I J C T A, 10(5) 2017, pp. 967-975

Study and Performance Analysis of Different MRI Brain Tumour Segmentation Methodologies for Medical Applications

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Abstract: In image processing segmentation methodology has been used to detect the tumour in human brain using different techniques which are not too most important applications based on analysing of digital image processing. However, Segmentation methods based on regions, threshold and histograms have the drawbacks in the detection of size and region of tumour. As of now there are many calculations accessible for picture division. Each of them has their own preferences and reason. In this paper, the algorithms used are K-means clustering algorithm, Fuzzy-C means clustering algorithm, Fast-border marker algorithm and Snakes algorithm with their prospects are reviewed. Snakes algorithm provides exact region of the tumour compared to K-means clustering, Fuzzy C-means clustering and Fast-border mark algorithms. These algorithms are compared pictorially. By this, we can help the pathologists to identify the region of tumour by which they can easily provide treatment to the patients.

Keywords: Brain Tumour, Image segmentation, K-means clustering, Fuzzy-C clustering, Fast-border mark algorithm, Snakes algorithm.

1. INTRODUCTION

The body of human beings is comprised of cells. Every kind of cells has exceptional capacities. The majority of cells in the body develop and afterward separate in a deliberate approach to shape new cells as they are expected the body to be solid and working legitimately. At the point when the cells lose their capacity to control their development, they isolate again and again with no request. The additional cells form a mass of tissue called the tumour. These tumours might be of any size, any shape and might happen at any area in the human body. The aim of our work is to recognize the tumour development so that proper treatment can be arranged in the early stage. The mind is a delicate tissue. It is secured by the skull bones and three dainty films known as meninges. Watery liquid called cerebrospinal liquid pads the cerebrum. This liquid moves around the gaps between the meninges and through the gaps inside the mind known as ventricles.

A system of nerves conveys information forward and backward around the mind and the remaining parts of body. A few nerves go specifically from the mind to the eyes, ears, and parts of the head. Different nerves go through the spinal rope to associate the cerebrum with parts of the body [1]. The mind coordinates the things we do (like strolling and talking) and the things our body manages without considering (like relaxing). The mind is additionally accountable for our faculties (sight, hearing, touch, taste, and notice), memory, feelings, and identity.

1.1. Benign and Malignant Tumours

Benign brain tumours don't have cancer cells. Usually, benign tumours can be inhibited, and they rarely grow back. The fringe benevolent mind tumour can be plainly seen. Cells from kind-hearted tumours don't attack cells around them or spread to various regions of the body. Be that as it may, kind-hearted tumours

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can push on touchy territories of the cerebrum and cause genuine wellbeing issues. Unlike benevolent tumours in various parts of the body, generous cerebrum tumours are dangerous to life. There are very rare cases in which benign tumours can be malignant.

Malignant brain tumours contain tumour cells. Harmful mind tumours are for the most part more genuine and frequently are life undermining. They are prone to become quickly and swarm or attack the encompassing sound mind tissue. Rarely, growth cells might split far from a threatening cerebrum tumour and pass to different regions of the brain, to the spinal string, or even to various regions of the body. The spread of malignancy is called metastasis. Here and there, a harmful tumour does not stretch out into sound tissue. The tumour might present inside the tissue. This sort of tumour is called encapsulated.

1.2. Different Types of Brain Tumours

- Astrocytoma, Oligodendroglioma, Schwannoma, Medulloblastoma, Craniopharyngioma, Germinoma, Ependymoma, Glioblastoma multiforme, Brain Metastasis, Brainstem gliomaz and Meningioma

There are many Medical Image Acquisition methods in recent years, including magnetic resonance imaging (MRI), ultra-sound (US), X-ray computer tomography (CT), single photon emission tomography (SPET), positron emission tomography (PET), etc. With the expansion in size and number of restorative pictures, the utilization of PCs in encouraging their preparing and examination has ended up important. Attractive Resonance Imaging (MRI) is a test that uses an attractive field and beats of radio wave vitality to make pictures of organs and structures inside the body. It is utilized to discover issues, for example, tumours, dying, harm, vein maladies, or disease. X-ray likewise might be done to give more data around an issue seen on a X-beam, ultrasound sweep, or CT check. Contrast material may be used amid MRI to demonstrate irregular tissue all the more effectively. For a MRI test, the region of the body being considered is set inside an uncommon machine that contains a solid magnet. Pictures from the MRI are modernized pictures that can be saved and set away on a PC for more study.

X-beams are a sort of radiation, and when they go through the body, thick questions, for example, bone piece the radiation and seem white on the x-beam film, while less thick tissues seem dark and are hard to see. Organs and tissues within the body contain magnetic properties. X-ray, or attractive reverberation imaging, consolidates a capable magnet with radio waves (rather than *x*-beams) and a PC to control these attractive components and make exceedingly nitty gritty pictures of structures in the body. Pictures are seen as cross areas or “cuts” of the body part being checked. There is no radiation included as with x-beams. X-ray outputs are every now and again used to analyze cerebrum tumours and joint issues.

2. SEGMENTATION

The procedure of isolating or gathering a picture into various parts is picture division. These assembled parts relate to something that people can without much of a stretch separate and view as individual articles. Since PCs have no method for insightfully perceiving items, thus a wide range of strategies have been produced to portion diverse sorts of pictures. The division process in taking into account different elements found in the picture. This may be shading data that is utilized to make histograms, or data about the pixels that demonstrate edges or limits or surface data. Most popular techniques still used by the researchers are Edge Detection, Threshold-based, Histogram-based; Region based methods and watershed Transformation.

2.1. Medical Image Segmentation Methods

2.1.1. Edge Based Segmentation

This is the most well-known methodology for identifying significant discontinuities in grey level. Different approaches are given for implementing first and second order derivatives for the identification of edges in an image. The edge location procedure is utilized to improve the examination of a picture by diminishing the measure of information to be prepared and in the meantime putting away key auxiliary data about the item limits [2]. Here, the channels are likewise utilized as a part of this procedure to find the sharp edges which are spasmodic. The edge discovery expects to distinguish focuses in an advanced picture at which the picture brilliance changes forcefully or suddenly.

2.1.2. Fuzzy Theory Based Segmentation

With a specific end goal to examine pictures, and give precise data from any picture Fuzzy set hypothesis is utilized. To expel commotion from a picture Fuzzification can be utilized. Fuzzification is used to change over a dark scale picture into a fluffy picture effortlessly [3]. Fuzzy-c means and K-means clustering are the widely used methods in this fuzzy segmentation [4].

2.1.3. PDE Based Segmentation

Partial Differential Equations models are widely used in image processing that too in image segmentation. This technique utilizes dynamic form model for division reason. A portion of the strategies for this PDE are snakes, level-set and Mumford shah technique. Dynamic forms or snakes are PC created bends that move inside of the picture to discover item limits affected by powers of the bend and picture itself [5].

2.1.4. ANN Based Segmentation

Pixel classification and edge detection are the two steps involved in this neural network based image segmentation [6]. In this Artificial Neural Network, every neuron is corresponding to the pixel of an image. Image is mapped to the neural network. Picture as neural system is prepared utilizing preparing tests, and afterward association between neurons, i.e., pixels is found. At that point the new pictures are fragmented from the prepared picture. The methods used in neural networks for image segmentation are Hopfield, BPNN, FFNN, MLFF, MLP and PCNN.

2.1.5. Threshold Based Segmentation

It is the simplest form of segmentation. Initially, a threshold is defined, and then every pixel in the image is compared with this threshold. In the event that the pixel lies over the limit esteem it is set apart as forefront, and on the off chance that it is beneath the edge it is set apart as foundation. The limit will all the more regularly be a power esteem or a shading esteem than not. Be that as it may, thresholding is a primitive method [7], and will work for extremely basic division undertakings. This method is simple in usage but the results that we are getting are not appropriate. Sometimes it is even not possible to find an output.

2.1.6. Region Based Segmentation

Compared with other methods region based division is straightforward furthermore commotion strong [8]. Depending upon colour, intensity or object it divides the image into different regions. Region based segmentation includes Region splitting, Region merging and Region growing. In region splitting, the entire picture is broken into various locales which are intelligent inside of themselves. At that point, checking every one of the pixels in the locale are comparative or not. This process will proceed until no further splitting can occur. In region merging, the image is initially segmented using 2x2, 4x4 and 8x8 pixels [9]. After the area portrayals are done in light of the measurable dark level properties, adjacent region properties are compared with the properties of neighbour region. If they are alike they combine into a big one and if not they are marked as non-matching. It follows for all regions including newly formed ones. On the off chance that the area can’t be coordinated with any of the locales then it is last and the consolidating process stops when all the picture areas are so stamped. In district developing, the locales are resolved specifically. It is anything but difficult to finish and register. Initially a pixel is selected in an image and it is compared to the neighbouring pixel, if matched they are combined and form a region similarly to all the pixels if matched, they will combine if not, no. When one region's growth stops, then choose another pixel which is alone and then repeat the process again. This procedure is continued until every one of the pixels have place with some area.

3. SEGMENTATION ALGORITHMS

This paper we will take MRI Brain tumor image refer **Figure 1** for segmentation and comparing the different segmentation techniques and gives the results in the form of pictorial.

Figure 1: Input MR Image

3.1. K-Means Clustering Algorithm

K-means clustering is the algorithm used to group the objects based on the attributes into a *k* number of classes where *k* is the positive integer. The clustering is made by reducing the Euclidean distance between the data points and the corresponding cluster centre/centroid [10].

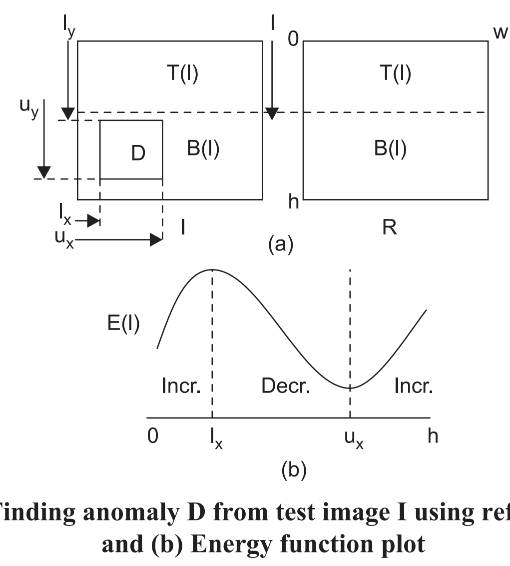

Figure 2: (a) Finding anomaly D from test image I using reference image R and (b) Energy function plot

One of most popular and the widely used the clustering algorithm is to separate the input data points in Euclidian region is the K-means clustering [11]. It is the non hierarchical method which follows simple and easy method to classify the given dataset points through the certain number of clusters that are known as a priori. The K-means algorithm is constructed using an iterative scheme where elements of data are interchanged between the clusters in order to satisfy the criteria reducing the constant change within the each cluster and maximizing the variation between the clusters [12].When no elements are interchanged between the clusters, process is stopped [13]. That we can refer from *below* **Figure 3**.

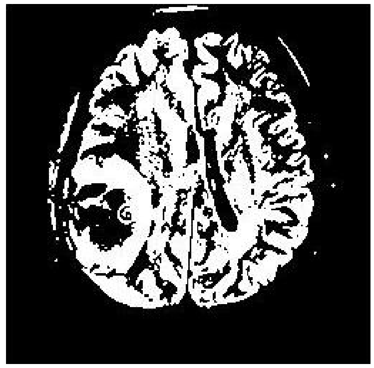

Figure 3: K-means clustering output

The 5 steps of the *k*-means algorithm are described below:

1. Initially figure the force appropriation of the intensities.
2. Initialize the centroids with k irregular intensities.
3. Rehash the accompanying strides until the group of the picture does not change any longer.
4. Cluster the points based on the distance of their intensities from the centroid intensities.

$$c(i) = \arg\min \| X(i) - j \|^2 \tag{1}$$

5. Compute the new centroid for each of the clusters.

$$m_i = \frac{\sum_{i=1}^{m} 1\{c(\mathrm{i}) = j\}\, x(i)}{\sum_{i=1}^{m} 1\{c(i) = j\}} \tag{2}$$

3.2. Fuzzy-C Means Clustering Algorithm

It is fuzzy clustering method where each point has a degree of belonging of clustering as in fuzzy logic, rather than belongs to just one cluster. In this, centroid of a bunch is the mean of all focuses, weighted by then level of fitting in with the cluster. It is also called soft *k*-means clustering method. The Fuzzy C-Means (FCM) clustering algorithm was first introduced by Dunn and later was extended by [14]. The result can be referred in below Figure 4.

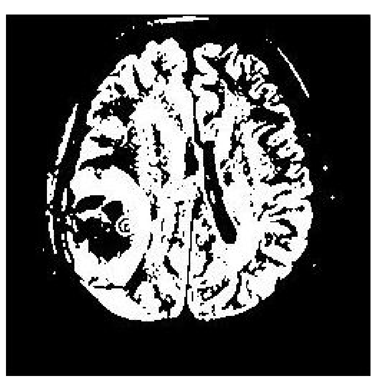

Figure 4: Fuzzy-C means clustering output

The calculation is an iterative bunching strategy that creates an ideal c segment by minimizing the weighted inside of gathering whole of squared mistake objective function.

$$Y_m = \sum_{i=i}^{N} \sum_{j=1}^{C} u_{ij}^{m} \| X_i - C_j \|^2 \tag{3}$$

Where, $X = \{X_1, X_2, X_3, ..., X_n\} \subseteq R_P$ is the data set

n is the number of data item

c is the number of clusters

p is a weighting exponent

Steps in fuzz y c-means algorithm: Let $X = \{X_1, X_2, X_3, ..., X_n\}$ be the set of data points and $C = \{C_1, C_2, C_3, ..., C_n\}$ be the set of centers.

1. Randomly select 'c' cluster centers.
2. Calculate the fuzzy membership 'μ_{ij}' using:

$$\mu_{ij} = \frac{1}{\sum_{K=1}^{C} \left[\frac{\| X_i - C_j \|}{\| X_i - C_K \|} \right]^{\frac{2}{m-1}}} \tag{4}$$

3. Compute the fuzzy centers 'C_j' using:

$$C_j = \frac{\sum_{i=1}^{N} u_{ij}^{m} . X_i}{\sum_{i=1}^{N} u_{ij}^{m}} \tag{5}$$

4. Repeat step 2 and step 3 until the minimum 'J' value is achieved or

$$\| U^{(K+0)} - U^{(K)} \| < \beta \tag{5}$$

Where,

'k' is the iteration step

'β' is the termination criterion between [0, 1]

'$U = (\mu_{ij})_{n*c}$' is the fuzzy membership matrix

'J' is the objective function.

3.3. Fast Border Mark (FBM) Algorithm

FBM Algorithm operates in two sequential steps. First, the input set of 2D MR slices are processed individually, to find axis-parallel rectangles (i.e., potential border markers) in. Next, these border markers are clustered to identify the ones that actually surround the tumour. In first step, we expand the essential standard behind FBM that is a change discovery rule, where a district of progress (D) is recognized on a test picture (I), when compared with a reference image (R). In FBM, in the wake of finding the hub of symmetry on a pivotal MR cut, the left (or the right) half serves as the test picture I, and the privilege (or the left) half supplies as the reference picture R [15]. The area of progress D here is limited to be a pivot parallel rectangle, which basically intends to delineate the irregularity. Our strategy is not the same as a large portion of the change location strategies proposed to date in that we see this change as an area based worldwide change that varies from most procedures, which see the change as a nearby pixel-to-pixel changes–here tumour or edema is considered as the "change" area in the test picture and regardless of other intracranial tissues from tumour or edema are considered as the 'no change' region [16]. I and R in *below* Figure 2 represent the test and the reference images, respectively, having same height h and same width w. The rectangular region $D = [l_x, u_x] \times [l_y, u_y]$ speaks to the area of progress/district of enthusiasm containing (tumour or edema that we are searching for) between pictures I and R.

FBM algorithm finds the rectangle D, *i.e.*, the four unknown parameters l_x, u_x, l_y and u_y in two linear passes of the image [17]. The result can be referring in *below* Figure 5.

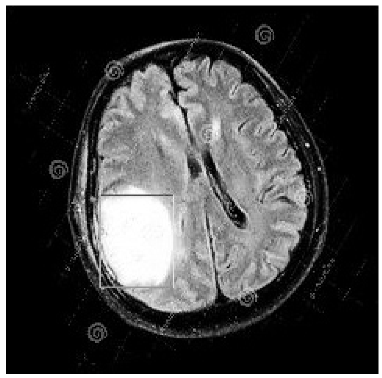

Figure 5: Fast Boundary Box algorithm output

It first finds the best l_y and u_y values in a vertical breadth and after that finds and in a flat range over the pair of pictures. In every range, the FBM calculation utilizes a score capacity. As the level score capacity compares to the vertical score capacity connected to the transpose of the pictures, we just portray the vertical score capacity.

3.4. Snakes Algorithm

Snakes or active contour models goal is to apply division procedure to a picture by doing twisting of the underlying shape towards the limit of the object of hobby. These are vitality minimizing splines that are guided by outer requirements and inside imperatives, and are affected by picture compels that force them towards highlights like lines and edges. They are intended to be intelligent, in that the client must be given a few hints as to where the limits may be, and the snakes are utilized to minimize vitality thus follow the form or limit. *Below* Figure 6 shows the output for the algorithm after execution.

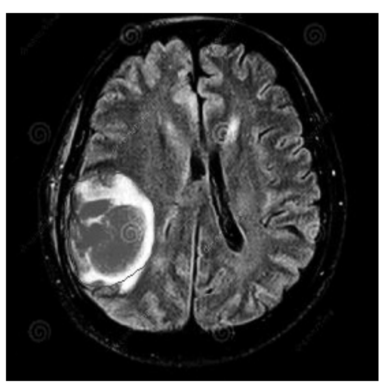

Figure 6: Snakes algorithm output

This model works on the assumption that edges are found not only by looking at the local gradient, but also at the long range distribution of the gradient [18]. This is done by using the curvature constraints as well as the continuity constraints. Snakes have an interior vitality capacity which decides their versatility and inflexibility, and an external energy function based on image information and user interaction.

$$E^{*}_{snake} = \int_0^1 E_{snake}(V(S))\,ds = \int_0^1 (E_{internal}(V(S)) + E_{image}(V(S)) + E_{con}(V(S))\,ds \tag{7}$$

Where,

E^{*}_{snake} – the energy function of the snake

$E_{internal}$ – The internal energy of the spline (snake) due to bending

E_{energy} – the forces of image acting on spline

E_{con} – the external constraint forces introduced by user

The capacity of snakes to give a straight portrayal of the article shape amid the season of merging without including additional handling is the principle point of interest of this model [19]. Be that as it may, what logically restricts the utilization of snakes is the need of the strategy to have solid picture slopes to have the capacity to drive the form.

4. RESULTS AND DISCUSSION

Here, the results of the work are mentioned in the figures [Figure No. 1-6] of the different proposed algorithms such as K-means clustering algorithm, Fuzzy-C means clustering algorithm, Fast-border marker algorithm and Snakes algorithm with their prospects are checked.

And Snakes algorithm provides exact region of the tumour compared to K-means clustering, Fuzzy C-means clustering and Fast-border mark algorithms. Therefore, the algorithms are compared pictorially as shown in above figures including the representations of tumour regions which are affected in medical Imaging.

5. CONCLUSION

In the medical diagnosis field, broadly assorted qualities of imaging strategies are available, such as CT and MRI scan. MRI scanned image is the well addressed image model used for diagnostic image properties for the brain tumour. K-mean algorithm can determine a brain tumour quicker than Fuzzy C-means, but Fuzzy C-means can determine tumour cells exactly. FBM is a quick segmentation technique that uses symmetry to enclose an anomaly (typically, tumours or edema) by a border mark within an axial brain MR image. As dynamic forms dependably give nonstop limits of sub-areas, they can deliver more sensible division results than customary division strategies.

Hence concluded, Snakes algorithm in which function is also based on user interaction makes the work reliable and provides good results.

References

1. N. Sasirekha, K.R. Kashwan Improved segmentation of MRI Brain images by denoising and contrast enhancement. *Indian Journal of Science and Technology*. 2015 September; 8(22), 1-7.

2. Viswa Priya, Shobarani An Efficient Segmentation Approach for Brain Tumordetection in MRI. *Indian Journal of Science and Technology*. 2016 May; 9(9), 1-6.

3. Naz S, Majeed H , Irshad H "Image segmentation using fuzzy clustering: A survey," in Proc. 6th *International Conference on Emerging Technologies*, 2010, 181-186.

4. Dehariya V, Shrivastava SK , Jain RC "Clustering of Image Data Set Using K-Means and Fuzzy K-Means Algorithms", *International conference on CICN*, 2010; 386-391.

5. Sethian JA, Level Set Methods and Fast Marching Methods, second ed., Cambridge University Press, 1999;1-2.
6. Shenbagarajan S, Ramalingam V, Balasubramanian C, Palanivel S, Tumor Diagnosis in MRI Brain Image using ACM Segmentation and ANN-LM Classification Techniques. Indian Journal of Science and Technology. 2016 Jan; 9(12), 1-12.
7. Kang WX, Yang QQ, Liang RR, "The Comparative Research on Image Segmentation Algorithms", *IEEE Conference on ETCS*, 2009;703-707.
8. Li B, Acton ST, Active contour external force using vector field convolution for image segmentation. *IEEE Transactions on Image Processing*, 2007;16(8), 2096-2106.
9. Thilagamani1 S, Shanthi NA Survey on Image Segmentation Through Clustering. International Journal of Research and Reviews in Information Sciences. 2011;1(1),1-4.
10. Zhang X, Tay A LP, "Fast learning artificial neural network (FLANN) based color image segmentation in RGBSV cluster space*," in Proc. International Joint Conference on Neural Networks,* 2007; 563-568.
11. Chan T F, Vese L A, Active contour without edges. IEEE Transactions on Image Processing 2001; 10(2), 66-277.
12. Caselles V, Kimmel R, Sapiro G, Geodesic active contours," in Proceedings, International Journal of Computer Vision, 1997; 61-79.
13. Brummer M E , Mersereau R M , Eisner R L, Lewine R J Automatic detection of brain contours in MRI data sets. *IEEE Trans. Medical Imaging* 1993; 12(2), 153-166.
14. Kass M, Witkin A, Terzopoulos D, Snakes: Active contour models. International Journal of Computer Vision 1987; 3(1), 321-331.
15. Pham DL, Xu CH, Princo JL A survey on current methods in medical image segmentation. Annual review of Biomedical Engineering. 2000; 2, 315-337.
16. Khotanlou H , Atif J olliot O, Bloch I, D Brain Tumour Segmentation using Fuzzy Classification and Deformable Models. WILF 2005;10(2), 312-318.
17. Liu J, Udupa J K, Odhner D, Hackney D, Moonis G, A system for brain tumour volume estimation via MR imaging and fuzzy connectness, CMIG-2005; 29(1), 21-34.
18. Wang Z, Hu Q, Loe K, Aziz A, Nowinski WL, Rapid and Automatic Detection of Brain Tumours in MR Images. Proceeding of SPIE 2004; 2(1), 602-612.
19. Moon N, Bulitt E, Leemput K, and Gerig G, brain and tumour segmentation. Proceedings of ICPR 2002; 1(1), l528-1531.