International Journal of Emerging Technology in Computer Science & Electronics (IJETCSE)
ISSN: 0976-1353 Volume 23 Issue 6 –OCTOBER 2016 (SPECIAL ISSUE)

ADAPTIVE APPROACH TO IMAGE CODING FOR TUMOR DETECTION IN MRI IMAGES

Somashekhar Swamy[#1] and P.K.Kulkarni[*2]

[#] *Research scholar , V.T.U.Belagavi, Karnataka, India*

[*] *Professor & H.O.D.(E&EE), P.D.A.College of Engg. Kalburgi, Karnataka, India.*

***Abstract*— In the process of image coding, images are processed to retrieve important information's from a given sample to achieve the objective of information retrieval in image coding. In the application towards processing of medical image data, images are processed for filtration and segmentation to retrieve proper regions for effective region detection. Towards this approach, the conventional coding uses median filtration and region based segmentation approach to localize effective regions. However, this coding approach is observed to be erroneous under dynamic conditions, which leads to misclassification of image data in adaptive manner. To develop an approach for improvising the region localization, in this paper an adaptive filtration approach with content based segmentation model is proposed. The suggestive approach observed to be improved for filtration and region localization tested over MRI samples, as compared to the conventional segmentation system.**

***Index Terms*— Adaptive coding, MRI segmentation, region localization.**

I. INTRODUCTION

Automation in medical image processing is in greater demand. Due to higher prelim testing cost, and lack of expert radiologist, time for such diagnosis is time taking. To overcome this issue, new hybrid methods are in development to achieve finer objectives of image segmentation and its information retrieval. Due to higher level of observation and large factor of analysis for disease detection, time for diagnosis is increasing. As well the accuracy of radiologist detection is more dependent on the expertization of the individual. The constraint of resources, manpower and time of diagnosis, automated systems are to be developed. Among various analysis of medical scan information, MRI analysis for brain tumor detection is observed to be an upcoming work. Automation of brain tumor detection helps in the preliminary diagnosis, and faster decision making. Wherein automated systems are having an advantage of time saving diagnosis, the accuracy of detection and complexity of coding is still a concern of development. Various researchers are focusing on the development of automated brain tumor detection based on advanced image coding and signal processing techniques. For the extraction of tumor region in MRI image the test image is to be coded for region detection. It is a primal requirement in MRI processing to extract the suspected region more accurately to obtain the exact detection. In this process, the localization of region is to be detected accurately so as the features could be detected accurately. To develop this objective, an orientation mapping based on spectral information is proposed. To extract the regions the image sample is pre-processed using spectral median filter and region is localized with orientation mapping of the test image. The process of segmentation for MRI region detection is in development from a long time. Various methods are developed towards representation and localization of MRI image. The past developments of the stated objectives are presented in following section.

II. LITERATURE SURVEY

To improve the accuracy in such coding, artificial intelligence are been incorporated. Towards such coding, in [1] a magnetic resonance spectroscopy (MRS) in the assessment of brain tumors and grading brain glioma was presented. In this approach a Pathology grading was correlated with metabolic ratios for the decision of brain glioma. In [2] a model was applied to distinguish normal brain tissue from brain metastases and to identify the primary tumor of brain metastases in 15 independent test images. The developed approach, demonstrates that significance of using magnetic resonance spectroscopy (MRS) for the diagnosis of tumor information in MRI diagnosis. A report on the new quality-improvement opportunities as well the further objectives for MRI analysis was outlined [3]. For the cause of tumor formation and defects observed in such case, in [4] a study for the determination of onset characteristics during tumor development was presented. The stage representation of tumor developments leads to the accurate training of the diagnosis system. In [5], an extensive comparative analysis was performed to illustrate the merits and demerits of various available techniques for automated diagnosis. It also explores the applicability of the techniques in brain disorder diagnosis in MR images. [6] presents a review of the existing methods to incorporate spatial dependency into the computation of mutual information (MI).A spatially dependent similarity measure was introduced, named spatial MI, which is extended to 3-D brain image registration. This extension eliminates the artifact for translational and misregistration process. In [7] Articles relating to application of ultrahigh field (UHF) MRI to brain anatomy and brain tumors with living subjects were presented. Studies were grouped into one of three categories based on area of focus: “Anatomical Structures Involved with Brain Tumors,” “Tumor characterization,” and “Treatment Monitoring.” The process of segmentation using watershed algorithm was outlined in [8].The method illustrates the ability of watershed segmentation to separate the abnormal tissue from the normal surrounding tissue. To get a real identification of involved and noninvolved area for analysis of data to distinguish the involved area more precisely. For the segmentation process, in [9] a graph-based concurrent brain tumor segmentation and a report to diseased patient registration framework was presented. Both segmentation and registration problems are modeled using a unified pair wise discrete Markov Random Field model on a sparse grid superimposed to the image domain. Segmentation is addressed based on pattern classification techniques, while registration is performed by maximizing the similarity between volumes and is modular with respect to the matching criterion. A substantial methodological framework including new data analysis method was developed in [10] to meet the challenge of working with big data. Malignant imaging phenotypes determined by MRI providing a mean of panoramic and noninvasive surveillance of oncogenic pathway activation for patients treatment was presented. In [11], to summarize and compare the methods of automatic detection of brain tumor through Magnetic Resonance Image (MRI), different stages of Computer Aided Detection (CAD) system was presented. In [12] a method to classification EEG signal for detection of primary brain tumor detection, in combination of multi-wavelet transform and artificial neural network was presented. Uncertainty in the EEG signals is measured by using the Approximate Entropy. This observation leads to the process of tumor detection based on EEG analysis. [13] Describes a Matlab implementation, to detect & extraction of brain tumor from MRI scan images of the brain. Incorporates with noise removal functions, segmentation and morphological operations which are used for MRI image coding.To implement and evaluate a magnetic resonance imaging atlas-based automated segmentation (MRI-ABAS) procedure for cortical and sub-cortical grey matter areas definition, suitable for dose distribution analyses in brain tumor patients undergoing radiotherapy (RT) was presented in [14]. The MRI-ABAS procedure consists of grey matter classification and atlas-based regions of interest definition was presented. The approach of automated classification of the proposed approach was outlined in this work. In [15]an artificial neural network (ANN) approach by Back propagation network (BPNs) and probabilistic neural network (PNN) was presented. The method is developed to classify the type of tumor in MRI images of different patients with Astrocytoma type of brain tumor. Image processing techniques have been developed for the detection of tumor in the MRI images. The Gray Level Co-occurrence Matrix (GLCM) used for feature extraction is proposed. For the noise free processing if MRI sample in [16] an Artificial Bee Colony Algorithm that try to abstract the tumor part using Fuzzy C-Means Clustering is proposed. In [18] present an overview of the current research being carried out using the data mining techniques for the diagnosis of brain tumor. Study to identify the most well performing data mining algorithms used on medical brain MRI and Clinical parameters were analyzed. various algorithms were been identified defined by, Decision Trees, Support Vector Machine, Artificial Neural Networks and their Multilayer Perceptron model, and Fuzzy C-Means. Analyses show that it is very difficult to name a single data mining algorithm as the most suitable for the brain tumor detection or classification. In [19], a comparative study of transform techniques namely Discrete Cosine Transform (DCT), Discrete Wavelet Transform (DWT) each separately combined with the Probabilistic Neural Network (PNN) is used for the classification of brain tumor is presented. The system was defined by three stages for the diagnosis of brain tumor. In the first stage, MR image is obtained and preprocessing is done to remove the noise and sharpen the image. In the second stage, DCT and DWT is used for feature extraction .In the third stage, Probabilistic Neural Network with Radial Basis Function distinguishes brains abnormality. Finally the performance of DCT and DWT in diagnosing the brain tumor is compared using the parameters such as sensitivity rate and precision rate. An approach useful for enhanced detection of brain tumor using Post -processing and Pre-processing steps of Digital image processing is presented in [20]. Six variant ways of processing an image for the detection of mass region is applied on to the MRI images. To correctly classify the histopathological type of defect in MRI images, a hybrid model of tumor detection is presented in [21,22,23], obtaining, about 99.93% of the cases used to build the model and in as much as 99.16% of new cases. Malignant and benign types of tumor infiltrated in human brain are diagnosed with the help of an MRI scanner. With the slice images obtained using an MRI scanner, image processing techniques are utilized to have a clear anatomy of brain tissues. A hybrid Self Organizing Map (SOM) with Fuzzy K Means (FKM) algorithm is applied, which offers successful identification of tumor and good segmentation of tissue regions present inside the tissues of brain. Wherein new developments were made towards atomization of brain tumor detection, intelligence logic were proposed following Neuro modeling, fuzzy logic etc. wherein such methods are more accurate in decision making, the accuracy of the system depend on the processing sample, algorithms been used for representation and approach of classification developed for decision making. To give an advantage of higher retrieval performance, a effective model of processing, representation and classification is required. The problem of system noise during testing, the effect of spatial similar regions in the image makes it difficult to detect the actual region for diagnosis leading to misclassification. This problem degrades the accuracy of estimation performance and hence minimizes the robustness of the automated processing unit. To achieve the objective of proper filtration and segmentation a new hybrid model of an adaptive filtration logic with region localization approach is presented. To develop the suggested approach, in this paper, section 2 outlines the past literature for region segmentation in MRI images. Section 3 outlines the suggested system architecture for image processing. Section 4 outlines the denoising approach to image coding, section 5 outlines the region localization approach for region segmentation. The observed experimental results are outlined in section 6. Section 7 concludes the suggested approach for the proposed system.

III. SYSTEM OUTLINE

With the objective of developing a robust recognition system, in this work, a focus is made on developing a new algorithmic approach for preprocessing, segmentation, and representation and classification process. A system architecture of the recognition approach for the tumor detection and classification is developed. A framework with such objective was developed in [24]. In reference to the past framework developed, a proposing system architecture for the developing approach is developed as shown in figure 1.

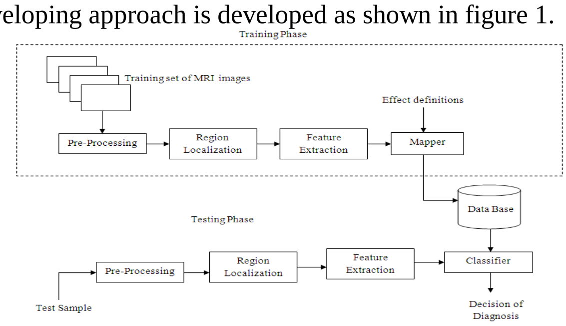

Figure 1: Proposing system architecture for the automated Diagnosis system

The suggested architecture constitute of a pre-processing, region localization, feature extraction, mapper and classifier unit. In the pre-processing unit the given sample is processed for a standard processing size, extracting the pixel values and performing filtration to eliminate noise effects. The process of denoising was observed in various literatures to eliminate noise effects at preprocessing level. In recent approach towards denoising of MRI sample at preprocessing median filtration was suggested [25]. Wherein median filtration are effective under a discrete level of noise effect, under dynamic noise variations the immunity is reduced. Towards improving the filtration performance, a intelligence to such filter were then developed. In [32] the filtration process was enhanced using fuzzification approach. Wherein KFCM approach was introduced for filtration. However in the fuzzification process it was observed that, the filtration process is governed by the fuzzy rules. These fuzzy rules are defined based on the observations developed over past processing. As the noise effects are dynamic, these rules would fail under noise with a abrupt variation in its effect level. Hence to achieve the objective of robust filtration process in this work, a focus is made on developing dynamic filtration process using a hybrid model of median filtration with fuzzy system following, dynamic decision processing. The suggestive approach, formulates the noise decision at median filter based on a dynamic framing, with the fuzzy rule adapting with the derived variance values based on adaptive median filtration. In the second stage of the processing, the processed sample is then processed for region localization and segmentation. Wherein most methods were developed for segmentation of regions from a given MRI sample, les focus is made on its localization. Localization of the mass elements in the MRI sample could minimize the overhead coming for processing the whole sample. With this objective a simpler however robust approach of mass localization in MRI sample using recursive Morphological approach with its fusion is suggested. In the approach of segmenting such region, a walker based approach was suggested in [26]. This logic present a simpler approach of region segmentation via boundary region tracking. In this approach the approaches of walker approach with a region localization will be developed. The approach of segmentation will then be decided based on, the mass density observation, to extract the required region of interest.

IV. DENOISING APPROACH

In the development of image coding for medical processing, new devices for image capturing and processing, with finer and high quality images were developed. Images while storage or capturing for such application, is observed to be constraint with noise effect. Hence, such systems are erroneous in processing, when coding for segmentation. Prior to segmentation, hence filtrations were applied in the pre-processing level to achieve the filtration operation.

A. Conventional Median filtration

Among different approach of filtration, in this work, median filter based filtration approach is been suggested for image filtration. Due a simpler approach of filtration this coding is considered. Median filtering approach is particularly adapted for suppressing impulsive noise. It has been shown that median filters have the advantage to remove noise without blurring edges, as are the nonlinear operators class range filters and output from one of the original gray values. The extension of the concept of median filtering of color images is not trivial. The main difficulty in defining a range filter color image is that there is no "natural" and unambiguous order data. In recent years, various methods have been proposed for use median filters in color medical image processing. Whatever the method of vector filtering, the challenge is to detect and replace noisy pixels that relevant information is retained. But it is recognized that in some more medical image processing filters vector blur the edges and fine details of the image. Generally impulse noise pollution medical images during data acquisition camera sensors and transmission in the communication channel. The simplest smoothing algorithm IS the median filter. The average filtration is a simple, intuitive and easy method to implement smoothing medical imaging that is,reducing the amount of intensity variation between two pixels. It is often used to reduce noise in medical imaging. The idea of filtering median is simply to replace each pixel value in an image with the mean value of its neighbors, including himself. This has the effect of eliminating the pixel values that are representative of their environment. The average value is defined by,

$$M_n = \frac{1}{m \times n}\left(\sum_{i=1}^{n}\sum_{j=1}^{m} x_{i,j}\right) \quad (1)$$

Where, m, n are the row and column of the image, and $x_{i,j}$ corresponds to the pixel value of i,jth position pixel value.

Median filtration technique is observed to be lower in preserving the edges in images. To improve this limitation in this paper, a technique of filtration based on spectral median filtration is suggested. The median filter is often used to remove noise from images or other medical signals. The median filtering is a preprocessing step in image processing. It is particularly useful to reduce speckle noise and salt &pepper noise. Its edge nature preserve makes it useful in cases where fuzziness edge is undesirable. However in case of dynamic condition where noise are variant with time, selection of filtration block and defining filtration parameter is difficult. Hence, to improve the coding, in this paper an adaptive spectral median filter is suggested.

B. *Proposed adaptive spectral filtration approach*

The adaptive spectral median filter is the MSE-optimal stationary linear filter for images degraded by additive noise and blurring. Calculation of the adaptive spectral filter requires the assumption that the signal and noise processes are second-order stationary (in the random process sense). Adaptive spectral filters is applied in the frequency domain. Given a degraded image x (n,m), one takes the Discrete Fourier Transform (DFT) to obtain X(u,v). The original image spectrum is estimated by taking the product of X(u,v) with the median filter G (u,v):

$$\hat{S}(u,v) = G(u,v)X(u,v) \qquad (2)$$

The inverse DFT is then used to obtain the image estimate from its spectrum. The medianfilter is defined in terms of their spectra:

$H(u,v)$=Fourier Transform of point spread function (PSF)

$P_s(u,v)$=power spectrum of signal process

$P_n(u,v)$=power spectrum of noise process

The median filter is:

$$G(u,v) = \frac{H^*(u,v)P_s(u,v)}{|H(u,v)|^2 P_s(u,v) + P_n(u,v)} \qquad (3)$$

Dividing through by P_s makes its behavior easier to explain:

$$G(u,v) = \frac{H^*(u,v)}{|H(u,v)|^2 + P_n(u,v)/P_s(u,v)} \qquad (4)$$

The term $|P_n(u,v)/P_s(u,v)$ can be interpreted as the reciprocal of the signal-to-noise ratio. Where the signal is very strong relative to the noise, $\frac{p_n}{p_s} \approx 0$ and the medianfilter becomes $H^{-1}(u,v$- the inverse filter for the PSF. Where the signal is very weak, $\frac{p_n}{p_s} \approx \infty$and $G(u,v) \to 0$.

For the case of additive white noise and no blurring, the adaptive spectral medianfilter simplifies to:

$$G(u,v) = \frac{P_s(u,v)}{P_s(u,v) + \sigma_n^2} \qquad (5)$$

Where$\sigma_n^2$is the noise variance. These noise variance is used for the filtration by masking the value to the limit value be coding over a block of processing image. To this denoised sample, then a segmentation approach is defined for tumor detection as outlined below.

V. Region Localization

To detect the region of interest in the given image, region localization is developed. The approach, extract the tumor regions, a logical ANDing operation over obtained eight orientations were carried out, where each orientation is transformed to a bi-level logic using global thresholding as illustrated. Thresholding is a simple technique for image segmentation. It distinguishes the image regions as objects or the background. Although the detected regions are consisting of tumor regions and non-tumor regions in every detail component resolution, they can distinguish due to the fact that the intensity of the tumor regions is higher than that of the non-tumor regions. Thus, an appropriate threshold can be selected to preliminarily remove the non-tumor regions in the resolution component sub-bands. A dynamic thresholding value is calculated as the target threshold value *T*. The target threshold value is obtained by performing an equation on each pixel with its neighboring pixels. Two mask operators are used to obtain mask equation and then calculate the threshold value for each pixel in the 3 resolution. Basically, the dynamic thresholding method obtains different target threshold values for different resolution images. Each resolution component resolution $e_s$is then compared with *T* to obtain a binary image (***e***).The threshold *T* is determined by,

$$T = \frac{\sum(e_s(i,j) \, x s(i,j))}{\sum s(i,j)} \qquad (6)$$

Where,

$$s(i,j) = \max\left(|g_1 ** e_s(i,j)|, |g_2 ** e_s(i,j)|\right)$$

and,

$$g_1 = [-1\ 0\ 1], g_2 = [-1\ 0\ 1]^t$$

Using Equation 5threshold 'T' can then be computed,and the test image (***e***) is given by,

$$e(i,j) = \begin{cases} 255, if \ e_s(i,j) > T \\ 0, otherwise \\ 1 \end{cases} \qquad (7)$$

A. *Orientation region coding*

To eliminate the miss classification Impact under affinity, a inter resolution correlation error for a set of image orientation is considered. Considering a set of k orientations (O_k), for the given image of, i=1 to M, generated by orienting the image in 8 distinct directions,

$$O_i(k) = [O_i(kN), O_i(kN-1), \ldots\ldots, O_i(kN-M+1)] (8)$$

Where, $O_i$is the resolution for a particular orientation, N is number of orientations and M are the dataset samples. To evaluate the noise effect in the orientations, a orientation error is computed defined by,

$$e_{i,o}(k) = O_{i,t}(k) - O_{i,t+1}(k) \qquad (9)$$

This error defines the difference in the two orientation component, and the orientation errors with lower values $\min(e_{i,o}(k))$are considered as feature element. However this error when observed over a period of orientation observation deviates a large and could be effective due to noise effect. Hence in such coding the intersection orientation would be made concentric with noise parameter. To eliminate this problem, and to improve the pixel selection more accurately, a orientation selection computed over a series of morphologied spectral orientation is computed. In this suggested approach, rather to taking the whole histogram from single orientation information, a selection of the resolutionbins is made. To derive the resolution selection, the resolution bins are initially normalized using a random weight factor.

$$O_i(k) = O_i(k)w(k) \qquad (10)$$

Where, $w(k) = [w_0(k), w_1(k), \ldots\ldots, w_{M-1}(k)]^T$ are the allocated weight factor for each frame.The estimated error is then defined as;

$$e_{i,o}(k) = O_{i,t}(k) - O_i(k)w(k) \qquad (11)$$

The error is recursively been computed over the total orientations (i=1….N), and the initial error is recorded as $e_{i,o,init}$.A weight factor is then updated as,

International Journal of Emerging Technology in Computer Science & Electronics (IJETCSE)
ISSN: 0976-1353 Volume 23 Issue 6 –OCTOBER 2016 (SPECIAL ISSUE)

$$w(k+1) = w(k) + \mu \sum_{i=0}^{N-1} \frac{o_i^T(k)}{\|o_i(k)\|^2} e_{i,o,init}(k) \quad (12)$$

Where μ is the updation step size, with an error updation factor. The objective of this computation is to select the bins satisfying the $\min(e_{i,o}(k))$ condition. To optimize the recursion overhead, a joint adjacent weight difference is computed defined by,

$$\tilde{w}(k) = w^o - w(k) \quad (13)$$

Where, w^o is the initial weight issued.The weight updation is then defined as,

$$\tilde{w}(k+1) = \tilde{w}(k) - \mu \sum_{i=0}^{N-1} \frac{o_i^T(k)}{\|uo_i(k)\|^2} e_{i,o}(k) \quad (14)$$

B. Logical And Operation

The logical AND operation is then carried on three kinds (vertical, horizontal and diagonal) of regions after morphological operation to isolate the tumor data from the scaled image. The operator Performs Logical AND operation element by element for the three images and results the final ANDed Image. The Morphologically operated image have higher uniformity at tumor regions compared to the graphic region which results in elimination of the graphic region when ANDed.

VI. Experimental Results

This section illustrates the performance evaluation of proposed approach. To test the proposed approach, various MRI images were used. For each and every MRI image, the proposed approach tends to segment the region with exact tumor and also with effective noise filtration. The MRI samples with tumor used for testing are shown in figure 2.

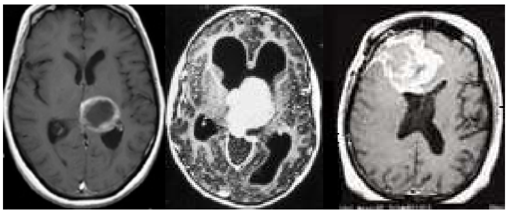

Figure.2. MRI test images

Original test MRI image

Figure.3. original test MRI image

Figure.3 represents the original MRI image used for testing. In the above figure, a tumor is observed at the lower region of the image. This image is processed for the region segmentation.

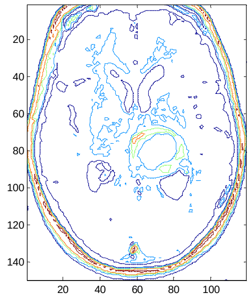

Figure.4. contour plot of test MRI image

Figure.4 represents the contour plot of test MRI image. In the above figure, each colour represnets one contour of image. Thus, the regions with tumor is also shown in a particular color to highligh the paert. The highlighted part is denoted as tumor.

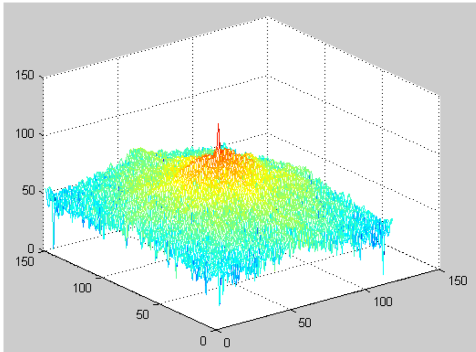

Figure.5. Power spectral density of MRI test image

Figure. 5 show the power spectral density plot of the test MRI image. The peak at the center of image shows the highest power spectral density value of the image. Here, the PSD gives details about the spectral features of image thus, the pixel at which there is a more noise existence will be traced out and that particular region will be thresholded through the proposed approach. This increase the quality of image.

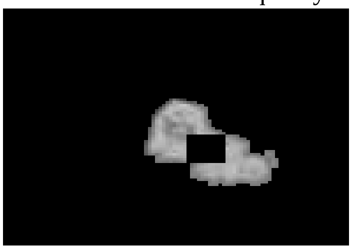

Figure.6. Extracted region

Figure.6 shows the final extracted region in which the tumor is existing. The above figure also shows the region with clear edges.

Original test MRI image

Figure.7. original test MRI image

Figure.7 represents the original MRI image used for testing. In the above figure, a tumor is observed at the center part of image. Now this image is processed for the region segmentation.

International Journal of Emerging Technology in Computer Science & Electronics (IJETCSE)
ISSN: 0976-1353 Volume 23 Issue 6 –OCTOBER 2016 (SPECIAL ISSUE).

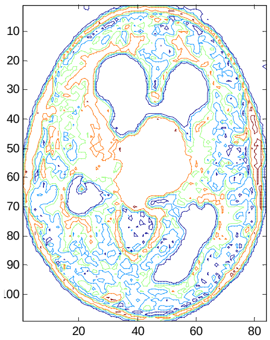

Figure.8. contour plot of test MRI image

Figure.8 represents the contour plot of test MRI image. In the above figure, each colour represnets one contour of image. Thus, the regions with tumor is also shown in a particular color to highligh the paert. The highlighted part is denoted as tumor.

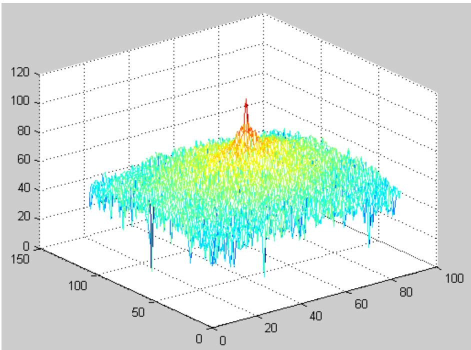

Figure.9. Power spectral density of MRI test image

Figure. 9 show the power spectral density plot of the test MRI image. The peak at the center of image shows the highest power spectral density value of the image. Here, the PSD gives details about the spectral features of image thus, the pixel at which there is a more noise existence will be traced out and that particular region will be thresholded through the proposed approach.

Figure.10. Extracted region

Figure.10 shows the final extracted region in which the tumor is existing. The above figure also shows the region with clear edges.

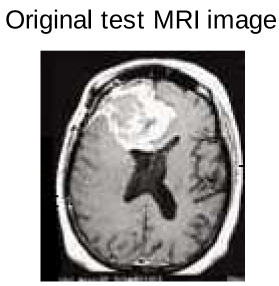

Figure.11. original test MRI image

Figure.11 represents the original MRI image used for testing. In the above figure, a tumor is observed at the upper part of image. Now this image is processed for the region segmentation.

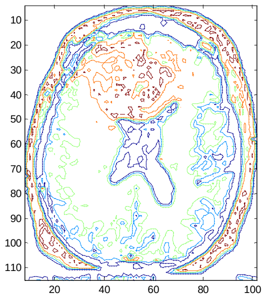

Figure.12. contour plot of test MRI image

Figure.12 represents the contour plot of test MRI image. In the above figure, each colour represnets one contour of image. Thus, the regions with tumor is also shown in a particular color to highligh the paert. The highlighted part is denoted as tumor.

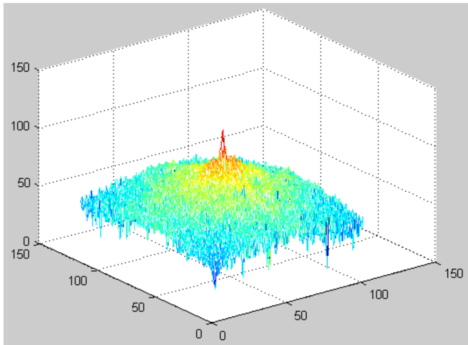

Figure.13. Power spectral density of MRI test image

Figure.13 show the power spectral density plot of the test MRI image. The peak at the center of image shows the highest power spectral density value of the image. Here, the PSD gives details about the spectral features of image thus, the pixel at which there is a more noise existence will be traced out and that particular region will be thresholded through the proposed approach. This increase the quality of image.

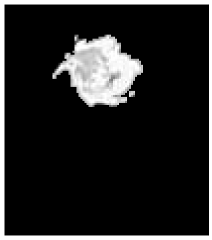

Figure.14. Extracted region

Figure.14 shows the final extracted region in which the tumor is existing. The above figure also shows the region with clear edges.

To verify the performance of proposed approach under noise variations, Peak Signal to Noise Ratio (PSNR) is evaluated. Peak signal-to-noise ratio, defined as a ratio between the maximum possible power of a signal and the power of corrupting noise that affects the fidelity of its representation. PSNR is usually expressed in terms of the logarithmic decibel scale. Peak signal to noise ratio is used to evaluate the quality of image after segmentation process.

The mathematical representation of PSNR is as follows:

$$PSNR(dB) = 10 log_{10}\left(\frac{I_{peak}^2}{MSE}\right) \quad (15)$$

Where $I_{peak}$is the peak values of the input image and MSE is the mean square error between original and segmented image. MSE measures the average of the square of the error. The error is the amount by which the estimator differs from the quantity to be estimated

$$MSE = \frac{1}{MXN}\sum(f - \hat{f})^2 \quad (16)$$

Where f is original image and $\hat{f}$ is the segmented image.

For all the above tested samples the PSNR is evaluated using the expression shown in (15) and the obtained values under different noise variations both for conventional and proposed approaches is shown in the following table.

TABLE.1 PSNR OBSERVED

Approach	PSNR		
	S1	S2	S3
Median filter	48.69	48.56	48.24
Spectral median filter	51.74	51.88	51.96
Orientation mapping	52.32	52.14	52.84

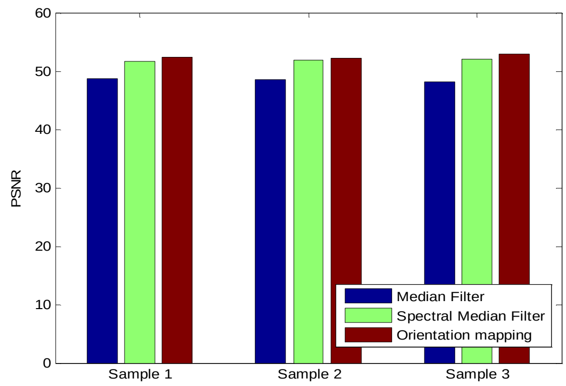

Figure.15 PSNR plot

The above figure illustrates the comparative analysis of the proposed approach with conventional approaches with respect to PSNR. As the proposed approach eliminates the noise present in the MRI image, the proposed approach achieves better PSNR compared to conventional ones. From the above it is clear that for the proposed approach, the obtained PSNR is high for all test cases.

VII. CONCLUSION

In this paper an image filtration and segmentation approach is suggested. The approach of image filtration using adaptive approach of median coding based on dynamic filtration is proposed. The spectral parameter of the given image is considered as the reference parameter to derive filtration coefficient, in contrast to a specified filtration as in median filter. The approach of segmentation is defined based on a simplified orientation logic and logical Anding operation, defined by a optimal weight parameter used for error minimization in region localization. The approach, defines the selection of pixels which are affine to rotational effect, hence the captured image are over come for affine and noise effect.

REFERENCES

[1] S Ahmed Shokry, “MRS of brain tumors: Diagrammatic representations and diagnostic approach”, The Egyptian Journal of Radiology and Nuclear Medicine 43, 603–612 Elsevier, 2012.

[2] Christoph Krafft, Larysa Shapoval, Stephan B. Sobottka, Kathrin D. Geiger, Gabriele Schackert, Reiner Salzer “Identification of primary tumors of brain metastases by SIMCA classification of IR spectroscopic images”, Vibrational Microscopic Imaging: Towards Molecular Pathology, Biochimica et Biophysica Acta (BBA) - Biomembranes Volume 1758, Issue 7, July 2006, Pages 883–891.

[3] J.F. Couat, J. Cegarra, T. Rodsphon, T. Geeraerts, C. Lelardeux, J.-C. Sol, P. Lagarrigue, V. Minville, V.F. Lubrano, “A prospective video-based observational and analytical approach to evaluate management during brain tumour surgery at a university hospital”, Neurochirurgie, 59 142–148, Elsevier Masson SAS, 2013.

[4] OlteaSampetrean, Isako Saga, Masaya Nakanishi, Eiji Sugihara, RaitaFukaya, Nobuyuki Onishi, Satoru Osuka, Masaki Akahata, Kazuharu Kai, Hachiro Sugimoto, Atsushi Hirao and Hideyuki Saya, “Invasion Precedes Tumor Mass Formation in a Malignant Brain Tumor Model of Genetically Modified Neural Stem Cells[1,2]”, 13, 784–791, Neoplasia, 2011.

[5] D. judehemanth, c. keziselvavijila, j. anitha, “A Survey On Artificial Intelligence Based Brain Pathology Identification Techniques In Magnetic Resonance Images”, International Journal of Reviews in Computing, 2009.

[6] Qolamreza r. razlighi, and nasserkehtarnavaz, “Spatial Mutual Information as Similarity Measure for 3-D Brain Image Registration”, Medical Imaging and Diagnostic Radiology, 2, 2168-2372, IEEE, 2014.

[7] Thomas F. Barrett, BA, Christopher A. Sarkiss, MD, Hadrien A. Dyvorne, PhD, James Lee, MD, PritiBalchandani, PhD, Raj K. Shrivastava, MD, “Application of Ultrahigh Field MRI in the Treatment of Brain Tumors: a Meta-analysis”, World Neurosurgery, 5,1878-8750, 2014.

[8] PadmakantDhage, Prof. M. R. Phegade, Dr. S. K. Shah, “Watershed Segmentation Brain Tumor Detection”, 2015 International Conference on Pervasive Computing (ICPC), 978-1-4799-6272-3/15, IEEE 2015.

[9] Sarah Parisot, William Wells III, StéphaneChemouny, HuguesDuffau , Nikos Paragios, “Concurrent tumor segmentation and registration with uncertainty-based sparse non-uniform graphs”, Medical Image Analysis 18 647–659, Elsevier, 2014.

[10] Whitney B. Pope, MD, PhD, “Genomics of Brain Tumor Imaging”, NeuroimagClin N Am, 25 105–119, Elsevier, 2015.

[11] Dr. Samir Kumar Bandyopadhyay, “Detection of Brain Tumor-A Proposed Method”, Journal of Global Research in Computer Science 2, 56-64, 2011.

[12] Mr. Ankush A Surkar, Ass. Prof. NitinAmbatkar, “Tumor detection with EEG Signals using Wavelet Transform”, International Journal on Recent and Innovation Trends in Computing and Communication, 3, 274 – 278, 2015.

[13] 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, 2, 2277-9477.

[14] Manuel Conson, Laura Cella, Roberto Pacelli, Marco Comerci, RaffaeleLiuzzi, Marco Salvatore, Mario Quarantelli, “Automated delineation of brain structures in patients undergoing radiotherapy for primary brain tumors: From atlas to dose–volume histograms”, Radiotherapy and Oncology 112 326–331, Elsevier, 2014.

[15] Shweta Jain, Shubha Mishra, “ANN Approach Based On Back Propagation Network and Probabilistic Neural Network to Classify Brain Cancer”, International Journal of Innovative Technology and Exploring Engineering 3, 2278-3075, 2013.

[16] Snehal kumar A. Patel, Utkarsh V. Shah, “Tumor Location and size Identification in Brain Tissues Using Fuzzy C- Clustering and Artificial Bee Colony Algorithm”, International Journal of Engineering Development and Research, 2, 2321-9939, 2014.

[17] Swapnali Sawakare and Dimple Chaudhari, “Classification of Brain Tumor Using Discrete Wavelet Transform, Principal Component Analysis and Probabilistic Neural Network”, international journal for research in emerging science and technology, 1, 2014.

[18] Parveen Khan, Amritpal Singh and Saurabh Maheshwari, “Automated Brain Tumor Detection in Medical Brain Images and Clinical Parameters using Data Mining Techniques: A Review”, International Journal of Computer Applications 98, 10975 – 8887, 2014.

[19] Shobana G, Ranjith Balakrishnan, “Brain Tumor Diagnosis From MRI Feature Analysis – A Comparative Study”, IEEE Sponsored 2nd International Conference on Innovations in Information Embedded and Communication Systems ICIIECS’15, 978-1-4799-6818-3, 2015.

[20] Abdul Kalam Abdul Salam, A. V. Deorankar, “Assessment on Brain Tumor Detection using Rough Set Theory”, International Journal of Advance Research in Computer Science and Management Studies, 2327782 , Volume 3, January 2015.

[21] AleksandraWandzilak, Mateusz Czyzycki, EdytaRadwanska, DariuszAdamek, KalotinaGeraki, MarekLankosz, “X-ray fluorescence

study of the concentration of selected trace and minor elements in human brain tumours", SpectrochimicaActa Part B 114 52–57, Elsevier, 2015.

[22] Dr. G. Vishnuvarthanan, Dr. M. Pallikonda Rajasekaran, Dr. P. Subbaraj, and Mrs. Anitha Vishnuvarthanan, "An Unsupervised Learning Method with a Clustering Approach for Tumor Identification and Tissue Segmentation in Magnetic Resonance Brain Images", Applied Soft Computing Journal 568-4946, 2015.

[23] Primi joseph, Er.D.Jagadiswary, "Classification Of Brain Tumour In MRI Using Probabilistic Neural Network", International Journal of Emerging Technology in Computer Science & Electronics (IJETCSE), 7, 0976-1353 –2014.

[24] NooshinNabizadeh, MiroslavKubat, "Brain tumors detection and segmentation in MR images: Gabor wavelet vs. statistical features", Computers and Electrical Engineering xxx, Elsevier, 2015.

[25] Eman Abdel-Maksoud, Mohammed Elmogy , Rashid Al-Awadi, "Brain tumor segmentation based on a hybrid clustering technique", Egyptian Informatics Journal 16, 71–81, Elsevier, 2015.

[26] Vasileios G. Kanas, Evangelia I. Zacharaki, Christos Davatzikos,Kyriakos N. Sgarbas, VasileiosMegalooikonomou, "A low cost approach for brain tumor segmentation based on intensity modeling and 3D Random Walker", Biomedical Signal Processing and Control 22, 19–30, Elsevier, 2015.