Segmentation of Brain MRI Images using Fuzzy C-Means and DWT

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Abstract

Medical image processing deals with enhancement, segmentation etc. of medical images like brain MRI, CT scan images of liver, pancreas etc. The segmentation of the part in image is to be done accurately. Especially in medical images, the segmentation result has to be accurate. In this proposed work, the brain MRI images segmentation using fuzzy c means clustering (FCM) and discrete wavelet transform (DWT). In this work, two algorithms are considered. One is level set segmentation using fuzzy c means by using special features (SFCM) and another one is segmentation of brain MRI images using DWT and principal component analysis (PCA) are further processed using support vector machine (SVM) for classification. The performance evaluation is done by computing mean square error, peak signal to noise ratio (PSNR), maximum difference, absolute mean error etc. Here DWT uses k- means clustering and level set uses fuzzy c- means clustering. The spatial constraints are named with different indexes such as the user can choose on particular region of interest and iterate the contour steps until more accurate result to be obtained.

Keywords: Fuzzy c means clustering, SFCM, PCA, DWT

I. INTRODUCTION

The processing of digital images using computer algorithm is nothing but digital image processing (DIP). For various categories of DIP, there are numerous benefits in excess of analog image processing which gives a large amount of input information algorithm which can keep away from troubles such as the rapid increase of noise during processing and distortion of signal. Meaning of segmentation is to divide a digital image into several regions or boundaries. It is also differentiating different objects which generate smoothing in images and simple to estimate. This method includes the techniques like thresholding, Region dependent, fuzzy-based, Edge-detection etc. In this thesis, a multiple number of fuzzy methods for image segmentation are considered. Several techniques for better clustering and segmentation have been evaluated.

Innovative development in radiological knowledge betrays the significance of image processing in clinical analytical interaction in last couple of years. An amount of medical equipments in treatment, diagnosis have been made-up. The general objective of entire these tools are to plan a well-organized segmentation algorithm. In addition, several image analysis and processing methods are developing to have appreciative images which may well support to create on time and precise decision. A few methods of medical imaging are PET (Positron Emission Tomography), Ultrasound, Magnetic Resonance Imaging (MRI) and X-ray CT (Computed Tomography). Usually all these techniques use automated computerization to practice of digital images. Thus analysis of multi-dimension images could demonstrate distinctive features through computers.

Images in medical field frequently include few precise characters like inhomogeneity as well as noise. Thus, detection of images in medical field appears as sophisticated, also defiant method. For the reason that the most researchers use MR images for diagnosis. A common segmentation sort of brain MRI is the procedure of labeling pixels w.r.t their kind of tissue containing grey Matter, particularly pathological tissues like edema and tumor, cerebrospinal fluid and white Matter.

The processing of brain image as well as segmentation is challenging task nowadays. The segmentation of these images gives the result such that the pre and post-surgery be made and time of the medication can speed up and recover very fastly. The MRI image assists to eradicate tumor growth. The tissue classification using DIP is a difficult task because of noise introduced by scanner. Thus intensity values ranges in different tissues. To overcome issues in proposed work, two algorithms has been considered and also segmentation on brain images is performed, its methodology and result can be compared by the feature values are shown in section 3 and 4. By observing the benefits of FCM algorithm gives better results can be validated. Segmentation is regarding split the entire image into several segments. This technique tells about isolating whole image into sub blocks that may perhaps comparison in similar or dissimilar images w.r.t. features.

The most commonly used are segmentation based on fuzzy clustering and fuzzy rule. The problem with segmentation based on fuzzy rule techniques is they depended on application along with the membership- function arrangement which are already defined in several cases and the parameters are developed manually. Benefits of FCM is to deliver accurate results for data set which is overlapped and it is much efficient than k-means algorithm. For image processing FCM is significant tool for clustering the objects. To obtain accuracy in the presence of noise researchers developed spatial name into FCM algorithm. Fuzzy geometrical measures such as index of area coverage and fuzzy compactness can be used to calculate the geometrical fuzziness of several regions of an image. The optimization measures can be applied to build crisp and/or fuzzy pixel classifications. Information of images (e.g. fuzzy divergence) and fuzziness measures (e.g. fuzzy entropy) can be also used in thresholding and segmentation tasks.

Wavelet transform is another effective tool for MR brain images to exact features, since it allows image analysis at different levels of motion suitable to its multi-resolution diagnostic property. On the other hand, this method requires huge storage and is computationally costly. Rapid increase in power as well as suddenly decreases characteristic vector dimensions, PCA i.e., the principal component analysis was used. PCA is interesting since it efficiently decreases the dimensionality of the information and consequently decreases the computational cost of analyze the new information. Then, the difficulty of how to categorize on the input data arises. In modern years, researchers have projected a lot of approaches for this purpose, which includes into two categories. Supervised classification is one category, containing k-NN and SVM. Whereas all these techniques gained good outcomes, and however, the supervised classifier performs better than unsupervised classifier in terms of accuracy classification.

The next section discusses about literature survey and section.3 discusses about methodology and at last shows the results and conclusion.

II. BACKGROUND AND RELATED WORK

Mohammad and Ahmed [1] recommend a segmentation method by employed K-means clustering for tumor detection. On the foundation of the resulting cluster values, tumors are detected from the MRI images. The major disadvantage of this algorithm is its sensitivity to fake edges.

In this work image segmentation using fuzzy clustering and fuzzy edge detector are calculated. Proficient edge detection method using fuzzy technique which would defer excellent segmentation outcomes as well as discussed about the number of methods for tracking of edge without their use of applications [5].

The literature is supplied with methods for images of MR used to extract tumors in person's brain. These consist of statistical models, region growing, clustering, active contour models and thresholding [2].

Several thresholding based methods can be established in this literature. Toriwaki and Suzuki [3] recommend thresholding method for segmentation of brain tumor guided by knowledge. One of the general method is region growing. It requires to segment each region to find out seed point along with homogeneity for certain threshold is introduced [4].

Li et al. [6] designed segmentation of brain using a watershed algorithm. This is a grade based method, furthermore it communicates on contrast of image during acquisition of image that could be corrupted and yields to incorrect outcome.

Anandhakumar and Rajaswari [7] considered segmentation of image based on a multi-label used for applications in medical field depended on graph cut. This technique is based on area adjacency produced morphology are applied on watershed transform. It provides higher speed in segmentation.

In some time, fuzzy C-means is being in used, e.g. Hall et al. [8] have intended segmentation of image for algorithm of FCM clustering. FCM defines a few value of intensity used in thresholding although in this, working of homogeneous as well as noisy images are failed.

M.N. Ahmed, N. A. Mohamed et al. [9] explained the fuzzy set theory application for medical imaging. A entirely usual method to achieve cluster is proposed. To provide a fuzzy partition, a modified fuzzy c-means algorithm classification is used. The technique is used to establish less amount of noise during clustering and is motivated by Markov random Field (MRF).

R. C. Staunton and Li Ma [10] represented a novel method for algorithm of FCM to be used when structured or active illuminations are predictable against a scene. The recursive method for algorithm of FCM is adapted to comprise influenced light field evaluation.

III. PROPOSED WORK

In order to differentiate the parts of data the segmentation is one which is used in image processing. In this chapter the algorithms of the proposed work will be discussed. The datasets considered in the proposed work are of T2-weighted MRI brain images in axial plane with 256 X 256 in-plane resolution, which were downloaded from the websites of Harvard Medical School, OASIS database, and ADNI dataset. We choose T2 model since T2 images are of higher-contrast and of clearer vision.The proposed work consists of two algorithms the first one is segmentation of brain MRI images using spatial features and fuzzy logic with level set, the another algorithm uses Principal component analysis (i.e., PCA) and Discrete wavelet transform(i.e., DWT) to extract features and classify the segmentation. The similar DWT and PCA is used for image obtained with spatial features and fuzzy. The classification gives the same result but level set evolution is the better approach to visualize the segmented image can be validated. The results obtained are discussed in next chapter.

A. Fuzzy c-means clustering

FCM is a technique of clustering which allow one piece of information which belongs to two or more clusters. This technique was discovered in 1974 by Dunn and enhanced in 1980 by Bezdek is frequently used in pattern recognition. The main aspect of this algorithm works by assigning membership values to each data point consequent to each cluster center on the basis of distances between the cluster and the data point, Higher the membership value then more the data near to the cluster center. Clearly, summation of membership of each data point should be equal to one.

$$J_m = \sum_{i=1}^{N}\sum_{j=1}^{C} u_{ij}^{m} \left\| x_i - c_j \right\|^2, \quad 1 \le m < \infty$$

where, number of data=N, number of clusters=C, Fuzziness exponent that is a real number > 1 is m, the ith of d-dimensional calculated information is x_i , membership degree of x_i in the cluster j is u_{ij} , the d-dimension cluster center is c_j, and ||*|| is any standard which express the similarity among any measured information and the center.

An iterative optimization of the objective function is carried out through fuzzy partitioning shown above, with the keep informed of membership u_{ij} and the cluster centers c_j by:

$$u_{ij} = \frac{1}{\sum_{k=1}^{C}\left(\frac{\left\|x_i - c_j\right\|}{\left\|x_i - c_k\right\|}\right)^{\frac{2}{m-1}}} \quad \text{--------- (1)}$$

where, $\|x_i - c_k\|$ is the Distance from point i to other cluster centers k, $\|x_i - c_j\|$ is the Distance from point i to current cluster centre j, the iteration will end when $\max_{ij}\left\{\left|u_{ij}^{(k+1)} - u_{ij}^{(k)}\right|\right\} < \varepsilon$, where ε is a termination condition among the 0 and 1, whereas k are the steps of iteration. These processes converge to a saddle point or a local minimum J_m.

The algorithm is composed of the following steps:

Randomly select the cluster centre from given image

Initialize U=[uij] matrix, U(0) (eqn-1)

At kth-step: calculate the centre vectors of the clustered data C(k)=[cj] with U(k)

$$c_j = \frac{\sum_{i=1}^{N} u_{ij}^{m} \cdot x_i}{\sum_{i=1}^{N} u_{ij}^{m}}$$

keep on updating: U(k) , U(k+1)

$$u_{ij} = \frac{1}{\sum_{k=1}^{C}\left(\frac{\left\|x_i - c_j\right\|}{\left\|x_i - c_k\right\|}\right)^{\frac{2}{m-1}}}$$

If the minimum J value is achieved or || U(k+1) - U(k)||< ε, then STOP; otherwise return to step 2.

B. Fuzzy c-means clustering with spatial features:

The clustering is used to group the data into similar groups of data mining. It exploits the segmentation of the part in an image for a quick view. In this algorithm, the fuzzy logic and the spatial features are combined together to get the level set segmentation of the brain MRI images. The membership of the cluster is derived by the evaluation of centroid of each one group and it will be assigned to object group of the nearby centroid.

The method used to minimize the entire cluster dispersion by iterative reallocation of the clusters centroid. The Fuzzy-C means allows the in more than one clusters depended on the fuzziness or membership value. Summing up the membership of each data points in the particular datasets must be equal to each other. Let C = {c1, c2, c3 ..., cn} be the set of centers and X = {x1, x2, x3 ..., xn} be the set of data points. The following equations μij and cj explain the membership and cluster center updation for each iteration.

$$\mu_{ij} = \frac{1}{\sum_{k=1}^{c}(d_{ij}/d_{ik})^{(2/m-1)}}$$

$$c_j = \sum_{i=1}^{n}\left(\frac{((\mu_{ij})^{m}\, x_i)}{(\mu_{ij})^{m}}\right)$$

Where,

c = the number of cluster, dij =the distance among the jth cluster center and ith data, n = number of data points.

μij = the membership from ith data to jth center of cluster, m = index of fuzziness, cj = the jth center of cluster.

Many researchers working with brain images include the spatial information of the images into the FCM algorithm in order to improvise the segmentation results [15,16]. The spatial features are extracted and updated based on the membership values of the neighboring pixels. In this work the spatial domain and its features are considered to improvise the segmentation results. The spatial features with the different structures are taken to analyze the segmentation results, for each different structure are named with different indexes and user or doctor can choose the particular index and that index corresponding is further processed for level set segmentation. The advantages of fuzzy with spatial constraints are, it overcomes the noise sensitivities of the standard algorithm of FCM and blurred images. The figure 3.2 represents the flow chart of the proposed algorithm.

The new fuzzy level set algorithm automates the parameter and initialization configuration, using spatial fuzzy clustering. It employs an FCM with spatial boundaries to establish the fairly accurate contours of interest in a medical image. Benefitting from the flexible initialization as in Equation shown below of Φ0, the enhanced level set function can accommodate FCM outcomes directly for estimation. Assume that the element of interest in an FCM outcome is R_k: {rk=fi$_n$k' n=xx.N$_y$+y}. It is subsequently suitable to instigate the level set function as:

$$\phi_0(x, y) = -4\varepsilon(0.5-\mathbf{B}_k),$$

where, e is a constant adaptable the Dirac function. It is then defined as follows:

$$\delta_\varepsilon(x) = \begin{cases} 0, & |x| > \varepsilon \\ \frac{1}{2\varepsilon}\left[1+\cos\left(\frac{\pi x}{\varepsilon}\right)\right], & |x| \le \varepsilon \end{cases}$$

B_k is a binary image obtained from

$$\mathbf{B}_k = \mathbf{R}_k \ge b_0.$$

where, b_0(e(0, 1)) is an modifiable threshold. Beneficial from spatial-fuzzy clustering, B_k be able to some sense estimated the element of interest, which can be willingly adjusted by b_0. The controlling parameters associated with level set methods (Table 3.1), all of which are used in this work for brain image segmentation. The configuration of these parameters is essential such that to build it vary correctly. At present there are simply a few common rules to direct these parameters configuration. For example, it is recognized with the purpose of a larger a leads to a.

Table 3.1: Parameters associated with level set methods

The parameters controlling level set segmentation.

Parameter	Significance
σ	Controlling the spread of Gaussian smoothing function
C	Controlling the gradient strength of initial level set function
ε	Regulator for Dirac function $\delta(\phi)$
μ	Weighting coefficient of the penalty term $\zeta(\phi)$
λ	Coefficient of the contour length for smoothness regulation
ν	Artificial balloon force
τ	Time step of level set evolution
T	Maximum iteration of level set evolution

Smoothening of image, but sacrifices an image detail. A larger time step t may accelerate level set evolution, but incur the threat of boundary leakage. Moreover, it is essential to select a positive v if the initial $4>_0$ is outside the component of interest, and vice versa. The flow chart of fuzzy c means with spatial constraints shown in figure 3.1.

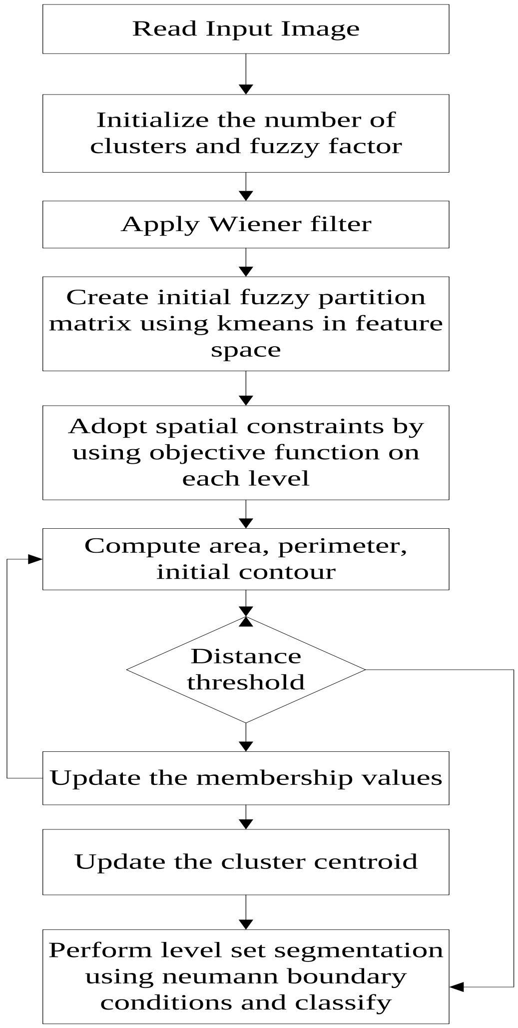

Fig. 3.1: Flow chart of fuzzy c means with spatial constraints

Level set segmentation algorithm steps are as follows:
1) Read the input image.
2) The image is filtered by using Gaussian filter. The filter is used to remove the noise from the image so as to make image more sharp and smooth.
3) Now the matrix values are converted into more uniform and simplified form so that further calculation can become easy with the help of formula

$$f = I x^2+I y^2$$

4) Create the initial fuzzy partition matrix using k-means in feature space. The image divided into sub matrices.
5) Obtain the spatial constraints or feature spaces by using objective function $\Phi 0$ with different indexes.
6) Compute the area, perimeter and initialize the contour for particular index choosen.
7) In this step all parameters are defined which change the topology of the level set speed and stability. The parameters (Table-4.1) are alpha, time step, MU, lambda and epsilon.
8) The gradient of the preprocessed image is computed.
9) This gradient image is used to compute the edges of an image. For calculation of edges following function is used:

$$g=1/1+f$$

10) Compute the feature values like standard deviation, Mean Square Error, structuring element etc which are utilized for classification.
11) Initialization of level set means starting the shape of contour which depends upon the region.
12) In this step all the parameters are passed and initialize level set to the evolution function with iterations. In this function, make a function that satisfies the Neumann boundary condition.
13) Calculate the gradient of the above function. Evolve the curve using Dirac function and curvature. Finally update the level set function.
14) The step 7 will be repeated until we do not get the final level set. The repetition depends on the number of iterations.
15) In this step, final level set will be displayed.

Segmentation of Brain MRI Images using DWT and K-means clustering

The next algorithm implemented in the proposed work is Discrete Wavelet Transform based segmentation of brain images using features from principal component analysis. The flow chart can be shown below in figure 3.2. First wavelet transform is applied to remove/extract features from images, follow through PCA i.e., applying principle component analysis to decrease the dimensions of features.

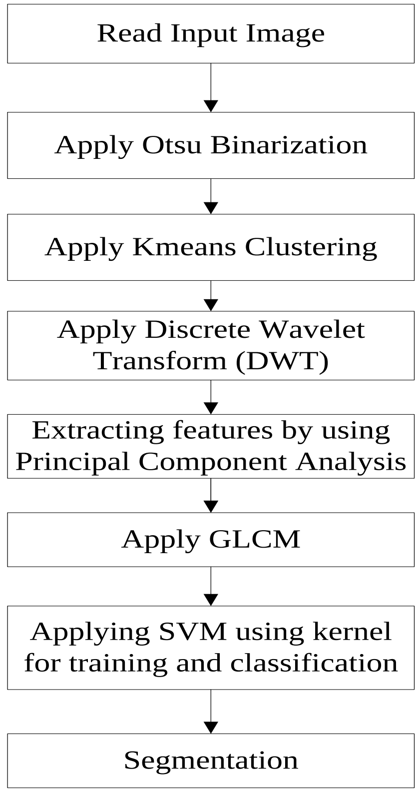

Fig. 3.3: Flow chart of segmentation of brain images using DWT

The steps involved in this process are shown below:
1) Read the input image.
2) Convert the image to black and white using otsu binarization.
3) Initially cluster the data using k-means clustering
4) Apply the discrete wavelet transform. For feature extraction the DWT is a more effective tool for feature extraction. It allows analyzing of images at various level of resolution.
5) Extracting the features using principal component analysis.
6) Applying gray level co-occurrence matrix to find the Energy, Entropy, RMS, Homogeneity, Mean, Standard Deviation, Variance, Smoothness, Contrast, Correlation, Kurtosis, Skewness, IDM and the Peak Signal to Noise ratio, Structuring element, Mean Square Error, maximum difference etc. utilized for the performance evaluation.

IV. EXPERIMENTAL RESULTS

The algorithms used in the proposed work are discussed in the previous section. This chapter deals with the results that are obtained with both algorithms. The database consists of brain MRI images with normal and tumor images. The both algorithm uses the features like Energy, Standard Deviation, Contrast, Smoothness, Kurtosis, Correlation, Entropy, Homogeneity, RMS, Variance, Mean, Skewness, IDM and the Mean Square Error, Peak Signal to Noise ratio, Structuring element, maximum difference etc utilized for the performance evaluation.

In the fuzzy c-means algorithm indexed image shown in figure 3.3. Is the option for the user to select which is obtained by spatial constraints or features? The user selects one of the indexes to next which make use for the level-set evolution. Subsequently, after that getting the fuzzy segmented image it is further processed to get features using DWT and PCA and classify the tumors. The DWT based algorithm uses the k-means clustering and features extracted using PCA and further the Support Vector Machine is used to classify and train the data.

The classification by both the algorithms with different indexes gives the correct result but the level set used can be further processed with number of time step iterations and shows the interested cluster chosen with contour representation. The results are obtained by using MatLab v-8.1, operating system used is windows-8, i3-processor and with 4GB of RAM.

Table - 4.1 (a-b)
The values obtained for image set of benign tumora

Images	Mean square error	Peak signal to noise ratio	Structural content	Maximum difference	Normalized absolute error
Img(1)	5.85E+03	10.4568	500.4588	260.2453	1.0476
Img(2)	6.10E+03	10.2799	26.5748	260.5892	1.0446
Img(3)	5.26E+03	10.9194	4.73E+02	260.8487	1.0571
Img(4)	2.82E+03	13.621	2.43E+02	237.0716	1.0683
Img(5)	4.76E+03	11.3533	3.87E+02	215.4371	1.0495
Img(6)	6.71E+03	9.8607	5.94E+02	258.9556	1.0204
Img(7)	3.75E+03	12.3955	3.42E+02	248.1452	1.0912
Img(8)	2.12E+03	14.8778	1.73E+02	207.7271	1.0452
Img(9)	6.04E+03	10.3173	6.45E+02	259.2565	1.0376

b

Images	Mean square error	Peak signal to noise ratio	Structural content	Maximum difference	Normalized absolute error
Img(1)	5.27E+03	10.913	442.4817	262.6	1.068
Img(8)	1.09E+04	7.741	939.5692	259.5953	1.032
Img(10)	1.61E+04	6.056	1.39E+03	262.3812	1.019
Img(15)	1.37E+04	6.7603	1.26E+03	261.2314	1.0252
m(1)	1.74E+04	5.7328	1.42E+03	261.407	1
m(2)	8.43E+03	8.8748	7.08E+02	759.3063	1.036
m(3)	4.10E+03	12.0099	2.95E+02	258.93	1.0665

The table 4.1-4.3 shows the results obtained for different type of brain MRI images. It can be observed that structural content and the MSE and the differences are almost same and PSNR is high.

Table - 4.3
The values obtained for image set of Normal brain images

Images	Mean square error	Peak signal to noise ratio	Structural content	Maximum difference	Normalized absolute error
b(1)	5.70E+03	10.5713	471.9487	253.4061	1.0455
b(2)	7.55E+03	9.3533	654.5371	258.6788	1.0321
b(3)	8.39E+03	8.8923	736.9971	244.8088	1.0332
b(4)	1.07E+03	7.8404	922.5397	260.8324	1.0364
b(5)	1.02E+04	8.0465	907.4445	261.3376	1.0239
b(6)	4.49E+03	11.6092	367.8379	252.9283	1.0643
b(7)	9.67E+03	8.2783	846.4856	261.9094	1.0391
b(8)	5.40E+03	10.8077	461.7295	261.748	1.0127
b(11)	1.43E+03	6.5879	1.27E+03	261.3789	1.0203
b(12)	9.70E+03	8.2647	831.7844	254.75	1.0341
b(13)	8.05E+03	9.0716	634.7381	261.2096	1.0264
b(15)	4.43E+03	11.6719	358.7675	257.9079	1.0259
b(19)	7.17E+03	9.5754	630.8254	259.4025	1.0342
b(20)	2.52E+03	14.116	213.2098	213.8332	1.091

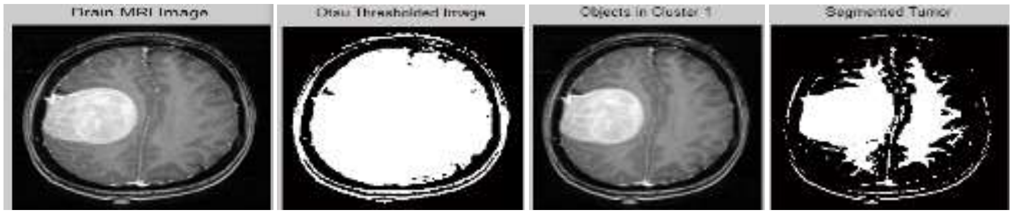

Fig. 4.10: Images of benign tumor using DWT

The figure 4.10 shows the images of benign tumor outcomes using DWT, otsu thresholded, the input image, and the number of clusters and the segmented tumor can be seen. The figure 4.10 shows the images with different spatial features, the user can be chosen the index value that he is interested and fig 4.12(a-d) shows the level set segmented results with different indexes.

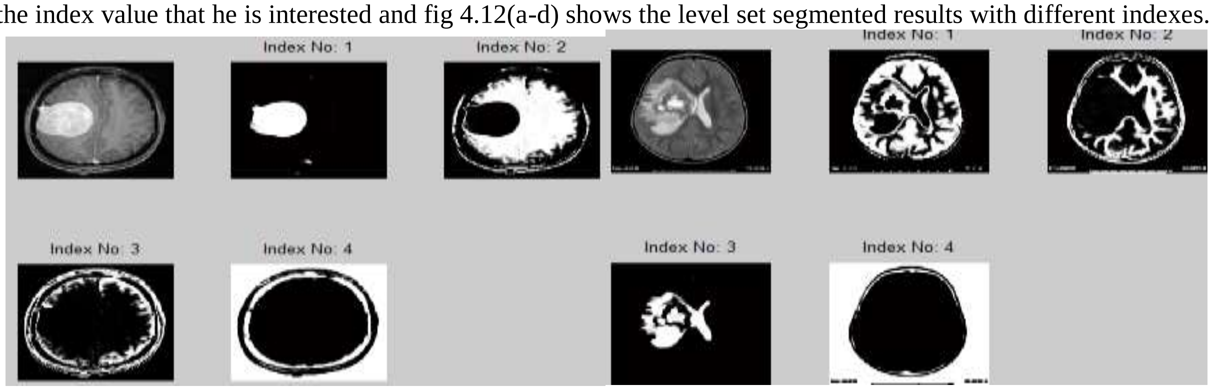

Fig. 4.11: Images of benign and malignant tumor of spatial constraints using fuzzy-c means

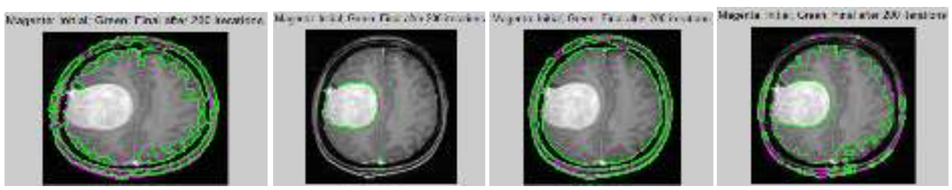

Fig 4.12: Results of level set segmentation along with different indexes

The figure 4.15 shows the images of malignant tumor outcomes using DWT, otsu thresholded, the input image, and the number of clusters and the segmented tumor can be seen. The figure 4.11 shows the images with different spatial features, the user can be chosen the index value that he is interested and fig 4.14 shows the level set segmented results with different indexes.

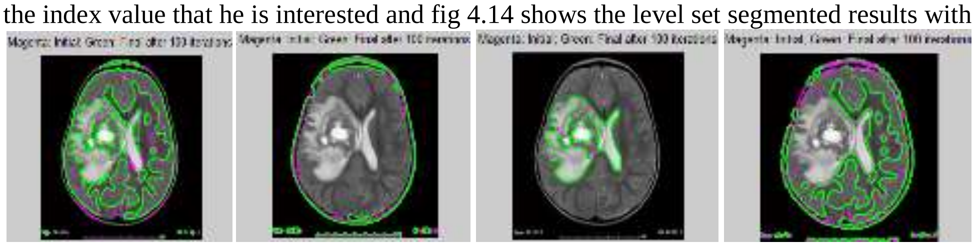

Fig 4.14: Results of level set segmentation along with different indexes

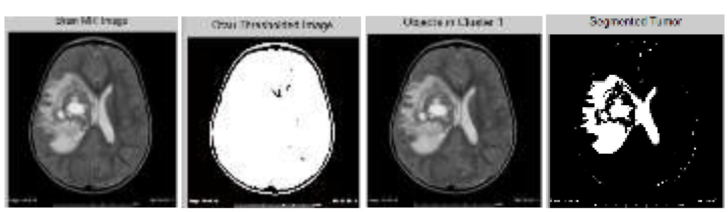

Fig. 4.15: Images of malignant tumor using DWT

V. CONCLUSION

The proposed work is used for segmentation of different brain MRI images and to classify. The algorithms implemented are of two types one is using fuzzy c-means and other is using DWT. By observing the results, we can conclude that features used for classification can be used for both the algorithms but the segmentation using DWT provides the direct outcomes of classification but the level set evolution using the fuzzy and spatial constraints gives the results with user selected index. The user can summarize the segmentation by means of particular region of interest and number of iterations can be validated.

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