An Effective Brain Tumor Detection from T1w MR Images Using Active Contour Segmentation Techniques.

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Abstract. In the medical imaging application, early detection of tumors from magnetic resonance imaging (MRI) brain images is a challenging task, it reduces the risk of human health and increases the chance of survival. The manual detection of brain tissue was requiring a lot of experience and time-consuming. Magnetic resonance images (MRI) scan helps to detect brain tumors in the early stage, and it has become a hot research topic in medical image processing. In this research article, an automated framework is presented intended to segment and extraction of brain tumors of MRI images in an efficient manner. In this work, three primary steps are involved in the suggested brain tumor segmentation system including pre-processing, image thresholding, and segmentation. This article focusses on to study the accurate brain tumor segmentation system by comparing the level set (LSM) and Chan-vese (C-V) techniques. All the experiments are conducted on Harvard datasets to validate the performance of both methods. The performance of the algorithms was calculated in terms of dice coefficient (DC), Hausdorff distance (HD), and Jaccard similarity index (JSI). It has been observed that KIFCM has performed better than the other clustering methods and Chan-Vase has shown better performance in tumor detection on selected datasets. The overall work shows that the presented framework outer performs for the detection of brain tumors with minimum distance error and loss of information over existing methods.

Keywords: Brain tumor, thresholding, level set, Chan-vese, Hausdorff distance.

1. Introduction
The growth of abnormal cells in the human brain that affects the normal brain cells and the main reason for cancer. The brain tissues were depending on so many factors such as brain location, size, and texture [1]. The brain tumors are characterized by two core types namely: malignant (cancerous) and benign (non-cancerous). The malignant tumors more aggressive and start rapidly inside the brain cells. The benign tumor starts from the body and extends to the cells of the brain [2, 3]. Approximately one-third of brain tumors are officially classified as cancer, ranked among the topmost cancer-associated deaths [4]. Therefore, the initial recognition of tissue is required to protect humans from the death rate. For this, new developments in medical imaging provide the solution to the doctors for further treatment purposes[5]. The manual assessment is a repetitive and time-consuming task for doctors. Computerized methods are therefore required to diagnose a tumor in a short time and with better accuracy [6]. Recently, numerous techniques were presented to segment the tumor from the brain MRI image by the several researchers.
such as region, edge, clustered-based segmentation, superpixels-based brain tumor segmentation, fusion-based segmentation, hybrid, optimization, and so on [7]. However, several challenges exist because of the variants in tumor border, shape, irregularity, and texture in the brain images. But still, several problems exist in these systems that affect system accuracy [8]. The major problems include tumor shape, size, location, and irregularity of the tumor. To solve these problems, in this article, an improved segmentation system was planned for accurate tumor segmentation [9].

The main objective is to study the brain tumor segmentation system by comparing the active contour segmentation techniques namely, level set and Chan-vese techniques to identify the tumor and examine the efficacy of introduced brain tumor segmentation system. An automated system is recommended for tumor extraction using MR images in this work. The proposed framework comprises of three primary steps. In the first step, pre-processing is performed to remove the unwanted area and eradicate noise in images of datasets. In the second stage, the pre-processed images were thresholded to get the isolated tumor in the images. Then in the next step, the tumor region is segmented by the active contour segmentation method.

The rest of the manuscript is organized into four steps: Section 2 presents the proposed brain tumor segmentation system, Section 3 explores some performance evaluation metrics, Section 4 exhibits the experiment results and discussion, finally, the conclusion given in Section 5.

2. Proposed brain tumor segmentation system

The suggested method involves three modules. The framework of the proposed system is split into three main modules. In the first module, the manual skull stripping method was utilized to remove the unwanted part in the brain tumor images and eliminate the noise (de-noising) using the median filter by preserving the edge's information. In the second part, the de-noised images were thresholded by using the FCM thresholding technique to get the isolated parts in that MRI images. The last module is segmentation which only an essential tumor image to detect the tumor section. The proposed flow diagram of the brain tumor detection system is shown in Fig. (1). The proposed system key element detail is also provided in the subsections.

2.1. Pre-processing stage

First, it is necessary to pre-process the images before further processing to increase the quality of the image and avoid thermal noise because the tumor images are more responsive than other health care images. This stage consists of skull stripping and de-noising sub-stages that briefly explained the below subsection.

2.1.1. MRI dataset. The algorithms were applied to detect the brain tumor images from T1w MRI datasets. The images are 256 rows in length and 256 in the column. The dataset: Benchmarked simulated MR images of the brain downloaded from the Harvard university database, were used because of the unavailability of segmentation ground truth for real MRI images [10]. This dataset, containing 120 images among them some of the quality images were used in this study for evaluation. The sample tumor images of the selected Harvard dataset and its ground truth images are presented in Fig. (2).
2.1.2. **Skull stripping.** In MR images, the aim is to identify the ROI that implies the tumor region. Therefore, initially, skull stripping is used due to a skull is a region which is neither a tumor nor ROI and to reduce the execution time. A manual skull stripping technique is employed to detect the brain tumor [11]. Therefore, all those regions which belong to brain tumor are of high priority whilst the rest of the information is of low priority.

2.1.3. **De-noising.** Next, a median filter is used to remove noise effects in the skulled images because these images hold a lot of speckle noise. For the removal of noise throughout preserving the edges an effective non-linear method of Median filter is being used. Each value is being replaced with the median value of the neighboring pixels; the filter works by moving the pixel by pixel through the image. For the removal of noise in the presence of edges, the median filter is considered better than the linear filter [12].

2.2. **Thresholding**

In clustering, the involvement function of removed structures for every pixel at each cluster variation relational to zonal mean values and gradient means of next to pixels. The direction of distinctions is detailed. using a hominoid interface. Their subdivision method was applied for the division of texture, documentation descriptions and the outcomes have shown that human collaboration to classification in quality, lessening of noise is segmenting images [13]. The presentation changed the FCM manner process to the segmentation problem this data working by allocating integration to every data is equivalent to cluster on the source of reserve between band and point. The extra data is nearer to cluster closer in associating of the direction of the midpoint [14].

2.3. **Segmentation**

The segmentation target is to partition the object into different regions. Segmentations were carried out through the distribution of pixel properties, namely, gray level or color values. Methods based on area and continuity [15]. The region-dependent segmentation divides a document image into a homogenous area of connected pixels by applying homogeneity criteria among sets of pixels for candidates. Concerning other characteristics or simulated properties such as the texture of intensity, each of the pixels in a region is identical. Failure to change the criterion for homogeneity would yield undesirable results accordingly [16]. These drawbacks were avoided by the global-based active contour methods such as level set and chan-vese model, both the techniques were described in the subsection.

2.3.1. **Chan-Vese model.** In this method, the area segmented may be smaller or larger than the real one and image over or under-segmentation (arising from pseudo objects or incomplete objects). Finally, the chan-vese text fragmentation area is the simple method of segmentation. This segmentation approach analyzes neighboring pixels of initial "seed points" and decides if the neighbor pixels add up to the area [17, 18]. The process is iterated on the identical series as general algorithms for clustering results. Approaches to the region growing leverage the essential fact that closeup pixels have identical grey value.

2.3.2. **Chan-Vese model.** It is used in image segmenting to track the boundary. Its aim will start from shapes of a boundary like closing curves. The method shows robust segmenting capabilities in any object which shows poor performance. There is a benefit of the level set because it partitions the object in sub-parts with continuous boundary [19]. Also, the detector of an edge will depend on the threshold and gives the results of discontinuous boundaries. And it gives more flexibility and convenience to implement contours. They use many properties like curves, texture, etc used for other methods. This method was explained by Lee [20].

The noise of the picture will be removed by using a median filter which removes little regions that long from the tumor. This step is called the post-processing step. So, these two steps will form one step if FCM uses the threshold function. Next, the thresholded image with the tumor is fed to level set. The
result of this thresholding image with a noisy tumor of contouring part. It can be calculated to compute white pixels of the image. [21].

3. Performance evaluation measures
The analysis was performed according to the following performance measures between the nine techniques tested.

3.1. Dice-coefficient (DC)
In dice, the coefficient will be used to prove the degree of similarity between the harvested tumor and the manually segmented tumor region.

\[
\text{Dice (} X, Y \text{)} = 2 \frac{|X \cap Y|}{(|X| + |Y|)} \tag{1}
\]

If the value of the dice coefficient value is 1 it performs the same overlap between \( X \) and else if its value is 0, then \( X \) and \( Y \) do not overlap [22].

3.2. Hausdorff distance (HD)
HD used to find the distance among ground truth contour A and segmented contour B. When the HD value is close to 0 the segmentation method gives the best segmentation result. HD is defined as.

\[
\text{HD (} A, B \text{)} = \max \{ \max p \{ \text{dist (} a, B \text{)} \}, \max q \{ \text{dist (} b, A \text{)} \} \} \tag{2}
\]

Where \( A \) and \( B \) contours comprise set of points \( A = \{a_1, a_2, a_3, \ldots, a \} \), \( B = \{b_1, b_2, b_3, \ldots, b \} \), respectively, and is the distance from \( a \) to the closest point on curve \( B \) [23].

3.3. Jaccard similarity index (JSI)
It is a measure of similarity between two sets of data and it is easy to interrupt.

\[
\text{Jaccard Index=}J (X, Y) = \frac{|X \cap Y|}{|X \cup Y|} = \frac{|X \cap Y|}{|A| + |B| - |A \cap B|} \tag{3}
\]

Where \( X \) & \( Y \) implies the detected and original contour [24]. It ranges from 0 to 100%, with higher values.

4. Results and discussion
The experimental results of the introduced framework are explained by numerical terms in this section. The work is validated on Harvard datasets. The T1w images with a dimension of 256 × 256 used for evaluation purposes and simulated in MATLAB 2020a with a system Core i6, 16 GB RAM, and 8GB of the graphics card. The experiments are performed in three steps namely pre-processing, thresholding, and segmentation.
Figure 2. Sample tumor images (a) Harvard dataset, and (b) Ground truth images.

In this work, three primary steps are involved in the suggested brain tumor segmentation system including pre-processing intended to remove the skull and noise by preserving the edge information using manual skull stripping method and median filtering, image thresholding considering the fuzzy c-means based thresholding utilized for isolate the particular tumor region, and segmentation techniques for extract tumor of our interest by preferring the level set method (LSM) and chan-vese model (C-V). The sample tumor images, and its golden standard images were shown in Fig. (2).

Figure 3. Segmentation results of flow diagram on Harvard dataset (a) Input image, (b) Skull stripped image, (c) De-noised image, (d) FCM thresholding image, (e) LSM method segmented image, and (f) C-V model segmented image.

The experiment is performed on the proposed framework by choosing the two high-quality images from the selected dataset. The overall results of each step in the framework shown in Fig. (3). After pre-processing, the thresholding techniques were applied but it failed to detect the exact tumor region due to image artifacts and improper isolation of boundary or edge regions. So, in the very next step, we are applying the active contour segmentation techniques namely LSM and C-V model to detect the tumor accurately without any ambiguity for diagnosis. The performance evaluation of the proposed method is calculated in terms of DC, HD, and JSI.

Table 1. The performance measures for segmented results of LSM segmentation technique.

| Type     | DC      | HD  | JSI   |
|----------|---------|-----|-------|
| Image 01 | 96.43   | 2.02| 97.26 |
| Image 02 | 97.51   | 2.08| 95.71 |
### Table 2. The performance measures for segmented results of C-V segmentation technique.

| Type | DC  | HD   | JSI  |
|------|-----|------|------|
| Image 01 | 98.82 | 1.58 | 98.93 |
| Image 02 | 98.47 | 1.79 | 96.27 |

Even pre-processing and thresholding steps applied, some unwanted areas that will be appeared in the abnormal brain image. After clustered by both clustering techniques, the output images were segmented separately by using the segmentation techniques, namely C-V and LSM respectively, and compared in terms of HD which is calculated regarding ground truth image.

The performance measures of segmentation results in both LSM and C-V were shown in Table 1 and Table 2. Among some performance measures, the C-V and LSM results were compared for two selected images from Harvard university in terms of HD that are shown in Fig. (4). When the HD value is close to 0 the segmentation method gives the best segmentation result.

![Figure 4. Comparison of the C-V segmentation method with the LSM segmentation method.](image)

The performance measures of segmentation results in both LSM and C-V were shown in Table 1 and Table 2. Among some performance measures, the C-V and LSM results were compared for two selected images from Harvard university in terms of HD that are shown in Fig. (4). When the HD value is close to 0 the segmentation method gives the best segmentation result.

As per metrics, the HD value is maximum that is 2.04 and 2.08 to images 1 and 2 respectively for the LSM segmentation method. For the CV model, the HD values are minimum that is 1.78 and 1.59 for two images, we can observe in Fig. (4).

As per the Table 3., the computational time and SDE values in the C-V segmentation technique with FCM technique takes less time (fewer iterations) and segmentation distance error with golden standard images compared to the LSM with FCM (multiple clusters) and K-means (single cluster) clustering algorithm to detect the tumor.

The C-V global-based segmentation technique gives better results compared to the level set method because of the energy minimum function. At the same time, LSM quite hard to describe the transformation numerically by parameterizing the boundary of the shape and its evolution. Because the C-V model is based on the Mumford-shah segmentation function and an energy minimization problem was reformulated within a level set, which leads to efficiently solving the problem and, in particular, the C-V model has gained popularity due to its efficiency in contour detection without considering the problem of curve initialization.

### 5. Conclusion

Segmenting is the main technique in medical image processing. In medical diagnosis, many segmentation methods are using mostly, like CT and MRI. MRI is a more efficient picture method used to detect the tumor in the human brain. MRI is much better than a CT scan for diagnosis due to low...
radiation and ionization. The work is validated on T1w MRI images of the Harvard university dataset with a dimension of 256×256 and simulated in MATLAB 2020a with a system Core i6. In this paper proposed framework has three steps: First, pre-processing step to remove the noise and unwanted surface area that is the skull, next the image thresholding step intended to isolate the tumor region from other regions, and finally segmentation to detect the tumor section only. The performance of both segmentation techniques was measured for selected datasets in terms of DC, HD, and JSI. The C-V global-based segmentation technique gives better results compared to the level set method because of the energy minimum function. At the same time, LSM quite hard to describe the transformation numerically by parameterizing the boundary of the shape and its evolution.

From the experimental outputs, we have demonstrated the efficacy of our framework in tumor segmentation and the C-V global-based segmentation technique gives better results compared to the level set method because of the energy minimum function. The LSM method is quite hard to describe the transformation numerically by parameterizing the boundary of the shape and its evolution. The overall shows that the presented framework outperforms for the segmentation of brain tumors with minimum distance error and loss of information over existing methods.

In the future, this framework will be implemented by using machine learning techniques to improve system accuracy and reduce the overall computational time.

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References
[1]  Jin Liu, Min Li, J. Wang, Fangxiang Wu, T. Liu Yi. Pan. A survey of MRI-based brain tumor segmentation methods. TSINGHUA SCI TECHNOL 2014;19(6): 578-595.
[2]  Sâleha Masood, Muhammad Sharif, Affîa Masood, Mussarat Yasmin, Mudassar. A Survey on Medical Image Segmentation. Curr. Med. Imaging Rev. 2015, 11(1): 3-14.
[3]  Nour-Eddine E, Harchaoui, Mounir, Ait Kerroum, Ahmed Hammouch, Mohamed Ouadou, Driss Aboutajdine. Unsupervised Approach Data Analysis Based on Fuzzy Possibilistic Clustering: Application to Medical Image MRI. COMPUT INTEL NEUROSE 2013; 3: 1-12.
[4]  Shrunthi Anand, Viji Vinod, Anand Rampure “Application of Fuzzy c-means and Neural networks to categorize tumor affected breast MR Images”, International Journal of Applied Engineering Research. 2015; 10 (4): 62-73.
[5]  S. Madhukumar a, N. Santhiyakumari Evaluation of K-Means and Fuzzy C-Means segmentation on MR images of the brain, A brief Article, The Egyptian Journal of Radiology and Nuclear Medicine (2015) 46, 475–479.
[6]  Pasha M.M., Suresh B., Babu K.R., Subhani S., Subbarao G.V. Barker coded modulated thermal wave imaging for defect detection of glass fiber reinforced plastic. ARPN Journal of Engineering and Applied Sciences 2018;13 (10):3475-3480.
[7]  Sasikala et al. Unifying Boundary, Region, Shape into Level Sets for Touching Object Segmentation in Train Rolling Stock High-Speed Video. IEEE Access. 2018; 6:70368-70377.
[8]  P. V. Nagajaneyulu, and K. Satya Prasad, "Brain Tumor Segmentation of T1w MRI Images Based on Clustering Using Dimensionality Reduction Random Projection Technique. Current Medical Imaging 2020; 16: 1. https://doi.org/10.2174/1573405616666200712180521.
[9]  http://www.med.harvard.edu/aanlib/cases/caseNA/pb9.htm-harvard
[10]  Pham and J. Prince, “Adaptive fuzzy segmentation of magnetic resonance images,” IEEE Trans. Medical Imaging, vol. 18, no. 9, pp. 737–752, Sep. 1999.
[11]  Rajesh Babu K., V.A.S. Chakravarthy, S. Sandeep reddy, G. Phani Kumar, M. Vamsi Kumar., “Automated Brain Tumour Detection In MRI Images Using Threshold Based FCM”, 2019, International Journal Of Scientific & Technology Research, Vol:8, issue:12, pp:224-227.
[12]  Maarten Jansen and Adhemar Bultheel, “Multiple Wavelet Threshold Estimation by Generalized Cross-Validation for Images with Correlated Noise”, IEEE Transactions on Image Processing, Vol. 8, No. 7, July (1999).
[13] Vallabhaneni R.B., Rajesh V. Brain tumor detection using mean shift clustering and glcm features with edge adaptive total variation denoising technique. ARPN Journal of Engineering and Applied Sciences, 2017; 12(3): 666-671.

[14] Panigrahi, Susant & Gupta, Supratim. Automatic ranking of image thresholding techniques using a consensus of ground truth. Traitement du signal. 2018; 35: 121-136. DOI:10.3166/ts.35.121-136.

[15] Anam Mustaqeem, Ali Javed, “An Efficient Brain Tumour Detection Algorithm Using Watershed & Thresholding Based Segmentation”, I.J. Image, Graphics, and Signal Processing. 2012; 10(3): 34-39.

[16] Sivakumar and V. Murugesh, “A Brief Study of Image Segmentation using Thresholding Technique on a Noisy Image,” IEEE, 2014.

[17] Boucif Beddad, Kaddour Hachemi, and Sundarapandian Vaidyanathan. "Design and implementation of a new cooperative approach to brain tumor identification from MRI images." International Journal of Computer Applications in Technology, 59 (2019): 1-10.

[18] Jay Patel and Kaushal Doshi, “A Study of Segmentation Methods for Detection of Tumour in Brain MRI,” IJRTE, Vol. 4, November 2014, pp. 279- 284.

[19] Inthiyaz S., Madhav B.T.P., Madhav P.V.V. Flower segmentation with level set evolution controlled by color, texture, and shape features', Cogent Engineering 2017;4(1).

[20] Syed Inthiyaz, B.T.P. Madhav and P.V.V. Kishore "Flower image segmentation with PCA fused colored covariance and Gabor texture features based level sets. Ain Shas Engineering Journal 2018; 9(4):3277-3921.

[21] Raghava Prasad C., Kishore P.V.V. Performance of active contour models in train rolling stock part segmentation on high-speed video data. Cogent Engineering, 2017;4(1): 215-223.

[22] Babu K.R., Naganjaneyulu P.V., Prasad K.S. (2019), 'Performance analysis of fusion-based brain tumor detection using Chan-Vese and level set segmentation algorithms', International Journal of Recent Technology and Engineering, 7(6), PP.2089-2096.

[23] S. H. Ahammad, V. Rajesh, and M. Z. U. Rahman, "Fast and Accurate Feature Extraction-Based Segmentation Framework for Spinal Cord Injury Severity Classification," IEEE Access, vol. 7, pp. 46092-46103, 2019, doi: 10.1109/ACCESS.2019.2909583.

[24] Ahilan et al. Segmentation by Fractional Order Darwinian Particle Swarm Optimization Based Multilevel Thresholding and Improved Lossless Prediction Based Compression Algorithm for Medical Images. IEEE Access. 2019; 7: 89570-89580. doi: 10.1109/ACCESS.2019.2891632