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A review on segmentation techniques and texture analysis techniques for brain tumor detection

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Abstract
The upcoming area of research is biomedical image processing that includes biomedical signal gathering, picture processing, image forming, and display to medical diagnosis based on various features extracted from the images. One of the most challenging and complex area of research in biomedical image processing is the segmentation and analysis of brain tumor. This paper reviews of different existing segmentation techniques and texture analysis techniques.

Keywords: segmentation, texture analysis, brain MRI and computer aided diagnosis

Introduction

Magnetic Resonance Imaging (MRI) is important to provide detailed and very precise information about tumor size, location and compression of adjacent brain structures. MR Images are of very high resolution that can be analysed using Computer aided tool for automatic segmentation and analysis of tumor. Computer aided systems are preferred over conventional manual segmentation because automated segmentation is highly accurate and precise, free from human error and much faster than manual segmentation. So, there is a lot of research on the design of efficient algorithms for segmentation and analysis of Brain MR Image. In the day-to-day life, computational applications are gaining much importance.

In today's health care arena, detection and analysis of Brain tumour is one of the most commonly occurring fatality.

One of the specific medical image analysis methodologies is fully computerized brain disorder diagnosis like brain tumour detection from MRI. Brain tumour is the uncontrolled growth of the tissue cell in the brain. The cells that supplies blood in the arteries are bounded tightly together which makes general laboratory test inadequate to analyze the chemistry of human brain. The various modalities of bio-medical imaging that allows the doctor and researchers to analyze the brain anatomy by studying the brain without surgical invasion are computed tomography, Magnetic resonance imaging and Positron emission tomography. MRI provides detailed information about soft tissue structural anatomy of human. MRI assist in diagnosis of the brain tumour. MR images are used for analyzing and studying the anatomy of the brain.

One of the most challenging task in today's medical image analysis is automated brain tumor detection from MRI images. MR produces images of the anatomy of soft human tissue. It is used to study the human anatomy without invasive surgery. Brain image segmentation that defines the process of creating partition and analyzing the image into visibly and anatomically different regions, is among the most vital and critical aspect of computer aided clinical diagnostic of tumor or other anatomical abnormalities. Various types of noise that are found in the Brain MR images are multiplicative in nature and reductions of these noises are critical. From the clinical aspect, it is very essential to ensure that the sensitive anatomical details are not removed by the noise reduction algorithms. Hence, highly precise segmentation of the MRI images is very critical for proper diagnosis by computer aided clinical tools. A wide variety of procedures for segmentation of MR images had been proposed till date. One of the major issues faced in the field of image processing and computer vision is texture analysis or recognition, which has been an active research topic since almost three decades.

Texture analysis was widely applied in various areas like remote sensing, object recognition, mobile robot navigation, estimation of 3D surface area from 2D images, contour based image retrieval and many more. Multiple algorithms or mathematical modeling methods have been proposed for texture analysis, and they can be classified into three major categories: statistical methods, model based methods and structural methods. Each method has its own merits and demerits.

Medical imaging is usually related to Radiology or clinical imaging" and the medical practitioner's or radiologist's responsibility for understanding as well as acquiring the images. Diagnostic radiography defines the technical details of capturing images in biomedical domain. The radiologist is responsible for capturing medical images of clinical quality. Bio-medical imaging is the domain of pathological investigation which combines different inter-disciplinary areas of technology like bio-medical engineering and physics and even medicine (in case of nuclear medicine imaging like PET-CT Scan), if required. Research in the domain of medical instruments, image acquisition (e.g. radiography), modeling and quantification are under the purview of bio-medical physics and engineering and also computer science to a great extent.

Existing Segmentation Techniques and Texture Analysis Techniques

There had been large multi-faceted and fast growth in the field on image processing in the last decade. In today's time, capturing, storage and analysis of bio-medical images is digitized [1, 4]. The challenge for radiologists is high especially in anatomical abnormalities with different color and shape that needs to be identified for further studies. The main objective in developing image processing and computer vision applications is to maintain highest standards of accuracy in segmenting medical images. Image segmentation is the process of partitioning several distinct regions of the image based on various criteria. Although there are many automatic and semi-automatic algorithms of segmenting images, they fail in many instances mostly due to unknown or non-regular noises, in-homogenity, low contrast or weaker boundaries that are very common to biomedical images. MRI or various other biomedical images consist of several complicated and minute anatomical variations which requires very precise and exact segmentation for doing diagnosis clinically [5].

Segmentation of brain from MR image is very critical and challenging but extremely precise and accurate segmentation is required for various clinical diagnosis like, detection, analysis and classifying various tumor categories, such as, edema, haemorage detection and necrotic tissues etc. Unlike CT scan, Magnetic Resonance image acquisition parameters are greatly adjustable for creating high contrast image having distinct gray levels for different cases of neuropathology [6]. Hence, segmenting MR images is the recent research focus in biomedical image processing domain. In neuro-science segmenting of Magnetic Resonance image is required in diagnosis of neuro-degenerative and also various psychiatric disorders [7].

Although there are many state of the art algorithms for de-noising but accurate removal of noise from MR image remains a challenge. There are various technologies such as using standard filters or advanced filters, nonlinear filtering methods, an-isotropic nonlinear diffusion filtering, Markov random field (MRF) models, wavelet models, non-local means models (NL means) and analytically correction schemes etc. Computational cost, de-noising, quality of de-noising and boundary preserving capabilities in those methods are almost similar. Hence, de-noising still remains a research problem and requires innovation and improvement. Linear filters mostly reduce noise by the updating of pixel value by calculating weighted average of neighborhood pixels but degrades the image quality. On the contrary, nonlinear filters although preserves edges but degrade fine structures.

In MRF, spatial correlation information is used to retain various fine details [8], i.e., the estimated noise is regularized in spatial domain. In this method, the value of pixel is updated by iteration of conditional modes and simulated annealing having a function that maximizes a posterior estimate.

In frequency domain wavelet based methods is implemented for removing noise and preserving the signal. The use of wavelet on MR images biases the wavelet and scaling coefficient. To remove the issue, the MR image is squared by non-central chi square distribution method. Hence the scaling coefficient become independent of the signal and is eliminated. Although in case having low Signal to Noise ratio images, liner details are not preserved [9].

Analytical correction method works by estimating noise and thereby generating noise-free signal from initial image. It uses maximum likelihood estimation (MLE) [10] for estimation of noise in the image and then generates images devoid of noise. Neighborhood smoothing is essential to calculate noise free images by taking signal in small region to be constant. Image boundaries are quite degraded.

Non-local (NL) uses the repetitive information of images [11]. The image pixel values are substituted by calculating weighted average of neighborhood. MRI images have non redundant details because of noise, complicated structures, blur in acquisition and the partial volume effect generating because of low sensor resolution which gets removed by Non-local method.

Thresholding, region growing, statistical models, active control models and clustering had been implemented for segmenting images. As the intensity distribution in biomedical images are complex, thresholding becomes a critical task and fails in most cases [12]. Fuzzy C means is a widely used technology for biomedical image segmentation but it considers only the image intensity thereby giving unsatisfactory output in noisy images. A set of algorithms are proposed to make FCM robust against noise and in homogeneity but it's still far from perfect.

In probabilistic classification, a very accurate estimation of the probability density function (PDF) is necessary. Non-parametric approach does not take any assumption in getting the parameters of PDF, hence makes it precise but costly. In parametric approach, a function is considered to be a PDF function. It is relatively simple to implement but at certain cases it lacks in preciseness and do not correlate with real data distribution.

FCM uses the initial cluster center positions from SOM clustering algorithm. The summation of the variances of weight vector when divided by size of the weight vector is less than element of weight vector then weight vector is expanded [13].

Learning vector quantization is the supervised competitive learning algorithm which calculates decision boundaries of input domain depending on training dataset. It creates prototypes of class boundaries, based on a nearest-neighbor rule and uses a winner-takes-it-all paradigm. It consists of input, competitive and output layer. The initial data gets classified in the competitive layer which are then mapped onto target class of output layer. The neuron weight gets updated in the learning phase depending on training datasets. The winner neuron is selected using Euclidean distance, then its weight is adjusted [6]. There are different methods to learn Learning vector quantization networks.

Self-organizing maps is an unsupervised clustering network which maps inputs that can be multiple dimensional to 1-D or 2-D discrete lattice of neuron units [6]. Input is organized into several patterns based on a similarity factor such as Euclidean distance and every pattern assigns to a neuron. Every neuron had a weight which depends on the pattern that is assigned to the neuron [6]. The input is classified as per their grouping in the input space and neighboring neuron. It also learns distribution and topology of input [6]. SOP have two layers: First is input layer where the number of neurons in the layer is equal to the dimension of the input and second is competitive layer where each neuron corresponds to one class or pattern. The number of neurons in this layer relates to the number of clusters and gets arranged in regular geometric mesh structure. Every connection from input layer to a neuron in competitive layer is assigned with a weight vector. The SOM functions in two steps, ie. [6] First by finding the winning neuron where the maximum similar neuron to input by a similarity factor like Euclidean distance, and secondly, by updating the weight of winning neuron and its neighbor pixels based on input.

Watershed is an image gradient-based segmentation algorithm where distinct gradient values are taken as distinct height. A void is created in every local minimum and submersed in water. Hence, the water level will increase till local maximums. When any two bodies of water connect, a dam is erected between those two water bodies. The water level increases slowly unto all points (heights) of the map are submersed. The image gets divided by the dam boundaries. Those dams are said to be watersheds and the segmented zones are known as catchments basins [14, 15]. The over segmentation problem still remains in this algorithm.

Active Control Method is a model for delineating the outline of an object from the noisy image which is dependent on a curve, X(s) = [x(s); y(s)], where s in range of [0, 1] is length of arc. It changes such that it reduces the energy function. The tension and rigidity of the deforming curve is controlled by the internal energy whereas external energy is used to modify the deforming curve toward the target [16]. It uses Gaussian Gradient Force to calculate external force. The advantage of this algorithm are in-sensitiveness to initialization of image contour, boundary concavities, reducing computational time, and high preciseness.

Markov Random Field Method or undirected graph model is a set of random variables that have Markov property that is defined by an undirected graph. Markov random field model is the statistical model that is implemented to model spatial relations which exist in the neighbor of pixels [17]. Image segmentation techniques use it to gain advantage of neighborhood information in the segmentation process, such as, in biomedical images most neighborhood pixels had the same class and hence by using neighborhood information, effect of noise in segmentation is reduced.

In Graph Cut Based, the image segmentation is treated as a graph partitioning problem and global optimization criteria which calculates both total dissimilarity within various groups and also total similarity within them is used. An efficient algorithm uses generalized eigen value approach for optimizing the criteria of image segmentation [18].

The main problem that exists in segmentation of brain images with varying anatomical deviation or abnormalities such as tumor having various shape, dimension, location and intensities. It not only makes variations in the part of brain where tumor exists but it also affects shape and intensities of other anatomical variations of the brain [19].

Different noise that exists in biomedical images are multiplicative in nature and reduction of those noise is challenging. The anatomical variations must not be compromised because of denoising from the clinical perspective. In case of brain, the tumor comprises of a dead necrotic part and an edima which is the active part in the adjacent brain. A radix-4 Fast Fourier Transform recursively partitions a Discrete Fourier Transform into four quarter-length DFTs of groups for every fourth time sample. The cost of computation gets minimized by shorter FFTs outputs that can be re-utilized for output computation.

Recent work by [20] used a combination of mathematical morphology, wavelet based segmentation and K-means to achieve tumor detection. Another novel approach using color based feature extraction using wavelet decomposition can be found in [21]. In [22] authors used Berkeley wavelet transform for feature extraction and a Support Vector Machine for classification of features. A paper by [23] gives introduction to frame and Gabor systems and its use in wavelet analysis. Moreover, a paper by [24] states the use of frame theory and wavelet in image restoration. Thus, it signifies that frame theory and wavelets can be used effectively in image processing [25]. Employed techniques of discrete wavelet transform (DWT) and principal component analysis (PCA), and used K-nearest neighbor (KNN) [26]. Employed stationary wavelet transform to take place of traditional Discrete Wavelet Transform. Afterwards, to train the classifier, they introduced a novel algorithm that is a hybridization of PSO and ABC [27]. Combined discrete wavelet transform with principal component analysis [28]. made a Pathological Brain Detection using Wavelet Packet Tsallis Entropy and Real-Coded Bio-geography-based Optimization (Denoted by WPTE + FNN + RCBBO) [29]. Also did a pathological Brain Detection technique using pseudo Zernike moment (Denoted as PZM + KSVM in comparative study later). Although those above mentioned algorithms give good results, still, segmentation accuracy could be improved further.

In image processing textural information plays a key role to identify the type of object present in the images. It dominates in the field of remote sensing, quality control and medical imaging due to its close relation to the underlying semantics. Texture features captures the granularity and the repetitive pattern in the image.

Another widely accepted approach is to use grayscale co-occurrence matrices (GLCM) by counting the number of occurrences of the gray levels at a given displacement and angle. The image is decomposed by applying successive operation using threshold value. The algorithm proves to have an efficiency of 76% when implemented with a KNN classifier [10, 11] and 80% when trained with a discriminant based classifier. It is time consuming algorithm.

Conclusions

The main challenge in bio-medical image processing of brain lies in segmenting the images. Many different methods of segmentation had been proposed in recent years but the challenge still remains in increasing the efficiency and precision of segmentation.

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