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Comparative Analysis between Active Contour and Otsu Thresholding Segmentation Algorithms in Segmenting Brain Tumor Magnetic Resonance Imaging

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Abstract

The accuracy of brain tumor detection and segmentation are greatly affected by tumors' location, shape, and image properties. In some situations, brain tumor detection and segmentation processes are greatly complicated and far from being completely resolved. The accuracy of the segmentation process significantly influences the diagnosis process, such as abnormal tissue detection, disease classification, and assessment. However, medical images, in particular, the Magnetic Resonance Imaging (MRI), often include undesirable artefacts such as noise, density inhomogeneity, and partial volume effects.

Although many segmentation methods have been proposed, the accuracy of the segmentation results can be further improved. Subsequently, this study attempts to provide very important properties about the size, initial location and shape of tumors known as Region of Interest (RoI) to kick-start the segmentation process. The MRI consists of a sequence of images (MRI slices) of a particular person and not one image. Our method chooses the best image among them based on the tumor size, initial location and shape to avoid the partial volume effects. The selected algorithms to test our method are Active Contour and Otsu Thresholding algorithms. Several experiments are conducted in this research using the BRATS standard dataset that consist of 100 samples. These experiments comprised of MRI slices of 65 patients. The proposed method is evaluated by the similarity coefficient as a standard measure using Dice, Jaccard, and BF scores. The results revealed that the Active Contour algorithm has higher segmentation accuracy when tested across the three different similarity coefficients. Moreover, the achieved results of the two algorithms verify the ability of the proposed method to choose the best RoIs of the MRI samples.

Keywords: Brain tumour, Magnetic Resonance Imaging (MRI), Segmentation, Active contour, Otsu threshold.

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Introduction

A brain tumour is becoming a worldwide government health issue with the increasing population growing older. According to the recent report statistic from the World Cancer Research Fund, the world’s leading cause of death is cancer. Each year, an average of 12.7 million cancer patients isreported worldwide, where 7.6 million from the cases come from brain cancer (Belaid and Loudini, 2020). Magnetic Resonance Imaging (MRI) is known for its high efficiency in diagnosing the multispectral brain images, mainly due to its ability to develop the contrast of the number of variables identified. However, precise brain tumour segmentation is a critical problem for many medical imaging technologies; in specific the MRI for brain diagnosis (Sharif et al., 2020). It requires precise detection of tumours in size, position, and clearance in order for the patients receives suitable treatment. Valid segmentation is also essential in lives-threatening instances. These would be cases in which the tumour is either next to or above one or closely related sensitive parts of the cerebellum. Hence, a high accuracy segmentation method is needed, particularly in detecting the boundaries between tumour and edema.

Nowadays, the usage of diagnostic computer-assisted systems for improving medical therapy level has become an interesting subject in medical imagery and radiology diagnostics research. Subsequently, many studies have been conducted and recorded in the literary works with regards to brain images segmentation such as using elastic fitting techniques or modelling (Liu et al., 2020). The fitting techniques are proven to be effective for tiny and confined tumor shape, in particular for ordinary tissue segmentation. Explicit models including Gaussian intensity models (Zhao et al., 2018), and Markov random field models are found to be practical in regular tissue segmentation (Arnab et al., 2018; Cao et al., 2018). Meanwhile, unsupervised or supervised classification techniques have demonstrated robustness and solid solutions (Sun et al., 2018).

Nonetheless, due to the complex anatomy and several issues inherent in the existence of the image, brain tumour segmentation remains a difficult task (Tiwari et al., 2019). The heterogeneous nature of the tumour images complicates the use of computational methods that can handle this large variety of structures. All image modalities also introduce difficulties and artefacts that need to be resolved by the segmentation techniques. MRI pictures, for example, are often compromised with soft inhomogeneity of different intensities, known as the bias field. For a specified tissue, this is a non-uniformed pattern of intensity over a picture is undetectable but extremely perceptible through an automatic method on a computer, making segmentation more complex. In addition, due to the complex brain form and the limited resolution of medical images, some voxels may be located at the edge between two or more forms of tissues, i.e. the same voxel intensity simultaneously reflects the contribution from various types of tissue.

In recent years, many methods (Tiwari et al., 2019; Soni et al., 2019) to satisfy the needs of an improved segmentation method were suggested based on the exactness and the percent of the MRI tumour part's coincidence with the ground truth. Based on the literature, Active Contour algorithm is an energy-based technique considered as among the strongest techniques for image segmentation (Ma et al., 2018; Essadike et al., 2018). It has been widely applied in several fields such as biology studies (Mohammed et al., 2020), river image segmentation in the satellite image (Song et al., 2016), and optical defect inspection for large steel roller surfaces (Yang et al., 2018). The thresholding segmentation algorithm, on the contrary, is found to be a simple and practical method for separating an image into a background and foreground (Chen et al., 2017). This method of image analysis segregates objects of interest by converting gray into binary images. Applications that are known for using the thresholding algorithms is for vegetation identification such as herbaceous crops in Arunkumar et al. (2020) and analysis of satellite images as in Suresh et al. (2016).

In this study, a Region of Interest (RoI) measurement method is proposed to provide very important properties about the size, initial location and shape of tumors in MRI slices order to kick-start the segmentation process. A comparative analysis is introduced to examine the performance of the method by using Active contour and Otsu threshold segmentation algorithms based on three similarity indices; the Dice, Jaccard, and BF score (Mohammed et al., 2018). The algorithms are evaluated and compared based on the common Multimodal Brain Tumor Image Segmentation (BRATS) dataset. The results are validated by comparing against a ground truth by calculating the same metrics of similarity coefficients. The remainder of this paper is organized as follows. Firstly, the theory of segmentation algorithms is being explained. Then, the definition of the used similarity coefficients is being described. Subsequently, the experimental results are being provided. Finally, the concluded remarks are presented in the Conclusion section.

Methods

This study is set to propose a RoI method that extracts the size, initial location and shape of tumors from MRI slices. Subsequently, it performs a comparative analysis between two image segmentation algorithms, which are the Active Contour algorithm and Otsu Thresholding algorithm and tested on the BRATS dataset. The main research steps to conduct this study are shown in Figure 1. In general, the research steps can be classified into four main phases.

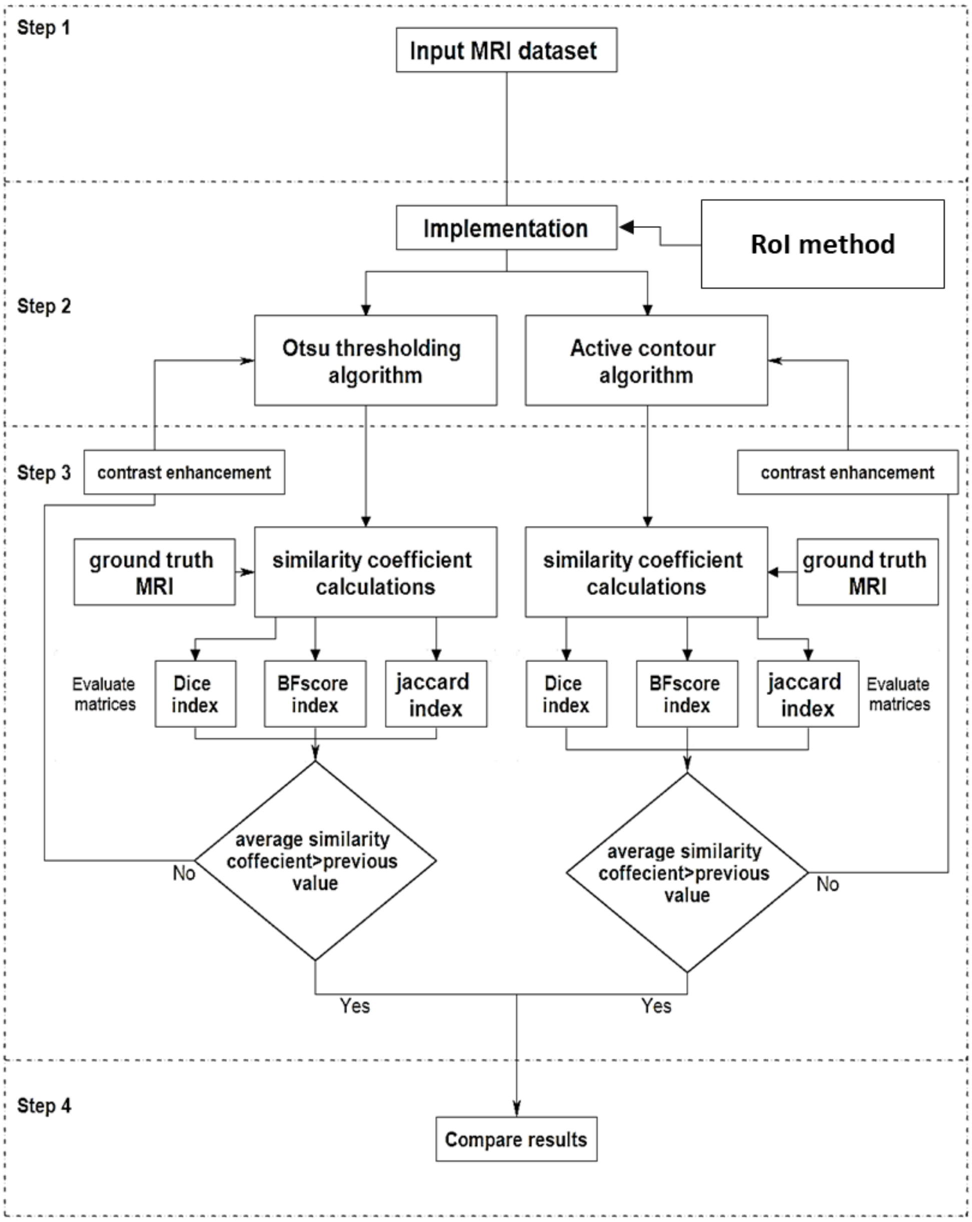

Figure 1. Research steps

The first is the selection of the medical image sets. In the second phase, the implementation of the RoI method and the segmentation process are being carried out using the Active Contour and Otsu Thresholding algorithms. In the third phase, the segmentation analysis is being performed based on three evaluation metrics, which are the Dice, Jaccard, and BF scores of similarity coefficients. Finally, in the fourth phase, all results are analyzed and compared.

Segmentation Algorithms

Segmentation entails separating an image into homogeneous and disjoint regions. This task can be accomplished by discovering regional borders or homogeneous areas based on mathematical models in analyzing the input MRI and segmenting the Region of Interest (ROI) (Mohammed et al., 2020).

Active Contour. Active contour is a segmentation algorithm that utilizes curve evolution to solve image segmentation or target detection based on partial differential equations on edge to identify a curve or surface power feature (Mohammed et al., 2018; Abd Ghani et al., 2020). Active contour has a smooth function that allows the grayscale distribution of the picture to be approximated and discontinuity when crossing the curve. By a piecewise smooth function, this method can approximate a function, therefore is being widely used in image processing (A Vese and Chan, 2002; Arunkumar et al., 2019). The Active Contour algorithm works as follows.

begin

1. read intensity pixel for each element in the input image and save as a matrix element (m, n);
2. convert input MRI to the matrix with m*n dimension and save it in location p;
3. determine intensity value distribution over the location of image pixels to compute histogram;
4. generate two sets of the intensity level value based on intensity gradient and the edge of the object;
5. determine fitting energy function;
6. determine the level set function and classify two areas in the MRI based on intensity level area inside and outside object;
7. calculate contour length and extract the object;

end.

Otsu Thresholding

A threshold is a particular intensity value containing a predetermined intensity valuation. The objective is to discover the threshold value in which the sum of background and foreground extents at the minimum. It is used to distinguish the object or ROI from the background picture selected between 0 and 255 (Sharif et al., 2020). One of the widely been using techniques for image segmentation process is a threshold. It is helpful to discriminate from the background in the foreground (Sharma et al., 2019). Otsu thresholding technique includes calculating a spread measure for each side of the limit for the pixel concentrations, i.e. pixels falling either in the foreground or in the background.

Otsu's method generally selects the threshold by minimizing the in-class variance of the two-pixel groups separated by the operator. Furthermore, the pixel classes are determined on the basis of the histogram probability as the following equation describes for an image with [1, 2, …, L] gray levels and each level i has a number of pixels denoted by n. The Otsu thresholding algorithm works as follows.

begin

1. read intensity pixel for each element in the input MRI image and save the intensity value as a matrix element with its location indices (m, n);
2. convert input MRI to the matrix with m*n dimension and save it in location q;
3. calculate intensity value distribution over the location of the pixel in an image in order to compute the histogram;
4. classify the calculated histogram;
5. apply threshold value for all pixel intensity and update each pixel intensity with the new threshold value compared with the previous intensity;
6. separate MRI into foreground and background;

end.

Testing Dataset

The dataset sourced from the Swiss Institute for Computer-Assisted Surgery (SICAS), which is the Multimodal Brain Tumor Image Segmentation (BRATS) dataset (Makropoulos et al., 2018). BRATS is a big dataset of brain tumour MR scans in which it is used to assess the performance of the segmentation algorithms. In this dataset, the structure of the tumours has been outlined. This dataset also includes the ground truth of the specified brain tumour as shown by Figure 2.

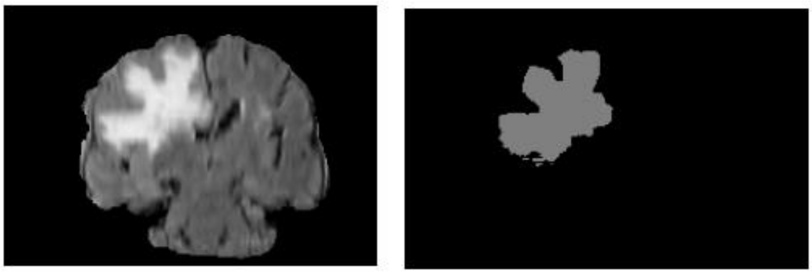

Figure 2. Brain tumour (L) and Ground truth segmented tumour (R)

It can be noted that a pre-processing for the MRI dataset have been carried out before the segmentation process. Pre-processing includes contrast enhancement based on the feedback of the similarity index to get an appropriate value due to a variety of the shape and brightness of dataset. However, the same pre-processing has been applied to the dataset for both algorithms to get comparable results.

Evaluation Metrics

To validate brain tumour segmentation for active contour and threshold algorithm, the similarity coefficient has been determined in order to calculate the matching between the outcome of the algorithm and the ground truth image provided by the dataset. Three evaluation metrics for determining the similarity coefficient have been used, which are the Dice, Jaccard (Thada and Vivek Jaglan, 2013; Soni and Chaurasia, 2019), and BF Score (Csurka et al., 2013; Obaid et al., 2018) similarity coefficients. The explanation of the similarity indices concept is described in Figure 3.

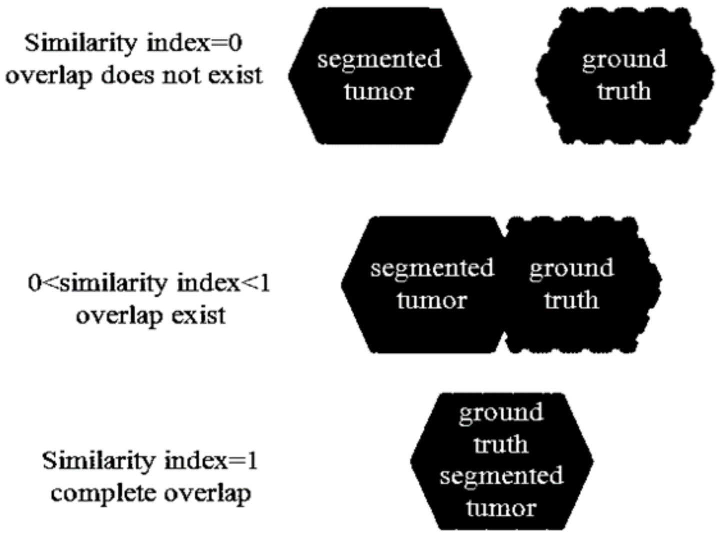

Figure 3. Similarity indices concept

Dice Similarity Coefficient

It is a statistical measure for the similarity between two interties (Soni and Chaurasia, 2019). It is expressed as Eq. 1.

$$dice(X,Y) = 2 * |\cap(X,Y)| / (|X| + |Y|) \quad (1)$$

where |X| denotes the cardinal of set X.

The Dice is also calculated based on the measurements of TP, true positives; FP, false positives and FN, false negatives as presented in Eq. 2.

$$dice(A, B) = 2 * TP / (2 * TP + FP + FN) \tag{2}$$

Jaccard Similarity Coefficient.

It is also known as IoU, intersection over the union (Thada and Vivek Jaglan, 2013). It is expressed as Eq. 3.

$$Jaccard\ (A, B) = |\cap (A, B)| / |\cup (A, B)| \tag{3}$$

Similarly, the Jaccard is also calculated based on the measurements of TP, true positives; FP, false positives and FN, false negatives as presented in Eq. 4.

$$Jaccard\ (A, B) = TP / (TP + FP + FN) \tag{4}$$

BF Score Similarity Coefficient

BF Score returns as a numeric scalar between [0, 1]; where 1 indicates that contours of objects and the ground truth have a perfect match (Csurka et al., 2013). The BF is used to evaluate the difference between the ground truth and predicted boundaries of an object as shown in Eq. 5.

$$score = 2 * precision * recall / (recall + precision) \tag{5}$$

where precision (positive predicted value) represents the proportion of related cases related to the retrieved instances and recall represents the fraction of the related instances found over the total number of related instances.

The Materials and Methods section of the paper should be very detailed, but concise.

Experimental

The segmentation accuracies from the Active Contour and Otsu Thresholding algorithm are obtained by calculating the similarity indices. The purpose of the similarity indices is to find the percentage of the overlap between the output of the segmented tumor for both algorithms against the given ground truth. 100 case studies were randomly selected as samples from more than 500 cases in the dataset. The results are considered good segmentation when there is overlap between segmented results and the ground truth above 70%.

Implementation

Implementation of the segmentation algorithms was carried out using the MATLAB 9.5 platform due to its ability to handle matrix operation. A Graphical User Interface (GUI) was implemented to interface user with the MATLAB environment where the algorithms were implemented. The GUI will also be using the same testing set MRI as input for the Active Contour and Otsu Thresholding algorithm. After the segmentation process is completed, the output segmented tumour area have been saved automatically in the same file directory in order to compare to the ground truth as shown in Figure 4.

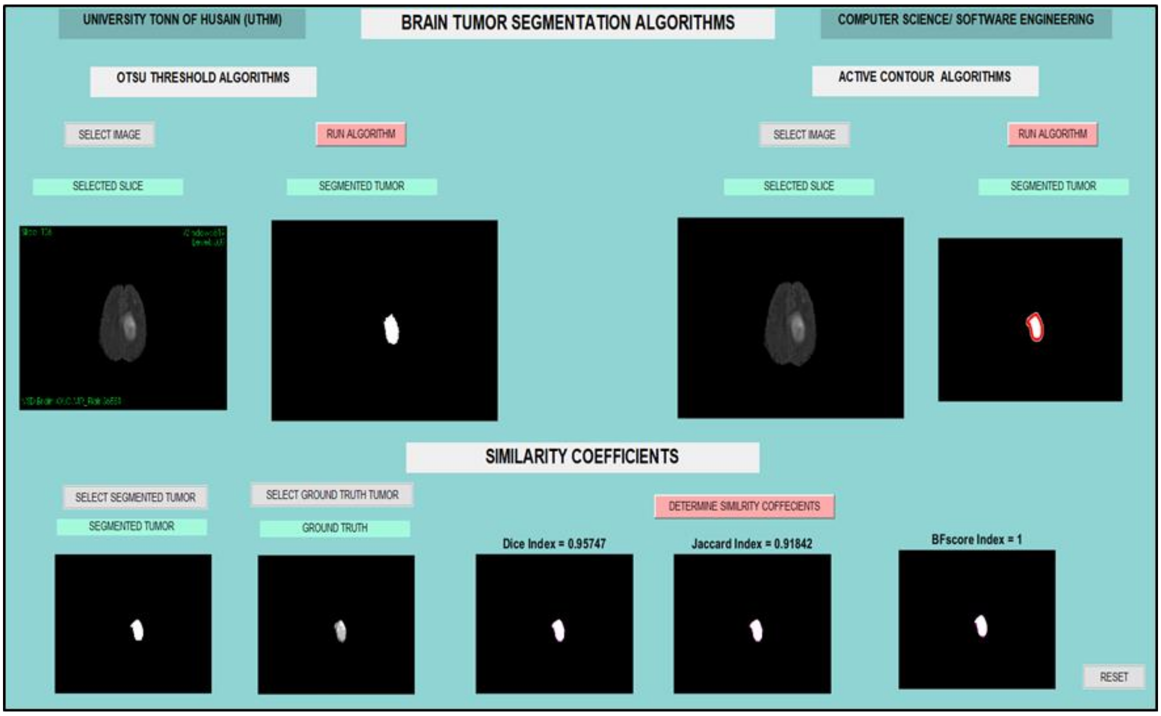

Figure 4. MATLAB GUI of the implemented testing program

Evaluation

An important characteristic of the level set mathematical methods is that desired contours can split or merge depends on the variables of the level set function. Therefore, the level set approach has the ability to detect more than one boundary synchronously, besides having multiple initial contours can be applied. Furthermore, the embedded energy function is used to make a statistic calculation to fit the curve stretch surrounding the region of interest by determining the energy inside the curve as compared with the external energy to prevent discontinuity of the determined contour. Dice coefficient is a statics method lead to finding the measuring of the spatial overlap between two proposed segmented areas, A and B target regions. The comparative explanation for the Dice results from both algorithms is illustrated in Figure 5.

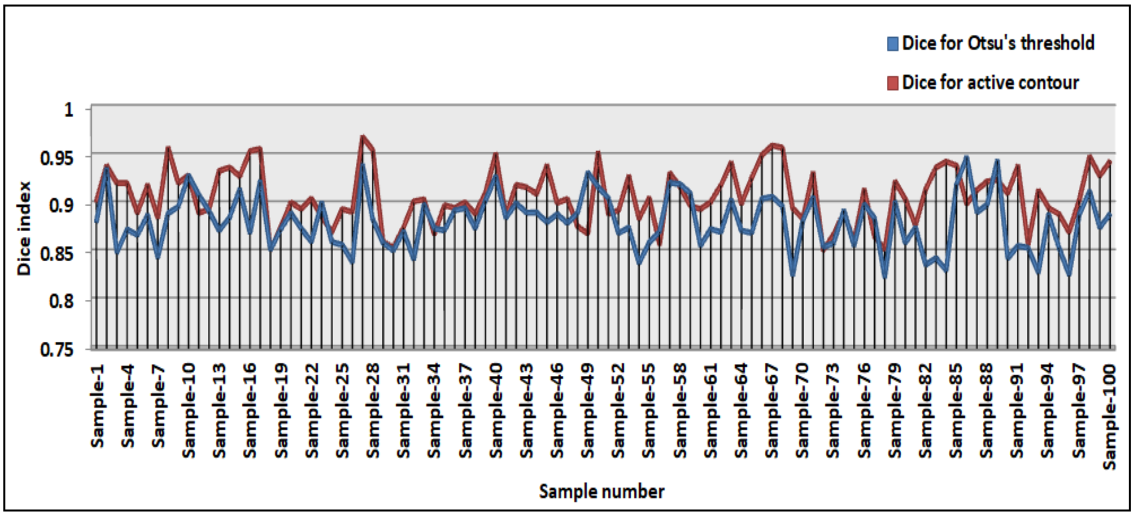

Figure 5. Comparative plot of Dice index

Jaccard considers both the missed values and the false alarms for each class. The comparison for the determined results obtained from the Active Contour and Otsu Thresholding algorithm is shown in Figure 6.

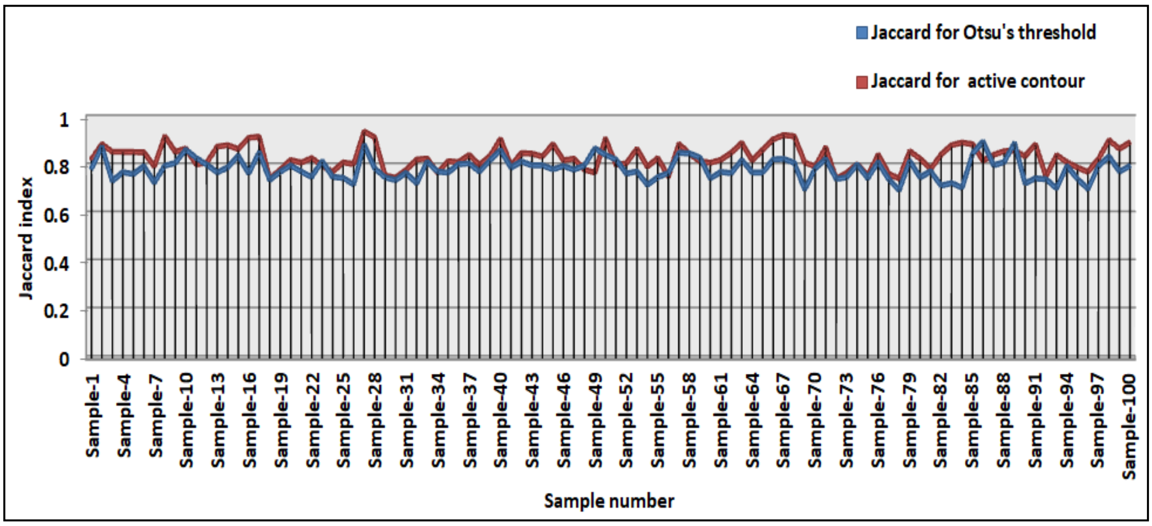

Figure 6. Comparative plot of Jaccard index

BF Score coefficients come in the form of a numeric scalar with qualities within the range of [0, 1]. A score of 1 implies that the forms of items in the comparing class in expectation and ground truth are an ideal match. So it indicates that there is matching between segmented area contour with the ground truth contour. The plot in Figure 7 shows the comparison between the results achieved from the Active Contour and Otsu Thresholding algorithm.

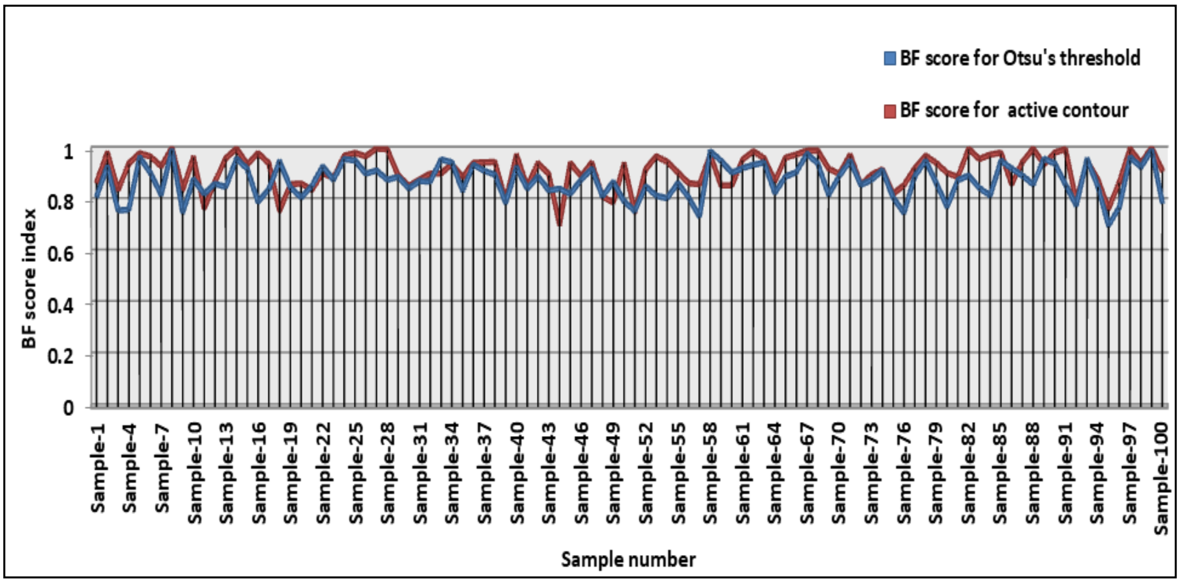

Figure 7. Comparative plot of BF Score index

To summarize the evaluation performance of both segmentation algorithms using the similarity coefficients as an indicator, the mean value for the calculated similarity index is presented in Table 1.

Table 1. Comparison results based on similarity coefficients

Algorithm	Similarity Coefficients Mean Value		
	Dice	Jaccard	BF Score
Active Contour	0.906122	0.830462	0.913105
Otsu Thresholding	0.882314	0.790214	0.880428

It can be seen based on the achieved results, that the Active Contour algorithm performed better than the Otsu Threshold algorithm with higher similarity coefficients values. This is because the basic idea of the Active Contour focuses on determining a curve, or curves applied to constraints from the input image data. The curve should grow until its boundary touches the object of interest. Active Contour achieved better performance than the Otsu Thresholding algorithm due to its capability to produce sub-regions with defined continuous boundaries. The ability of level set theory helps to give more flexibility in the implementation process of Active Contours because it is possible to start with a closed curve in a two-dimensional plane or a surface in three dimensions and allow the curve to expand perpendicular to itself at a predefined configuration.

Meanwhile, the Otsu algorithm work on setting the weighted sum between variances of foreground and background classes for the entire input MRI image to the maximum limit in order to determine an optimum threshold value. The algorithm determines the desired threshold value to segment the region of interest. From the experiment, it is noted that the drawbacks of Otsu Threshold segmentation algorithm due to irregular boundaries generated from neighbouring pixels. This results in segmentation regions not connected, hence the lower similarity coefficients values. The results from Otsu Thresholding algorithm is also unsatisfactory when the object has a significant contrast of gray-level than the background. Isolated pixels are often missed especially within the region of pixels neighboring the point of interest region. On the other hand, thresholding approach has several problems and the main of which is that it only deliberates the intensity and neglects the possible relationships between pixels. Subsequently, thresholding segmentation does not insure contiguous pixels' segmentation.

Conclusion

This paper proposes a RoI method that extracts the size, initial location and shape of tumors from MRI slices. Subsequently, it explained and illustrated the comparative implementation and results of the Active Contour and Otsu Thresholding segmentation algorithms based on brain tumour segmentation of BRATS dataset. The Dice, Jaccard and BF Score similarity coefficients are used to evaluate the segmentation output for both algorithms based on mathematical calculations. The coefficients basically scored the overlap percentage between the segmented tumour and given ground truth. Based on the experimental results provided by the similarity coefficients, it can be concluded that the achieved results of the two algorithms verify the ability of the proposed method to choose the best RoIs of the MRI samples. The comparative analysis revealed that both algorithms have almost the same pattern for the plotted curve with higher amplitude values recorded to Active Contour algorithm for the three similarity indices. This indicates that Active Contour has higher similarity index value. Nonetheless, the Otsu Thresholding algorithm still involves in many applications due to its simple implementation as compared with the other algorithms.

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