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Automatic Tumor Extraction from MRI Brain Images Using Hybrid Clustering Algorithm

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ABSTRACT

This study focuses on the implementation of an improved method for detecting single and multi-tissues in MR brain images and accurately estimating their respective areas. The proposed approach utilizes hybrid clustering techniques and estimates tissue areas in terms of square millimeters (mm^2) by leveraging typography and digital imaging units. The implementation demonstrates enhanced accuracy and reduces computational time compared to existing algorithms. To validate the effectiveness of the proposed method, simulation results were compared with those obtained using other algorithms. The findings indicate that the proposed approach yields favorable outcomes in terms of tissue detection and area estimation. Furthermore, this methodology holds the potential to be extended to 3D multi-modal medical image segmentation, incorporating more effective and accurate clustering algorithms. The successful implementation of this approach contributes to the advancement of tissue detection and area estimation in MR brain images, offering improved accuracy and computational efficiency. This work paves the way for further research and development in the field of medical image analysis, with potential applications in clinical diagnosis and treatment planning.

Keywords: Single and multi-tissue detection, MR brain images, Medical image analysis.

1. INTRODUCTION

In radiology, magnetic resonance imaging (MRI) [1] is used to investigate the human body processes and functions of organisms. These images can be formed by using the magnetic fields and radio waves. In hospitals, this technique has been using widely for medical diagnosis, to find the disease stage and follow-up without exposure to ionizing radiation. MRI has a broad range of applications in medical diagnosis and in all over world there are over 25,000 scanners to be in use. It has an impact on diagnosis and treatment in many specialties although the effect on improved health outcomes is uncertain. MRT is preferable over computed tomography (CT) since it does not use any ionizing radiation, when either modality could yield the same information. The sustained increase in demand for MRI within the healthcare industry has led to concerns about effectiveness of cost and over diagnosis. Segmenting an image is an effort to group similar colors or elements of an image into a cluster or group. This can be achieved by clustering, which clusters the number of colors or elements into several clusters based on the similarity of color intensities and gray intensities of an image.

Main objective of clustering an image is dominant colors extraction from the images. By extracting the information from images such as texture, color, shape and structure, the image segmentation can be very important to simplify. Because of the information extraction in any images, the segmentation has been used in many fields such as Enhancing the image, compression, retrieval systems i.e., search engines, object detection, and medical image processing [2].

From the past decades, there are so many approaches developed for the image segmentation. Among those, Fuzzy c-means (FCM) is a well-known method and very popular clustering scheme, which will segment the image into several parts based on the membership function [4] and [5]. After

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FCM, the K-means algorithm has been proposed to reduce the computational complexity of FCM. Because of its ability to cluster huge data points very quickly, K-means has been widely used in many applications [4], [7], [8] and [9]. Later years the Hierarchical clustering is also widely applied for image segmentation [12], [13] and [14]. Then after, Gaussian Mixture Model has been used with its variant Expectation Maximization for segmenting the images [17] and [18].

Here in this, hybrid clustering with estimate arguing algorithm is proposed for detecting the multi tissuesin brain images with an improved performance over conventional segmentation techniques such as fuzzy c means (FCM), K-means and even that of manual segmentation in terms of accuracy. This system has mainly four modules: pre- processing, segmentation, Feature extraction, and estimate arguing. Pre-processing is done by median filtering. Segmentation is carried out by unified iterative partitioned fuzzy clustering (Hybrid Clustering). Area estimation is done by calculating tissue area and number of cells it occupied.

2. LITERATURE SURVEY

Idanis Diaz introduced automatic brain tumour segmentation (ABTS) method for segmenting different constituents of the tumour in the brain. The approach was applied on four magnetic resonance image modalities to find the edema and gross tumour volume (GTV). The ABTS segmentation algorithm uses a histogram multi-thresholding technique and morphological operations like geodesic transformations. The registered images containing the standard MR sequence was applied as input. The first step was thresholding, followed by Skull, Edema and gross tumour volume (GTV) segmentation. The method is fast and accurate for images produced from different scanners as it automatically identifies thresholds based on the histograms.

Meiyan Huang derived a novel classification framework. In this paper, the local independent projection was introduced into the classical classification model. Calculations of the local independent projections for LIPC (independent projection-based classification) method are carried out where Locality is an important parameter. LIPC technique also takes into consideration the data distribution of different classes by learning a model called soft max regression. This can further improve classification performance. The proposed method consists of four major stages, i.e., pre-processing, tumour segmentation using the LIPC method, feature extraction, and post-processing with spatial constraints. A multi-resolution framework was embedded to reduce the costs of computation. Experimental results were obtained for Synthetic Data as well as Image data. The challenges of tumour segmentation methods which arise due to the complex characteristics exhibited by the brain tumour MRI images, such as high diversity in the appearance of tumour and the ambiguous boundaries of the tumour, were addressed by this method.

Jin Liu provided a comprehensive overview for MRI-based tumour segmentation methods and described the different imaging modalities. The pre-processing operations and the state of the art methods of MRI-based brain tumour segmentation were explained in details. Then, the results of the MRI-based tumour segmentation were evaluated and validated. Finally, an objective assessment was presented to address the future developments and trends of the brain tumour segmentation methods using MR Images. Many segmentation techniques have greatly aided in finding a solution to the various challenges posed by the semiautomatic and fully automatic systems.

Dr Mohd Fauzi Bin Othman proposed an overview of MRI brain tumour classification using Field Programmable Gate Array (FPGA) implementation. Field Programmable Gate Arrays are the most suitable option for real time analysis of algorithms used in image processing, as they can be customized and are flexible. They save time and money for implementation of new segmentation techniques on hardware. In this approach, an advanced kernel-based technique such as Support Vector

Machine (SVM) is used for classifying the MRI data images as normal (without a brain tumour) and abnormal (with a brain tumour). Wavelet transform is used to eliminate noise and then inverse wavelet transform is applied to obtain the output image which is free from noise. Thus, a wavelet-based feature extraction is performed. However, SVM is not very precise with large data sets as it is dependent on the size of the input data. Hence, it is suggested that the SVM could be collaborated with clustering method to obtain better evaluation results.

Deepthi Murthy T.S. suggest that efficient segmentation can be performed by using the thresholding technique followed by application of morphological operations. In this paper, features of the brain tumour like centroid, perimeter and area, are calculated and evaluated from the segmented tumour image. Pre-processing was done using sobel operator which was followed by the process of histogram equalization (to equalize the intensities/pixels of the image) for the enhancement of the image. Then, the process of segmentation using morphological operations was performed in order to acquire the region of interest. Thus, the tumour was detected. In future work, it is suggested to determine more features in order to classify the different types of tumour.

Hongzhe Yang presented a comprehensive survey on brain tumour detection methods and also the technologies using MR images. Some segmentation techniques discussed were based on Classification and Clustering Technology, Continuous Deformable Models, Spatially Discrete Approaches, Hybrid Methods with Feature Information and Atlas–based Segmentation. The experimental results gave measurements of Overlap, Hausdorff Distance, Dice Coefficient (and False Ratio), Sensitivity and Specificity.

Heena Hooda have discussed the performance efficiency of various techniques used in segmentation of MR images. The evaluation and performance parameters were obtained on the basis of percentage calculation of the amount of error which was later compared to the ground truth.

The radiologists in clinics spend about 10-15 minutes to diagnose one report. Manual detection is not only time consuming but also prone to human errors. Automatic systems can accurately detect tumours, saving time and yielding reliable results. In this paper, an approach to detect brain tumours automatically, without initial estimates, is illustrated. The average dice coefficient gives a reliable and accurate value for the database used. The segmentation algorithm is simple which is followed by labelling. Fuzzy C-Means clustering technique which uses the fuzzy logic to establish a degree of belonging to each pixel is used. This technique is also known as soft clustering and gives accurate results.

The author in [3] presented a segmentation algorithm that was based on improved watershed approach. This approach provided some better enhancements over manual segmentation algorithms, but it was suffering from few restrictions like over segmentation and sensitive to false edges. In [4], a fuzzy implementation has been presented by the author named fazel. Fuzzy is a set of rules and regulations, in which the segmentation depends on the membership values. However, fuzzy wasn't without drawbacks, it suffers from computational complexity due to its dependency on membership function. Later, many researchers tried to implement hybrid combos with the integration of FCM algorithm. Author in [5] presented an effective segmentation of tissue in brain images by utilizing the combo of spatial information and FCM, this resolved the issue found in [4], but it was also taking more computational time to segment an image and also suffer from false edges. To overcome the limitations of above-mentioned segmentation algorithms, the author in [6] proposed an efficient segmentation algorithm which utilized k-means clustering for segmenting MR brain image. This approach was an extended version for the watershed, manual segmentation and FCM based algorithms. Segmented output of k-means is quite better than those algorithms and this takes very less time to compute the segmented images. From then many researchers tried to implement integrated algorithms with the

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combination of k-means clustering to get the enhanced performances in [7-10]. However, this K-means depends on the selected centroids initially. It needs new centroids to be updated by calculating the mean of obtained clustered points in the first iteration. The mean of these values provides the floating values which were not favorable for replacing as a new centroid. Therefore, K-means must optimize for the integer or scalar centroid to be replaced with the existing centroid. In [11], the author has proposed a pillar- based approach to optimize the K-means clustering, in which the maximum value is selected instead of calculating the mean value to replace the initial centroid. Authors in [19-21] presented a hybrid algorithm for tumor detection and extraction from brain images, but they failed to detect the tumor with higher accuracy.

3. PROPOSED METHODOLOGY

Here in the proposed clustering algorithm, we optimized the k-means clustering by applying fuzzy algorithm.

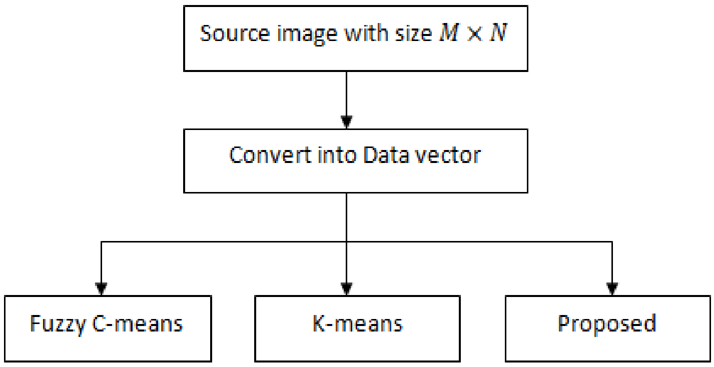

Fig. 1: Brain Tumour segmentation flow diagram

Algorithm 1

Input image = I

Output image = O

Step1. Select and read the input brain image ‘I’

Step2. Reshape ‘I’ into data sets of column vector (C_v) for segmentation.

Step3. Determine the number of clusters (K) i.e., centroids.

Step4. Calculate the distance (D) between C_v and ‘K’ for each pixel to cluster point

Step5. Find number of C_v which are neighbouring to the ‘K’.

Step6. Select the ‘K’ with minimum distance and then move the C_v to the closest relevant centroids.

Step7. Re estimate the centroids by selecting the maximum pixel value from the set of relevant centroid data points.

Step8. Repeat the process until the new centroids and the previous centroids are symmetrical.

Algorithm 2

Input image = O

Output image = S

Step1: Read the output image ‘O’, which has been obtained from algorithm1

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Step2: Apply fuzzy algorithm to the image 'O'

Step3: Display the segmented brain tissue image in which we had a tumour

Step4: Then calculate the area of the tumour using estimate arguing method, in which the area of the tumour will be calculated by considering the number of white pixels

Step5: And also compute the CPU time in seconds for the comparison of proposed and existing techniques

K-means clustering

- First, we will select the number of centroids randomly i.e., depends on number of clusters
- Now, partition the objects within each cluster.
- It finds partitions such that pixels within each cluster are as close to each other as possible, and as far from objects in other clusters as possible.
- The objects that are in the cluster or not will be calculated by measuring the distance between the cluster pixels. When the calculated Euclidean distance has minima value then the pixels will be grouped with the respective cluster.
- Do the above process for remaining clusters also. Then, we will get three clusters with similar pixels.
- Now, calculate the mean of each cluster and replace the mean values with the centroids.
- Repeat the same process with these new centroids by giving the number of iterations until unless the convergence occurrence i.e., the mean value of clusters = cluster centroid value.

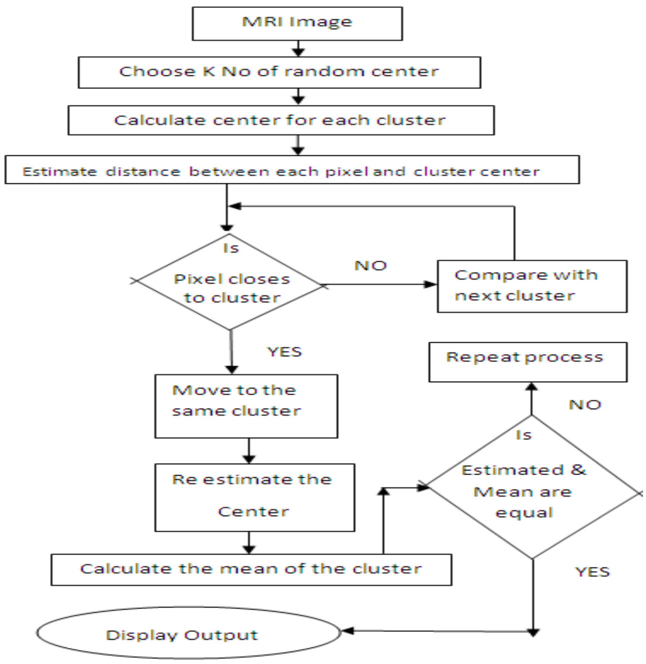

Fig. 2: Flow chart of K-means clustering

HC-EA algorithm

Here in this section, we described our proposed clustering in brief. First, the pre-processing has been done using median filter, which is used to remove the noise from digital images and will improve the quality of the image. Then the output of the first stage will be given to the k-means clustering which gives the segmented output of de-noised image. Now, fuzzy clustering will be applied for the k-means segmented output to improve the segmentation accuracy and exact detection of tumor from MR brain

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images. Finally, binarization will be used to calculate the size of the tumor based on typography and digital imaging units [20]. As mentioned in above section, while calculating the mean of cluster centroid pixels sometimes we might get the floating values, but the pixel values in an image will always be integers which does not have decimal values. Hence, we proposed a novel algorithm in fig3 to fix this error. In the proposed approach, segmented k-means output will be further segmented by fuzzy clustering for improved accuracy. Then after, the EA method will be applied to calculate the size of tumor which has been detected by using proposed hybrid clustering algorithm. Here, we considered the images of size 256 x 256 and the pixels in the segmented image having only two values i.e., either black or white, where the pixel value 0 denotes the black and 1 denotes the white.

Hence, we can represent the segmented output image as a summation of total number of white and black pixels.

$$M = \sum_{x=1}^{L} \sum_{y=1}^{L} [f_{x,y}(0) + f_{x,y}(1)]$$

where L=1, 2, 3…256

$f_{x,y}(0)$ = black pixel having the value of zero,

$f_{x,y}(1)$= white pixels having the value of one

$$P = \sum_{i=1}^{L} \sum_{j=1}^{L} f_{x,y}(1)$$

Where,

P = number of white pixels

Now, by using the above equation, we can calculate the area of the segmented tumor based on the typography and digital imaging units [20], where one pixel is equal to 0.264583 millimeters. i.e., 1 pixel = 0.264583 mm

Then the area of tumor can be expressed as follows:

$$A_{Tumor} = (\sqrt{P})*0.2646mm^2$$

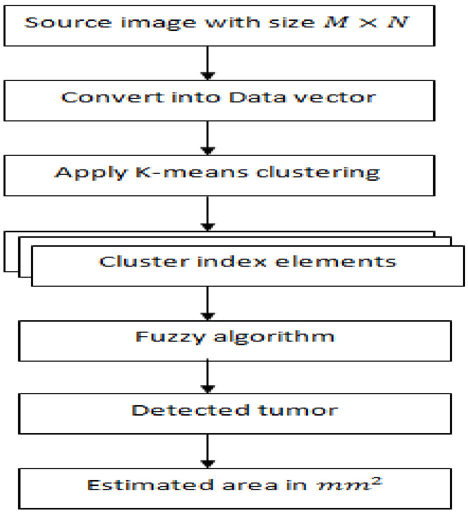

Fig. 3: Block diagram of proposed model.

4. EXPERIMENTAL RESULTS

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In this section, we had given an overview of conventional and proposed segmented results with the area of tumor. All the experiments have been done in MATLAB 2016b 64-bit version with 4GB RAM. We tested five sets of images with various sizes such as 400x400, 512x512 and 600x600, which have different stages of tumors. Then we evaluated the performance of conventional schemes Fuzzy c means, K-means and manually segmented algorithms with the proposed hybrid clustering algorithm for detection of single and multi-tissues in MR Brain images. The experimental results of MRI tumor detection using proposed hybrid algorithm and existing algorithms will be shown in the figures below. By comparing the results our proposed approach is more effective and accurate. Fig5.1 and 5.2 shows the segmented outputs of single tissue of MR brain images with manual segmentation, FCM clustering, K-means clustering and proposed hybrid clustering algorithms. From the obtained outputs, we can observe that the proposed hybrid clustering algorithm has detected the tumor more effectively with higher accuracy. Although our proposed algorithm running time will be quite bit of more than the k-means clustering but however the accuracy of segmented output will be more i.e., tumor area will be estimated more precisely to diagnosis further.

(a) (b) (c) (d)

(e)

Fig. 4: (a) Original Image (b) manual segmentation (c) Fuzzy C Means clustering (d) K-means clustering (e) proposed hybrid clustering.

(a) (b) (c) (d)

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(e)

Fig. 5: (a) original image (b) manual segmentation (c) fuzzy C means clustering (d) K-means clustering (e) proposed hybrid clustering.

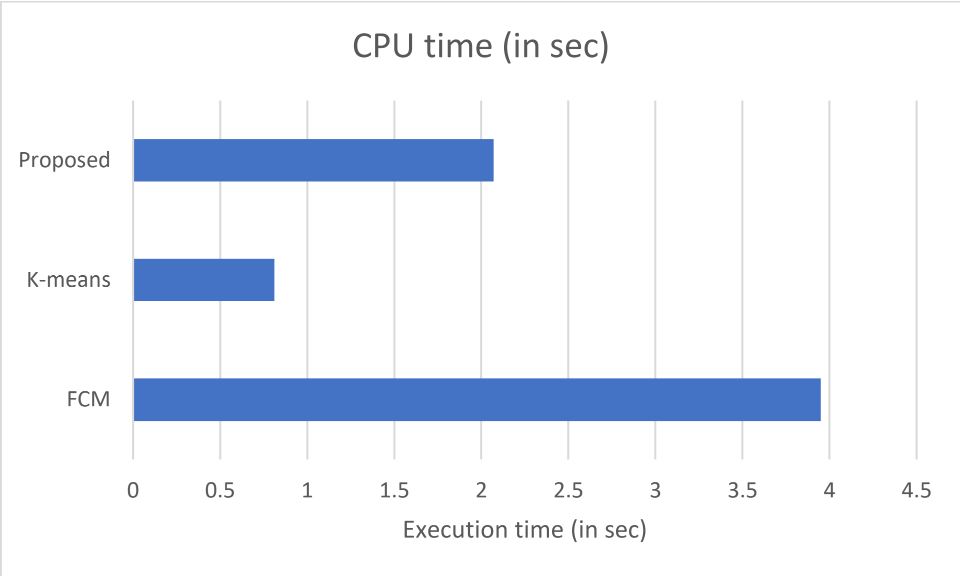

Fig. 6: Performance evaluation with CPU running time for multi tissues detection.

5. CONCLUSION

The implementation of detecting single and multi-tissues in MR brain images and to estimate the area of the tissue has been done with an improved accuracy and reduced computational time. Utilization of hybrid clustering and estimation of the area in terms of mm^2 based on the typography and digital imaging units has done successfully. We also compared the simulation results with the existing algorithms. Furthermore, this can be extended to 3D multi modal medical image segmentation with more effective and accurate clustering algorithms.

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