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A Comparative Study of Medical Image Segmentation Methods for Tumor Detection

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***Abstract*—**Image segmentation has a fundamental role in analysis and interpretation for many applications. The automated segmentation of organs and tissues throughout the body using computed imaging has been rapidly increasing. Indeed, it represents one of the most important parts of clinical diagnostic tools. In this paper, we discuss a thorough literature review of recent methods of tumour segmentation from medical images which are briefly explained with the recent contribution of various researchers. This study was followed by comparing these methods in order to define new directions to develop and improve the performance of the segmentation of the tumour area from medical images.

***Keywords*—**Features extraction, image segmentation, medical images, tumour detection.

I. Introduction

IMAGE segmentation is an important technique for segmenting images without overlapping each other and having their own features. It has been rapidly developed in the field of medical imaging. In fact, automated segmentation of organs throughout the body using computed tomography and magnetic resonance imaging has increased rapidly. Among the most widespread applications in the medical field, we can cite the detection of the localization of tumours, estimation of their volume, delineation of the cells, and their surgical planning [1]. Indeed, research in many medical conditions has greatly benefited from these approaches by allowing the development of faster and reproducible quantitative imaging markers. These markers have been used to help diagnose different pathologies, determine the estimate of disease progression, select and monitor appropriate treatments. As some of these tools are moving from research environments to clinical practice, it is important for radiologists to become familiar with the different methods used for automated segmentation. Indeed, this information should help radiologists better evaluate automated segmentation tools and apply them not only to research, but also to clinical practice.

This article presents an in-depth study of the literature on recent methods of tumour segmentation from MRI images. It includes performance and quantitative analysis of advanced methods. Different image segmentation methods are briefly explained with their advantages and disadvantages, not only for comparative analysis but also for recent contribution from various researchers.

This review paper is organized as follows: On the first section, we start by presenting the introduction. The second section is devoted to the presentation of the different methods of segmentation of tumors from medical images. Subsequently, in the third section we elaborate the comparative study with a discussion, and we finally close with a conclusion.

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II. Medical Images Segmentation

Various approaches to automated segmentation of computed tomography (CT) and magnetic resonance (MRI) images are widely used in research environments and promise to transform clinical practice and radiologists involved in image interpretation for patients with cancer, obesity, cardiovascular disease, neurodegeneration, osteoporosis, arthritis, etc. Such approaches will help clinicians diagnose the disease, determine the prognosis, select the patients for treatment and to monitor responses to treatment. To enable this transition from research to patient care, radiologists must become familiar with the different methods used for automated segmentation of CT and MRI images.

A. Semiautomatic vs Automatic Segmentation

As an indication, segmentation consists in identifying the limits of an object in the image. Frequently, the object is an organ, tissue, pathological lesion or other structure used for the diagnosis or treatment of a particular disease. Traditional approaches to segmentation rely on manual or semi-automated delineation of the object of interest. While these approaches are effective, they are time consuming and impractical for large-scale research studies and even less practical for clinical practice. As a result, many fully automated approaches to tissue segmentation are under development. This is because automated segmentation methods using CT and MRI generally rely on basic image processing of pixel intensities and textural features (relationships between groups of pixels, for example) and may incorporate techniques: advanced model-based, atlas or machine learning. Segmentation techniques can be broadly divided into supervised and unsupervised, as will be highlighted in the next subsection.

B. Supervised and Unsupervised Segmentation

Supervised segmentation techniques require prior training, usually done manually. These methods typically include pre-processing such as intensity normalization, followed by classification (artificial neural networks, nearest k-neighbours, etc.). The selection of features is based on intensity, texture or contextual information. They are considered more precise but require expert annotation, which is both expensive and time consuming. In contrast, unsupervised segmentation techniques do not require training and are generally considered to be less accurate than supervised techniques. These methods typically incorporate grouping and spatial information to segment the image. They also commonly use labelled atlases. Thereupon, the reported performance of supervised and unsupervised segmentation techniques varies widely, in part depending on the used validation metrics. Usually, validation is based on expert assessment. Since a single expert's assessment can be biased, several experts can also be involved using techniques such as simultaneous estimation of truth and level of performance [2].

1. Supervised methods

1.1. K-Nearest Neighbour

The k-NN algorithm is a memory-based supervised learning algorithm that directly compares new unlabelled problem instances with a collection of labelled samples in the training set. The k-NN classification is performed in two steps. In the first step, the closest neighbours of an unlabelled instance are identified, then in the second step, the class or label of the instance is determined using those neighbours [2]. In this context, the k-NN method was used in [3] to segment light and dark abnormalities within both medium and low background grey level values in the MRI brain images. Significant improvement in the segmentation of white matter lesions has been noticed in [4] due to inclusion of tissue type priors in feature set and use of variance scaling for intensity normalization.

1.2. Random Forests (RFs)

The Random Forest is a set learning scheme. Indeed, it is a supervised and simple classification technique generally functioning in a powerful and efficient manner on large datasets. This method manages thousands of input variables without suppression while estimating important characteristics for classification. As a result, it is correlatively powerful and robust to noise and outliers. [2]. In literature, several techniques are developed using the application of RF based classification. Tustison et al. [5] applied several features including intensity, geometry, and asymmetry from multiple modalities to a random forest's classifier. In the same context, Koley et al. [6] were based on the implementation of the RF method for classification of patterns after identification and extraction of the tumour area. Therefore, the extracted tumour region is quantified with 86 features to develop the training data, which is at a later stage entered as inputs to the classifier.

1.3. Artificial Neural Networks

Artificial Neural Networks (ANNs) are one of the most proven machine learning models. Generally speaking, a neural network is made up of certain connected computing units, called neurons, arranged in layers. Indeed, the network has an input layer where data feed into the network, followed by one or more layers that transform the data as it goes before it ends at the output layer which generates neural network predictions. [7]. As a rough guide, ANNs are very flexible, and able to solve complex problems, but at the same time they are very expensive and difficult to model. In this context, Pereira et al. [8], [9] introduced an automatic method for segmentation into five classes: necrosis, edema, non-enhancing, enhancing tumour and normal tissue. At the evaluation level, three tumour regions were mainly taken into consideration namely; Improvement of tumour, nucleus and complete tumour (all tumour classes). Indeed, this process is completely automatic except for the preliminary phase which requires the identification of the glioma grade manually by the user. As known, the intensity distribution in an image for various tissue types does not allow adaptation to variations in scanners or individuals or time. To overcome this problem, Zhang et al. [10] have used multi-modality information from T1[A], T2[B], and FA[C] images as input to Deep-CNN[D] (Deep Convolutional Neural Networks) for segmenting isointense stage brain tissues. A Deep-CNN has been used in [11] that can handle an arbitrary number of modalities. In the same context, Dong at al. [12] contributed by proposing a fully automatic brain tumour segmentation method using U-net based Deep-CNN. Therefore, their results are robust and effective for the central region and the same for the entire tumour region. At the same time, a new DNN (Deep Neural Network) is exhibited in [13] in which the authors were based on a two-phase training procedure in order to effectively train CNNs as the allocation of tumour markers was unbalanced. Therefore, two types of architecture have been explored namely: two-lane architecture and waterfall architecture. As an indication, the two-way architecture jointly models the local and global contextual characteristics while the cascade architecture has taken into account the dependence of the labels of the pixels. Two CNNs are stacked wherein the segmentation outputs from one CNN are taken as input to the following CNN which has helped to achieve higher performance.

1.4. Deep Learning

Deep learning is a new kind of machine learning method based on neural networks with multiple layers and which extracts a complex hierarchy of features from the raw input images due to their ability to self-learning as opposed to the extraction of classical features at the level of usual machine learning algorithms [14]. Indeed, deep learning resulted in a major dominant position in the field of computer vision when neural networks began to precede other techniques on several high-level image analysis criteria [15]. Indeed, deep learning methods are widely used to improve clinical practice through

[A] T1 In a T1-weighted MRI image, the fat appears hyperintense (light color) and the water hypointense.

[B] T2 In a T2-weighted MRI image, water appears hyperintense (light in color) and fat a little darker than water.

[C] FA Fractional anisotropy (FA) is a scalar value between zero and one that describes the degree of anisotropy of a diffusion process.

[D] Deep-CNN Deep Convolutional Neural Networks (ConvNets or CNNs) are a category of Neural Networks that have proven very effective in areas such as image recognition and classification.

their effective application in MRI [7].

In medical imaging, the main focus for deep learning is driven by convolutional neural networks (CNNs), which represent a powerful and robust solution to learn images and other structured data. As a guide, before effective use of CNNs, this solution usually had to be modelled manually with much less robust machine learning models. As part of the use of automated segmentation of the muscular system by CT (Computerized Tomography), Lee et al. [15] used a deep learning (DL) system to automatically segment the muscle cross-sectional area of CT slices at the L3 vertebral body level, with an average of less than 3.7% difference between predicted and ground truth muscle cross-sectional area, while reducing segmentation time from 30 minutes to 0.17 seconds. Current challenges for automated segmentation of muscle using CT include a tendency to underestimate muscle area in general, while overestimating muscle area in subjects with oedematous fat [16].

2. Unsupervised Methods

2.1. K-means

The k-Means clustering is a key technique in pixel-based methods [17]. Unfortunately, k-Means algorithm, though simple and computationally efficient, may not give an optimum value even after many iterations. In the context of medical images segmentation, the k-Means method and the hierarchical clustering are used to separate the position of tumour tissues from the healthy ones as used in [18] by first rendering the original MRI image and then applying pseudo-colour transformation to convert it into RGB image to enhance its features. In the same context, Juang and Wu [19] also work on the same idea and gave encouraging results to determine exact lesion size and region. In contrast, Ahmed and Mohamad [20] combined Perona and Malik [21] anisotropic diffusion model for image enhancement and k-means clustering for classifying different tissues and tumours and reliable results are witnessed.

2.2. Fuzzy C-means

The algorithm Fuzzy c-means (FCM) is a method of clustering which allows one piece of data to belong to two or more clusters. This algorithm works by assigning membership to each data point corresponding to each cluster centre based on the distance between the cluster centre and the data point. More the data are near to the cluster centre more is its membership towards the particular cluster centre. As known, the major disadvantages of the standard FCM algorithm are that it uses the non-robust Euclidean distance, and it is sensitive to noise. The solution of the problem has been dealt with in [22], [23]. At this level, robust distance measurements have been adopted to reduce the effect of noise and outliers on the results. In addition to it, Mahalanobis distance has been used in [24] to reduce the influence of the geometrical shape of the different classes. The second limitation is dealt by designing algorithms incorporating spatial information into account by many researchers. In the same context, computational time was further reduced by Benaichouche et al. [24] using FCM by working on grey level histogram rather than the image pixels.

2.3. Active Contour Models/Deformable Models

Active Contour Model (ACM) is a model-based segmentation method, in its 3D version, it is also often called the deformable model method. Indeed, this technique is mainly used in the context of the segmentation of 3D images [25]. As an indication, the method of deformable models compromises the evolution of the surface with the speed function given an initial propagation surface, so that it corresponds to the structure of the original object. The deformable models are classified according to two categories namely geometric ACM and parametric ACM. Indeed, geometric ACMs are used in the Eulerian framework like sets of levels. While parametric ACMs are implemented using techniques such as the spline or finite element method [26].

3. Conventional Methods

3.1. Thresholding

Thresholding is an image segmentation method considered among the simplest techniques. Indeed, this technique is characterized by its comprehensibility, rapidity and simplicity of implementation. Its operation is based mainly on the idea of converting a scalar image to a binary image, in which a threshold value is chosen, based on the intensity values of the image which are compared to the threshold value. At this level, pixels with an intensity value equal to or greater than the threshold value are assigned the value 1, while pixels with intensity values less than the threshold value are assigned to 0, while separating in parallel foreground (white pixels) and background region (black pixels) [2]. In this context, Otsu's method [27] aims to find the optimal value of the global threshold in order to successfully separate the object from the background of the image while assuming the bimodal histogram in this method. This method fails if two classes are of different sizes or with variable illumination across the image [28]. Sujan et al. [29] have used Otsu's thresholding along with morphological operations like dilation and erosion to detect brain tumour from MRI image. A new threshold method is presented in [30] to produce more accurate results. The authors in [31] have attempted to find a global threshold using level sets for segmentation of tumour and non-tumour regions. If the production of a single threshold value from the histogram of the image remains impossible, these methods are then suitable for segmentation [2].

The thresholding technique is mostly used as a pre-processing step to segmentation of complex images like those of brain MRI because of their incapability to exploit all the relevant information from the image [2].

3.2. Region Growing

The region growing is a widespread fundamental and popular image segmentation technique used primarily in the segmentation of homogenic regions having identical intensity values. Indeed, this method does not require any initial knowledge of the shape and can therefore be implemented on any objects having various shapes. The main concepts of implementation of the growth by region method require that each pixel is in a region, the pixels of the same region must be connected, disjoint, and satisfying certain conditions of similarity, and at the same time two different regions must not. have the same properties [32]. In this context, Fabijanska [33] implemented the region growth method for tumour segmentation while contributing it with some pre-treatment, which produced satisfactory results, and the adaptive threshold may turn out to be more reliable. Indeed, the inclusion of the orientation constraint led to better results when only the orientation constraint was considered. In the same context, an improved version of the growth by region method has been developed in [34].

3.3. Combined Methods

The combined methods consist to combine two or more techniques to provide better segmentation results. It concatenates two or more methods by using their advantages and eliminates their disadvantages to get performant and reliable outcomes. In this context, several research works have been developed. For example, k-Means detects the tumour faster than FCM whereas FCM predicts tumour cells more accurately in comparison to k-means [35]. So, [35] proposed an automatic algorithm that uses the strengths of both methods in order to perform a robust and efficient segmentation in a shorter execution time due to a reduced number of iterations. In this case, and as a post-treatment step, the authors opted for the extraction of the tumour mass and then represented it using each of the techniques of sweating and active contours. In other side, and since the Machine learning helps to deal with intensity in homogeneities whereas region based and ACMs deals efficiently with poorly defined boundaries and misclassified pixels, Machine learning and region-based ACMs have been integrated for effective segmentation using their respective advantages. Indeed, Region-based ACM for segmentation and ANN based LM algorithm for classification process are integrated together to classify the MRI image efficiently as normal and tumours as suggested by Shenbagarajan et al. [36]. In the same context, Soltaninejad et al. [37] proposed an automated segmentation of brain tumour in MRI images. In this study, a combination of Fully convolutional neural network[E] (FCNN) with Random Forest (RF) is presented. The FCNN method has been used primarily to form machine-learned characteristics while the RF method for classification of normal and tumour tissue. In the same context, [38] opted for the proposal of another combined approach combining both the RF and ACM methods. Indeed, the RF technique is used as feature learning kernel with an iterative way of representations of multiscale entities from multimodal MR volumes. Thereby, tumour structure is extracted from concatenated forests which are considered an initial contour to an active multi-scale patch-driven contour model for final segmentation. As an indication, this method is efficient and robust to low contrast tissue and does not require too much calculation and memory space compared to other machine learning methods such as CNNs.

In the same context of segmentation using the combined methods, [39] proposed the use of the region growing algorithm for segmentation of brain tumour core. Automatic Seed point selection is done using fuzzy C-means algorithm. Hence, the proposed method succeeds in the automatic detection of seeds for region growing using the Fuzzy C-means algorithm.

In the same direction of hybrid methods of segmentation, [40] opted for a learning based automatic method, which is proposed for segmentation of brain tumour in MRI images. The method is a hybrid approach in which the machine-learned features extracted using the fully convolutional neural network (FCN) are used alongside with hand designed applied to the state-of-the-art of Random Forest (RF) classifier.

C. Comparative Study and Discussion

To assess the performance of a developed segmentation approach, it is essential to compare its performance against other existing methods related to the same context. In general, most algorithms are evaluated on different data sets and report different similarity metrics. This makes it difficult to compare the performance of different algorithms against each other. That's why and in order to assess the performance of the medical image segmentation methods cited at the state-of-the-art level, these techniques were tested on the same universal image database, namely the BRATS 2013 [41] data sets image database. The experimental evaluation provided results based on quantitative measurements on the segmentation of the region of interest i.e., the tumour area from the medical images.

	Quantatives Measurements			
Methods	**Precision**	**Sensitivity**	**Dice Score**	**F1 Score**
SOLO METHODS				
KNN	0.90	0.86	0.88	0.87
CMeans	0.74	0.67	0.71	0.70
Fuzzy CMeans	0.80	0.79	0.80	0.79
Growing Region	0.57	0.70		0.63
Random Forest	0.80	0.95	0.88	0.86
Active Contour Model	0.84	0.54	0.69	0.66
Fully Convolutionnal Neural Network	0.77	0.83	0.79	0.80
CNN	0.88	0.89	0.89	0.88
DNN	0.89	0.87	0.88	0.88
HYBRID METHODS				
FCN + Random Forest	0.90	0.74	0.82	0.81
FCMeans + Growing Region	0.57	0.70	0.63	0.63
Deep Learning+FCNN+ RF	0.90	0.89	0.94	0.90
Symmetric multimodal template + RF	0.85	0.89	0.87	0.87

Fig. 1 A comparative analysis of segmentation methods

Fig. 1 represents a quantitative analysis of various state-of-

[E] FCNN Fully-convolutional neural network is a deep learning model based on traditional convolution neural network (CNN) model.

the-art methods through different evaluation parameters such as Precision[F], Sensitivity[G], Dice Score[H] and F-Score[I] for tumour segmentation of medical images. The different methods of segmentation explored in this review study, whether applied alone or combined with others, have been evaluated on BRATS 2013 challenge dataset. Indeed, the BRATS 2013 challenge dataset is mainly used in the evaluative phase of testing different methods of segmentation of brain tumours from multiparametric magnetic resonance images. Indeed, according to Fig. 1 the test results showed that it is true that the segmentation methods each applied separately have shown more or less satisfactory results as is the case for the CNN and the DNN methods. But according to the experimental studies, which highlight the combined application of several methods at the same time, it has been clearly shown that these hybrid methods segmentation of medical images for tumour detection are more efficient in achieving more satisfactory results for abnormal detection as is the case for the hybrid method which combines both each of the segmentation methods of DNN, FCNN and RF. Indeed, this hybrid method has shown according to the experimental study the most satisfactory results compared to other methods in terms of precision, sensitivity and dice score (Fig. 2). The main goal to combine segmentation methods is to improve the quality of segmentation while benefiting from the advantages of each technique and trying as much as possible to eliminate weak points which reduce the performance of the segmentation of each method (Figs. 1, 2).

To the best of our knowledge, no method is reported in the literature that provides the best result for all the evaluation parameters. To that purpose and after this comparative and evaluative study of these segmentation methods, our research axes will be oriented towards the proposal of new hybrid method of segmentation of medical images for the detection of tumour areas. In addition, we aim to highlight the advantages of the existing methods that have shown effective results and specially to improve the drawbacks of these techniques which have slowed down their potential for optimal detection of tumours.

III. Conclusion

To conclude, automated segmentation techniques will be used in routine clinical practice to help improve patient care. Radiologists, biomedical engineers and medical physicists will play a key role in transforming the practice of clinical radiology, which will focus on the qualitative interpretation of the image towards a more objective quantitative identification of disease markers. Indeed, in this article we have presented an exhaustive and comparative study of the various existing methods of tumour segmentation from medical images.

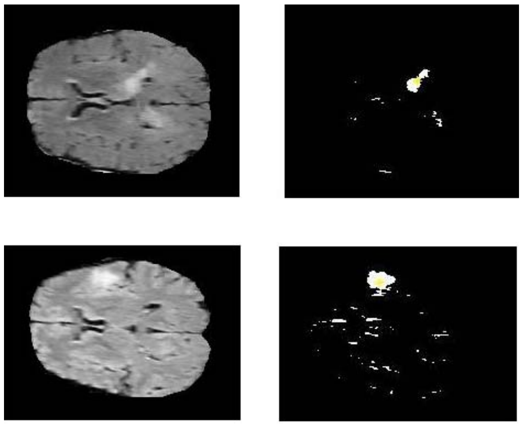

Fig. 2 Segmentation result of the combined method of Fuzzy CMeans and Growing Region

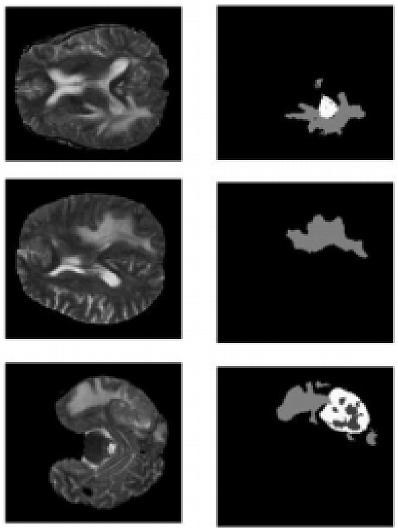

Fig. 3 Segmentation result of the combined method of DNN, FCNN and RF

The quantitative analysis provided through the different evaluation parameters has helped us to identify our perspectives and our future research work in order to define new directions to develop and improve the performance of the segmentation of the tumour area for medical images from a local base, namely that of the Hedi Chaker regional hospital in Sfax, and help us to obtain and guarantee an accurate diagnosis of the tumour.

[F] Precision (also called positive predictive value PPV) is the fraction of relevant instances among the retrieved instances.

[G] Sensitivity (also known as Recall) is the fraction of the total amount of relevant instances that were actually retrieved.

[H] Dice Score is an used metric for the evaluation of segmentation tasks in medical imaging.

[I] F1 Score can be interpreted as a weighted average of the precision and recall, where an F1 score reaches its best value at 1 and worst score at 0.

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