Automatic Tumour Extraction in MRI Scan: A survey

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Abstract: **Tumour segmentation from magnetic resonance imaging (MRI) data is an important but time consuming manual task performed by medical experts. Automating this process is a challenging task because of the high diversity in the appearance of tumour tissues among different patients and in many cases similarity with the normal tissues. MRI is an advanced medical imaging technique providing rich information about the human soft-tissue anatomy. There are different brain tumour detection and segmentation methods to detect and segment a brain tumour from MRI images. We have reviewed these detection and segmentation approaches with an importance placed on enlightening the advantages and drawbacks of these methods for brain tumour detection and segmentation. The use of MRI image detection and segmentation in different procedures are also described. Here a brief review of different segmentation for detection of brain tumour from MRI of brain has been discussed.**

***Keyword*-MRI scan, Tumour Segmentation, Tumour Detection, Optimization, SFLA**

I. INTRODUCTION

Image segmentation is one of the most important and active research area in the medical imaging domain. It can be defined as the delineation of one or several structures of interest within the image. Automated methods are sought in order to avoid the time consuming burden of manually contouring the structures. The problem is particularly difficult in the context of brain tumours. Indeed, most tumours have heterogeneous appearances and their intensity range overlap with the healthy tissues'. The presence of a necrotic core is frequent (especially for glioblastomas, but it also occurs for DLGGs) resulting on a strong contrast with the "active" tumour. Prior information regarding the shape of the tumour cannot be used as they have variable sizes and shapes. DLGGs in particular, have very fuzzy and irregular boundaries due to their infiltrative nature. Edema (swelling of brain tissue around the tumour) and mass effect (tissue displacement induced by the tumour) are quite uncommon due to the slow-growing nature of the DLGGs [Sanai 2011]. In this context, the simplest segmentation methods such as thresholding or region growing are insufficient [Gibbs 1996]. Despite extensive and promising work in the tumour segmentation field, obtaining accurate and reliable segmentations of brain tumours remains a difficult task. Segmentation methods can be grouped in two categories: surface and region-based approaches. The objective of surface based methods is to find the organ or tumour's boundary by propagation a curve/surface with a flow that is determined according to curvature and image constraints (generally the image gradient). Snakes and level sets are typically used in this context. The former defines the object's boundary explicitly as a parametric curve, while the latter defines the contour via an implicit function allowing for more complex geometries and topological changes. Region based methods consider the segmentation problem from a different angle. Here, the goal is to identify all voxels belonging to the object and separate them from the rest of the image. Supervised statistical pattern classification techniques have been the basis of the majority of recent region based tumour segmentation methods. The voxels are separated by a classification score or probability, the ultimate goal being to label each pixel of the image as tumour or background. The tumour is frequently separated into active tumour, necrosis and an additional class is introduced in the context of fast growing tumours. The obtained segmentations are refined by the use of graph based methods that model spatial dependencies and prior anatomical knowledge.

Magnetic Resonance Imaging (MRI) is a powerful visualization technique that allows images of internal anatomy to be acquired in a safe and non-invasive way. It is based on the principles of Nuclear Magnetic Resonance (NMR), and allows a vast array of different types of visualizations to be performed.

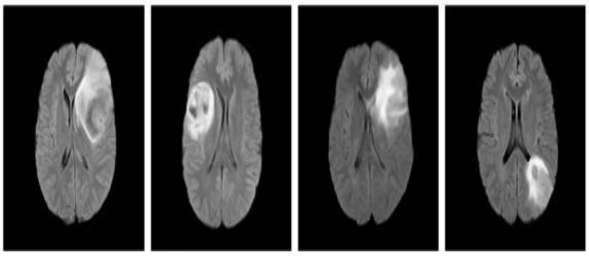

Fig.1.1: Examples of different DLGG appearances on FLAIR T2 MRIs [6]

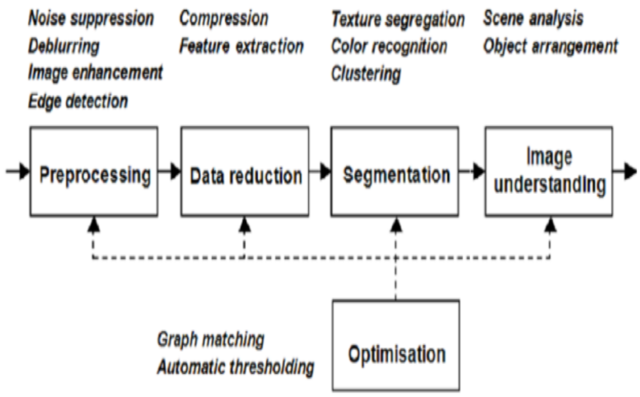

Fig.1.2: General block diagram of MRI imagesegmentation

This imaging medium has been of particular relevance for producing images of the brain, due to the ability of MRI to record signals that can distinguish between different 'soft' tissues (such as grey matter and white matter). In this paper we focus on the literature study of the brain tumour segmentation without prior knowledge of actual location of tumour.

II. LITERATURE REVIEW

M. Kaur, R. Mittal [1] developed a simple approach for detection of brain tumour which is based on the method using Euclidean distance classifier and making use of feature vector table and which over comes the limitations of conventional in which combination of supervised and unsupervised learning have been implemented to build cancer detection system, as there is huge overhead in this approach and there is a need to maintain large size training datasets.

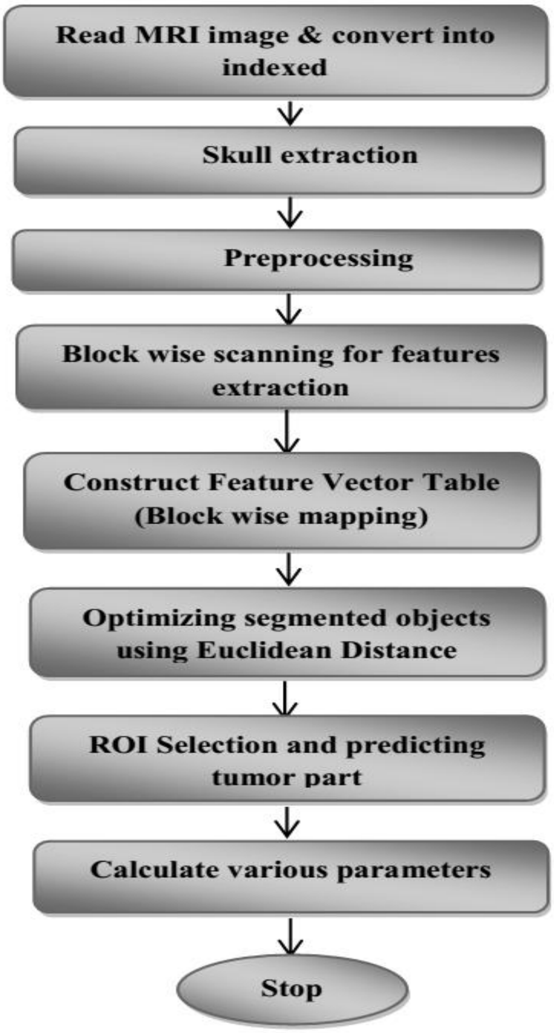

Fig.2.1: Block schematic diagram of brain tumour detection using Euclidean distance [1]

The proposed method first convert the image into indexed image, than after de noising it with 3*3 mean filter, it conducts the block wise scanning to get feature set of statistical features in both frequency and time domain and finally based on Euclidean distance measures an optimized tumour part is segmented which is ROI (region of interest) then this segmented part is validated and test to arrive at exact brain tumour part required. The result show high reduction of time, increases specificity with better accuracy in terms of true positive rates. A flow chart for suggested work by paper is shown in figure 2.1.

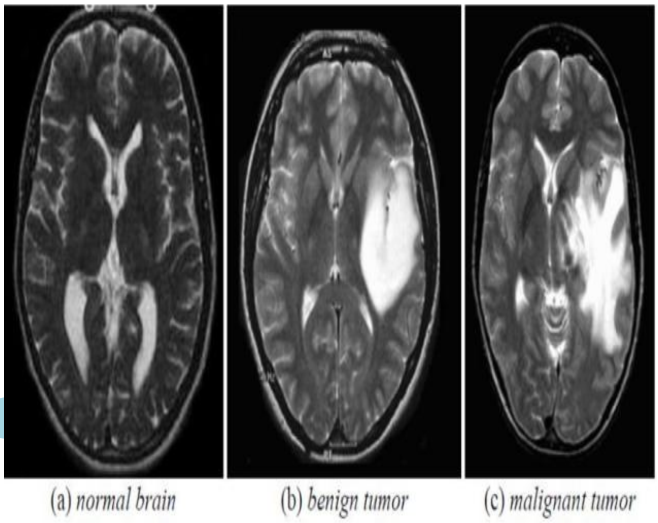

Fig.2.2: Tumours studied in [3]

C. Biradar, Shantkumari [3] used SVM classifier to detect the type of tumour. They have extracted features based on are, skewness and kurtosis and classified theses features after cascading using linear SVM. They have also used the discrete wavelet transform for features extraction in combination with texture features. The type of tumours they have classified are shown in figure 2.2.

K.Selvanayaki, Dr.P.Kalugasalam [4] proposed the meta-heuristic methods such as Ant Colony optimization (ACO), genetic algorithm (GA) and Particle swarm optimization (PSO) for segmenting brain tumours in 3D magnetic resonance images. Here this paper is divided into two stages. In the first stage pre-processing and enhancement is performed using tracking algorithms. These are used to pre-processing to suppress artefacts, remove unwanted skull portions from brain MRI and these images are enhanced using weighted median filter. The enhanced technique is evaluated by Peak Signal-to-Noise Ratio (PSNR) and Average Signal-to-Noise Ratio (ASNR) for filters. In the Second stage of the intelligent segmentation is three algorithms will be implemented for identifying and segmenting of suspicious region using ACO, GA and PSO, and their performance is studied. The proposed algorithms are tested with real patients MRI. Results obtained with a brain MRI indicate that this method can improve the sensitivity and reliability of the systems for automated detection of brain tumours .The algorithms are tested on 21 pairs of MRI from real patient's brain database and evaluate the performance of the proposed method.

Continuing the methodology used in [4], PSO is used to segment the image and tumour form brain in [5]. Results for different segmentation level are shown in the paper. For example figure 2.3 shows them.

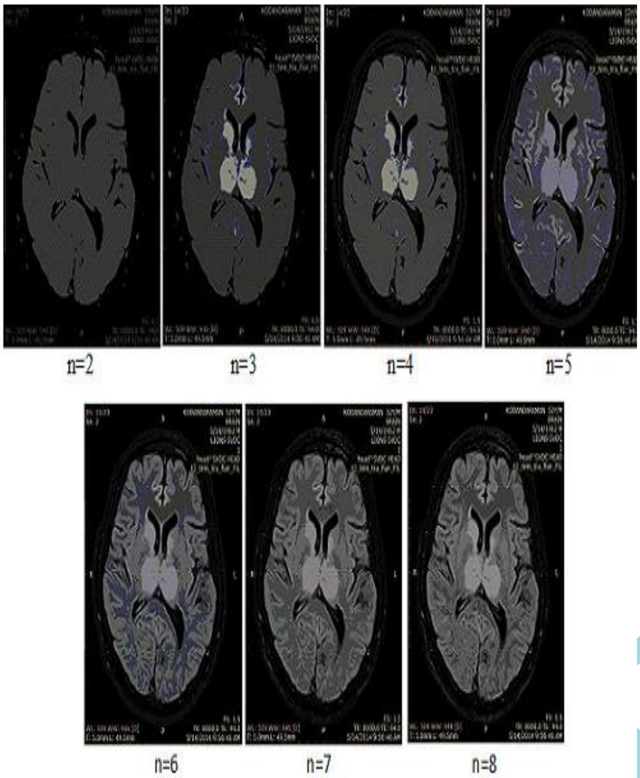

Fig.2.3: different segmentation level tumour extractionby PSO [5]

The third stage is by taking the resultant images of the axial and coronal plane, with the help of the elapsed time. The best resultant image is calculated by [5]

$$\frac{\sum_{n=2}^{8} P_n}{n+2} \qquad \text{Eq. 1}$$

In equation 1, Pn determines the elapsed time of the plane either axial or coronal, n represents the total number of segmentation level and n denotes the segmentation level. The best resultant image from the different segmentation level is achieved with the equation 1.

A step ahead in using heuristic algorithms [6] used a latest modified frog leaping algorithm which is also a bio inspired algorithm but this paper uses the method to calculate the threshold value and comparison of test image pixel with this threshold will give the tumour part. Results have been compared with convention frog leaping algorithm are results are quite improved. This frog leaping algorithm attracts us so we studied a bit more on this algorithm.

Paper [7] compared previous researches on SFLA(Shuffled frog leaping algorithm) and its effectiveness, with the most applied optimization algorithms reviewed and analyzed. Based on the literature, many efforts by previous researchers on SFLA denote the next generations of basic SFLA with diverse structures for modified SFLA or hybrid SFLA. As well, an attempt is made to highlight these structures, their enhancements and advantages.

Moreover, this paper considers top improvements on SFLA for solving multi-objective optimization problems, enhancing local and global exploration, avoiding being trapped into local optima, declining computational time and improving the quality of the initial population.The results of recognition of T2 weighted MRI tumours isshown in figure 2.4

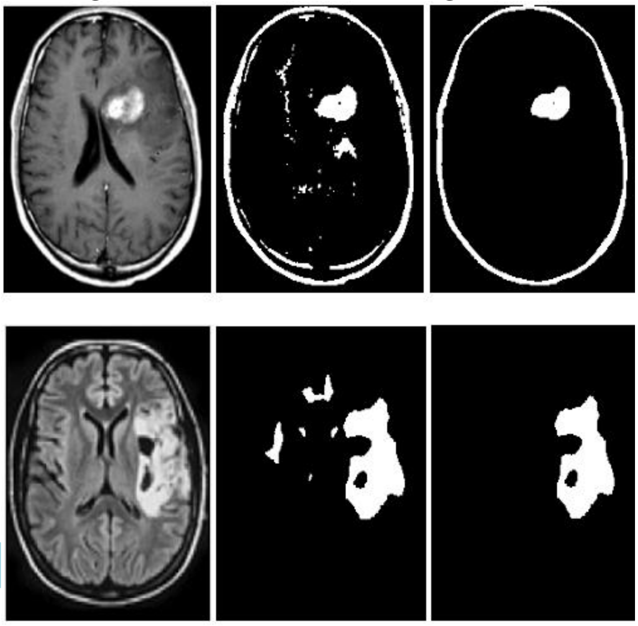

Fig.2.4: Results of recognition of T1-weighted MRI tumours (a) original image, (b) applying conventional SFLA, (c) applying MSFLA [6]

The measured enhancements in SFLA are based on the statistical results obtained from 89 published papers and by considering the most common and effective modifications done by a large number of researchers. Finally, the quantitative validations address the SFLA as a robust algorithm employed in various applications which outperforms the other optimization algorithms.

In recent years form 2013-2015, a lot work on bio inspired algorithm in brain tumour detection is done. Fractional PSO and fuzzy K means [9] is also a gem in that. In [13] a framework is proposed which is a combination of region-based and boundary-based paradigms. In this framework, segment the brain using a method adapted for pathological cases and extract some global information on the tumour by symmetry based histogram analysis .The objective of this paper is to present an analytical method to detect lesions or tumours in digitized medical images for 3D visualization. This research opens a new window in the field of image processing by 3D Volume Representation oftumour through the use of Magnetic Resonant Imaging and an integrated software tool called 3D Slicer. The authors developed a tumour detection method using three parameters; edge (*E*), gray (*G*), and contrast (*H*) values. The method proposed here studied the *EGH* parameters in a supervised block of input images. These feature blocks were compared with standardized parameters (derived from normal template block) to detect abnormal occurrences, e.g. image block which contain lesions or tumour cells. The proposed method shows more precision among the others. Processing time is less. Thiswill helpthe physicians in analysing the brain tumoursaccurately and efficiently.

In [15] E. Ben George explored the CS algorithm, performing a profound study of its search mechanisms to discover how it is efficient in detecting tumours and compare the results with the other commonly used optimization algorithms. The author has also used the MRF based algorithm along with cukoo search algorithm. The process is shown in figure 2.5.

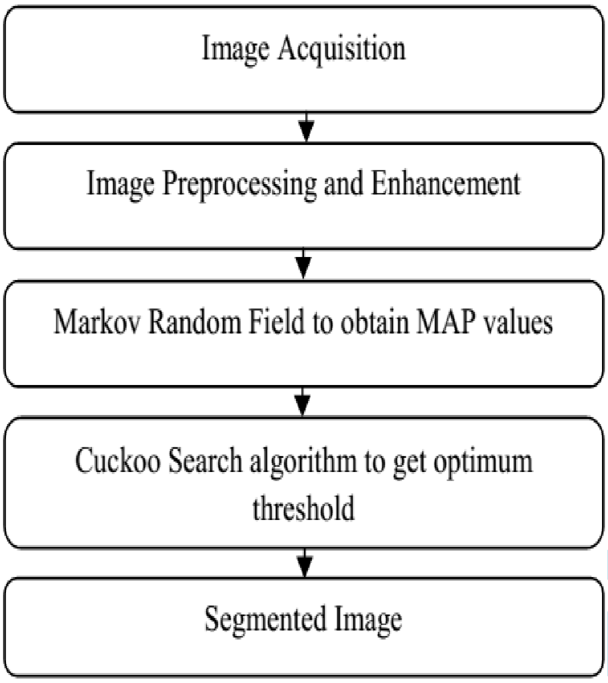

Fig.2.5: Overall process of segmentation of the brain tumour

III. III. CONCLUSION

In our study various papers on brain tumour segmentation form MRI images have been studied which are published in between 2013-2015. A lot of researchers are preferring to use bio inspired optimisation algorithm for the segmentation of unknown area form the MRI image. Some of them suffer the problem of local minima due to which it does not provide optimal solution. To get better and accurate results sometimes a hybrid using two techniques is used. Still an NP hard problem and simple mathematical calculation can't give result. Some of them also worked towards the categorising the tumour using machine learning algorithm specifically SVM and MRF. A very less work is seen on 3D MRI images of brain.

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