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MRI Brain Tumor Segmentation Algorithms And Approaches-A Survey

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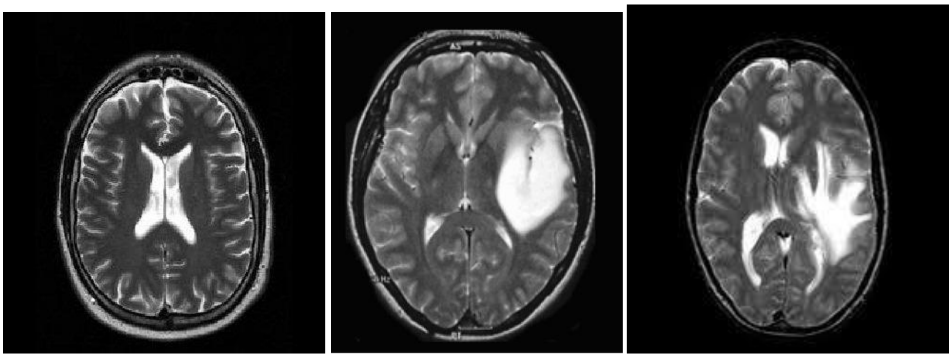
Abstract: The diagnostic values of MRI are greatly increased by the automated and accurate classification of the MRI brain images. Accurate detection of the type of brain abnormality is highly essential for treatment planning to minimize the fatal results. Accurate result can be obtained by using CAD systems. This is expected to improve consistency by providing a standardized approach to the MR brain image interpretation and increasing detection sensitivity. This paves way for sustainability for effective brain image screening, interpreting and sensitive detection using Magnetic Resonance Images. This survey paper provides a comprehensive over view of the research done in this area.

Keywords: MRI images, Image processing, Segmentation, Brain Tumor

1. Introduction

Medical field produces huge number of image data to diagnose the major diseases of human beings at regular intervals. At most, all data are in the form of digital image formats. Physicians are in a position to consult experts to take necessary remedial actions for the identified medical problems. As a kind of cancer, brain tumor is a very malignant and harmful disease. It is an abnormal mass of tissue in which some cells grow and multiply uncontrollably. The development of a brain tumor obtains some space within the skull. This will later disturbs the normal activities of brain. A tumor can cause damage by increasing the pressure in the brain, by shifting the brain or pushing against the skull, and by invading and damaging nerves and healthy brain tissues [1]. Figure 1.0 shows the difference between normal and tumor brain images.



(a)Normal Image (b) Benign Image (c) Malignant Image
Figure 1.0 Illustrations of Normal, Benign and Malignant Image

MRI is an effective imaging technique in neuroscience and neurosurgery and is useful in the discovery of the type of MR images. The accuracy of interpretation of screening MRI is affected by several factors, such as image quality, the radiologist's level of expertise, and the high volume of cases. CAD techniques and systems can support radiologists in the role of a second reader, prompting the radiologist to review areas in a MRI considered to be suspicious by specialized computer algorithms. Therefore, for the development of a successful CAD scheme it is necessary not only to develop computer algorithms, but also to investigate the usefulness of the computer output for the radiologists in their diagnosis, and to quantify the benefits of the computer output for the radiologists and to maximize the effect of the computer output on their diagnosis. This paper identifies the earlier work on brain tumor segmentation techniques from MRI images.

2. Literature Review on MRI Brain Tumor Segmentation

Segmentation of brain MRI is a challenging problem that has received an enormous amount of attention by various researchers. MR Brain tumor image segmentation can help to identify regions like gray matter, white matter and cerebrospinal fluid and tumor for functional visualization in the diagnosis of diseases like stroke and cancer. Brain segmentation research has increased in importance over the last decade. It is difficult to perform the brain MR image segmentation manually as there are several challenges associated with it. Radiologist and medical experts spend plenty of time for manually segmenting the brain MR images, and this is a non-repeatable task. In view of this, an automatic segmentation of the brain MR images is needed to correctly segment the tissues of the brain in a shorter time span. The accurate segmentation is crucial as otherwise the wrong identification of disease can lead to serious negative consequences. Automatic detection and segmentation of brain tumor from brain MR images offer a mechanism for overcoming the tedium involved in the manual segmentation of large datasets. It also promises reproducibility which is affected by inter and intra observer variability. However, automated systems have significant problems to achieve these objectives. The major problems are that pixel intensities violate the independent and identically distributed assumption within and between images due to the nature of brain MR images, and the presence of a significant amount of artifacts and intensity in homogeneity in MR images. Therefore, the automated method must consider these problems to achieve reproducible segmentation results and developing clinically accepted automated methods remains an active research area. Hence, the importance of having effective tools for grouping and recognizing different anatomical tissues, structures is growing with the improvement of the medical imaging systems. Several methods are employed for MR brain image segmentation such as clustering methods, thresholding method, classifier, region growing, deformable model and markov random model etc.

The present research has mainly focused attention on clustering methods, because it is widely used in biomedical applications particularly for brain tumor detection in abnormal magnetic resonance images. It is one of the widely used image segmentation techniques which classify the samples belonging to different groups. Many techniques have been proposed to automate the brain tumor detection and some notable methods are reviewed in the following sections. Those techniques are summarized in this paper.

Region based fuzzy c-means clustering for brain tumor segmentation was discussed in [2]. The method utilized the tumor class output of fuzzy clustering to initialize the region based algorithm. The method has been validated for efficiency on 15 MR images. The results found that Jaccard coefficient average value of 83.19% and sensitivity of 96.37% is achieved by this algorithm.

Authors in [3] developed a tumor tracking method of MRI brain image using color-converted segmentation with modified fuzzy Cmeans clustering technique. Firstly, contrast applied MRI was converted into YCbCr color model the image was then classified into the region of interest and background by modified fuzzy C-means clustering algorithm. The method is capable of solving contoured lesion objects problem in MRI image by adding the color-based segmentation operation. A preliminary evaluation on MRI brain image showed encouraging results. Color-converted segmentation with MFC-means clustering algorithm for tracking objects in medical images was found to be very promising for MRI applications. The brain regions related to a tumor or lesion can be exactly separated from the colored image. This work has paved way for superior segmentation performance.

Authors in [4] investigated a new approach for automated detection of brain tumor based on k-means and possibilistic C-means clustering with color segmentation, which separates brain tumor from healthy tissues in magnetic resonance images. The MR brain images used in this work is T1-weighted and T2-weighted images of axial slices. It was reported that segmentation accuracies of k-means and possibilistic C-means are 74% and 89% respectively. The experimental result showed the superiority of the possibilistic C-means clustering method. The limitation of this work is that clustering techniques applied on RGB color space translated image yielded low segmentation accuracy.

Authors in [5] explained several methods employed for medical image segmentation such as clustering, thresholding, classifier, region growing, deformable model and markov random model. Their work was mainly focused on clustering methods, specifically k-means and fuzzy cmeans clustering algorithms. They combine these algorithms together to form another method called fuzzy k-c-means clustering algorithm, which results better in terms of time utilization but lower in segmentation performance. The algorithms have been implemented and tested with MRI images of the human brain. The results have been analyzed and recorded.

Authors in [6] have presented a new fuzzy clustering algorithm for brain tumor segmentation. The proposed algorithm was based on new spatial FCM that incorporates the spatial information into the membership function to get better segmentation results. To detect the abnormalities of brain MRI images he made a comparative analysis of a new spatial FCM results with k-means and FCM techniques. Twenty MRI Brain images have been tested and the similarity of the metrics evaluated. The results showed that from the performance view point, efficiency of K-means is 78.13%, FCM is 87.48 and proposed spatial FCM is 94.05%.The preliminary results of this work revealed that the new spatial algorithm yielded better results than K-means and FCM algorithms. The drawback of this work is that, because of the higher spatial weighting used blurring of some of the finer detail occurs.

Authors in [7] compared brain tumor segmentation with the help of three segmentation techniques; K-means clustering, FCM and hierarchical clustering method. He researched his segmentation techniques on 60 brain tumor images in non-medical format and in images in DICOM format in their work and the efficiency and outcome of the three methods has been found out. K-means clustering achieved about 86.6% and Fuzzy C means and hierarchical clustering achieved an overall efficiency of 83%. They also reported that the time required to detect the tumor in hierarchical is least and that for FCM is the maximum, however from the performance view point, tumor detection is much more prominent in FCM than in the other methods.

Authors in [8] presented new approaches for brain tumor detection using Meta heuristic algorithm. It was observed that pre-processing, enhancement and segmentation are deeply analyzed in their work. In the preprocessing stage, film artifacts and unwanted portions of MRI brain image are removed. In the enhancement process, the noise and high frequency components are removed using median filters. The different segmentation process like block based (non algorithmic), PSO and HPACO algorithm segmentation were carried out. The experimental results showed that the block based technique produces the detection rate of 92% and the PSO with FCM approach produces around 74.6% and the meta-heuristic Hybrid Parallel Ant Colony Optimization (HPACO) with Fuzzy Algorithm produces 95.1% accuracy. It was observed that the meta-heuristic MRF-HPACO hybrid with FCM performed well.

Authors in [9] carried out a new fuzzy clustering approach for the automatic segmentation of normal and pathological MRI brain datasets. Authors reformulated FCM algorithm to take into account any available information about the class center. The uncertainty in this information is also modeled. Experiments using simulated and real, both normal and pathological, MRI volumes of the human brain showed that the proposed approach has given better segmentation accuracy, robustness against noise and faster response compared with fuzzy and non-fuzzy techniques. The average dice and convergence speed achieved by FCM technique is 86%, 41s, Neighborhood information FCM has yielded 92% & 221s.The proposed PIGFCM algorithm (Prior-Information Guided FCM) provided an accuracy rate of 97% and a convergence speed of 25s.This work has not accounted bias field which may have affected the accuracy of automatic processing tools.

Authors in [10] proposed a hybrid system for tumor detection in MR images and categorized them using Artificial Neural Networks (ANN) and k-Nearest Neighbor (KNN). The features were extracted using Discrete Wavelet Transform (DWT) and Principle Component Analysis (PCA) method was used for the selection of the best extracted features. These selected features were given as input to classifiers as KNN and ANN. These two classifiers KNN and ANN categorize MR images as normal and abnormal images. The negative aspects of these systems are every time new information arrives new training is needed and KNN precision can rapidly degrade when the numbers of features grow.

Authors in [11] reported an automatic method for classification of brain tumors into malignant or benign using fusion of shape and texture features. Linear vector quantization was used to classify the images. The results showed that texture and shape features can give classification efficiency of 85% in the analysis and classification of brain tumors. The main limitation in this study is that the features are directly used for classification and size of the dataset is significantly small.

Automated and accurate classification of MR brain images has been suggested in the paper [12]. In their study neural network based method is used to classify a given MR brain image as normal or abnormal. This method first employs wavelet transform to extract features from images, and then applies the technique of PCA to reduce the dimensions of the features. The reduced features are sent to a Back Propagation (BP) NN classifier with which Scaled Conjugate Gradient (SCG) was adopted to find the optimal weights of the NN. This method is applied on 66 images (18 normal, 48 abnormal). The classification accuracies on both the training and test images are 100%, and the computation time per image is 0.0451s.

Authors in [13] classified brain tumor using wavelet based feature extraction method and SVM. Feature extraction was carried out using daubechies (db4) wavelet and the approximation coefficients of MR brain images were used as feature vector for classification. Accuracy of only 65% was obtained, where only 39 images were successfully classified from the 60 images. It was concluded that this approach has limited precision, since it cannot work accurately for a large data due to training complexity.

Authors in [14] described automatic classification technique to classify normal and abnormal MR brain images. Their work was based on two components: feature extraction and classification. PCA and GLCM were used for feature extraction. Next brain MRI images were classified by SVM classifier. The authors obtained 100% accuracy and an execution time of 10.3172 seconds for features extracted by GLCM classified with SVM using RBF kernel function whereas with PCA with same kernel function yielded an accuracy of 57.69%. GLCM with SVM for linear and quadratic kernel functions yielded a classification accuracy of 96.15% and 100% with execution time of 10.4848 seconds and 10.3837 seconds respectively. They reported that such maximum accuracy is not possible with features by PCA. The major drawback of this system is that the small size of the dataset used for the implementation and texture features alone are considered for classification and the features are extracted directly from the image excluding segmentation phase.

Authors in [15] presented an efficient method of brain tumor classification. In their work, MR images were classified into normal, non cancerous (benign) brain tumor and cancerous (malignant) brain tumor. Their method consisted of three steps, wavelet decomposition, textural feature extraction and classification. Daubechies wavelet (db4), employed for decomposing the MR image, then texture statistics energy, contrast, correlation, homogeneity and entropy were obtained. The Probabilistic Neural Network (PNN) is used for classification and tumor detection. The proposed method has been applied on real MR images, and the accuracy of the classification using probabilistic neural network is found to be nearly 100%.

Authors in [16] discussed CAD system for the classification of the type of tumor using Probabilistic Neural Network in MR images. Image preprocessing, histogram equalization, thresholding, square based segmentation, component labeling, feature extraction and PNN have been used to construct a CAD system for the detection of brain tumor in the MRI images of cancer affected patients. This system provides precision detection and classification of astrocytoma type of cancer. The overall accuracy of the developed system was found to be 94.87%.The limitations of this proposed system is that GLCM features are directly used for classification.

In paper [17] authors proposed a novel **Convolutional Neural Networks (**CNN)-based method for segmentation of brain tumors in MRI images. The authors used an effective pre-processing step, which consisting of bias field correction, intensity and patch normalization. Then the number of training patches is artificially augmented by rotating the training patches, and using samples of HGG to augment the number of rare Low Grade Gliomas (LGG) classes at the time of training. The CNN is built over convolution layers with small 3* 3 kernels to allow deeper architectures. Authors evaluated method in BRATS 2013 and 2015 databases.

3. Conclusion and Summary

This paper reviews the recent researches of CAD systems for automatic detection of brain diseases. Automated detection of the abnormalities in medical images is an important and necessary procedure in medical diagnosis planning and treatment. In this review, it is intended to summarize and compare the methods of automatic segmentation and classification of brain tumor through MRI used in different stages of CAD system. In this review, an extensive comparative analysis is performed to provide the merits and demerits of various available techniques. This work also explores the applicability of the techniques in brain tumor diagnosis in MR images. From the literature review presented, the following conclusion is drawn.

There is limited literature available on the detection of brain tumor using color converted K-means clustering segmentation. Color features can be used for clustering the objects with little or no modification. It has also been found that there is no mechanism adopted to select the optimal cluster centroid in color based K-means approach. SVM based classification has been found to be a suitable approach for classifying MRI brain image. Majority of the work discussed and the features extracted from the image are directly used for classification. However, the features used directly have the disadvantages of low convergence rate and low classification accuracy. It is found that CAD system developed till date has not been utilized for color converted clustering segmentation approach.

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