.67	31.89	22.31


(6a) Original Image

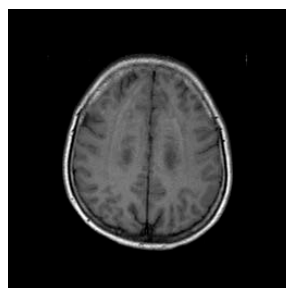

(6b) Proposed Method

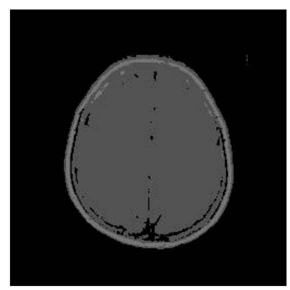

(6c) Original Image

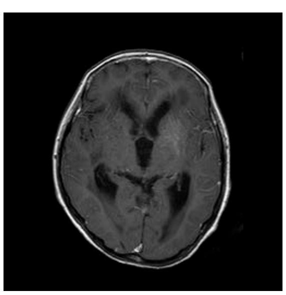

(6d) Proposed Method

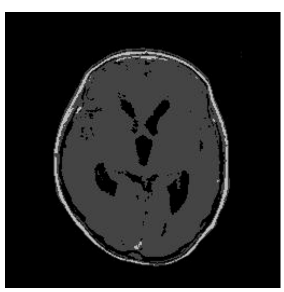

(6e) Original Image

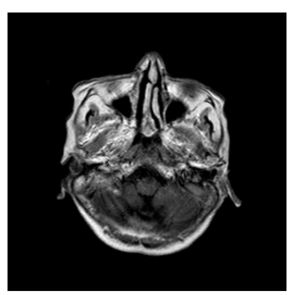

(6f) Proposed Method


(6g) Original Image


(6h) Proposed Method


(6i) Original Image


(6j) Proposed Method


(6k) Original Image

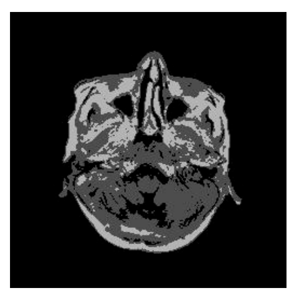

(6l)Proposed Method

Figure 6: Results of our Proposed System

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5. CONCLUSION AND FUTURE WORK

In this paper, we have presented an iterative method which is capable of performing automatic segmentation of brain MR images. Multiscale and directinal technique Contourlets transform is performed on the images for the noise reduction purpose as a preprocessing step. Kmeans clustering method is performed for the segmentation process which is based on the an objective function. This proposed technique calculate the optimal number of clusters in an automatic way. For Computer-Aided Diagnosis System (CAD), this is just the first step which is still under development. The results obtained from the proposed system are shown on various MR images. One great advantage of technique which is presented in our paper is that there is no need of any prior information about the input image type and it does not need any human expert interference.

The further phase we are still working is on brain tumor detection. At this stage, our method is just at a demonstrational/ experimental stage and needs to be evaluated through a double blind procedure by a number of radiologists, with comparison with their current methods of detection of the brain tumor.

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