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IMAGE SEGMENTATION TECHNIQUES IN MEDICAL ANALYSIS "A BOON FOR DETECTION OF CANCER": A REVIEW

Ms Shinde Ashwini Shivdas
Department of Electronics and Tele communication
ADCET,Ashta Sangli,
Maharashtra,India

Dr Mrs S B Patil
Department of Electronics
Dr J J Magdum COE,Jaisingpur
Maharashtra,India

Mrs. M N Chavan
Department of Electronics and Telecommunication Engineering
ADCET Ashta,Sangli
Maharastra India

Abstract—Image processing and computer vision systems can enhance the diagnostic capability of physicians by reducing the time required and resulting in accurate diagnosis. This paper presents the review of resent published segmentation and classification techniques for detection of Brain Tumors using Magnetic Resonance Images, which is an open challenge in the field of medical science till date. We present the comparative study of a couple of algorithms based on the technique of segmentation, extraction and classification of the images. Initially we start with segmentation based on local independent projection-based classification, followed by segmentation using adaptive clustering and Level set method comparing these with the result of computer-aided detection /diagnosis involving the process of pulsed coupled neural network for image segmentation, followed by discrete wavelet transforms for feature extraction and feed forward back propagation neural network for classification.

Index Terms—Region based segmentation, Edge detection, feed forward back propagation, Computer-aided diagnosis, neural network.

I. INTRODUCTION

The anterior most part of the nervous system is the Brain, functioning of an individual gets affected by the presence and location of the tumor in the brain. Magnetic Resonance Imager is used for diagnosis of brain tumor, caused by abnormal growth of cells; it is something different from cancer. Tumor grows abruptly defecting the neighboring tissues of the organ it gives the abnormal structure of a healthy tissue. In image processing detection of tumor starts with the segmentation process. Which is the most important task of image analysis, it is a process of partitioning the image into sub regions to change the representation of image into something that is easier to understand and analyze. A segmentation method finds the sets that are different in structure from each other; the completion of segmentation covers the entire image resulting in those sets that collectively corresponds to region of interest or anatomical structures. Although there are numerous segmentation methods it is a challenge for segmentation in brain tumor MRImages as it exhibits complex characteristics in appearance and ambiguous tumor boundaries.Even today in practice multimodal MRI images are used simultaneously by radiologists in segmenting brain tumor images because multimodal MRI images can provide various data on tumors [1]. Different MRI image modalities can reveal different parts in the tumor area.The contrast-enhancing regions, of the tumor are highlighted by The T1C (T1-weighted images with contrast enhancement) whereas the edema regions are highlighted by the T2 (Fig. 1). The Brain tumors are with various sizes and shapes and appear at different locations in the brain. The tumors are heterogeneity, with complex edges and visually vague (Fig. 1). And also the tumors may deform surrounding structures in the brain because of the mass effect or edema (Fig. 1). Additionally, artifacts and noise in brain tumor images increase the difficulty when segmenting tumors. Hence designing of semi-automatic or automatic brain tumor segmentation is a difficult task, numerous algorithms have been developed to perform brain tumor detection and segmentation.

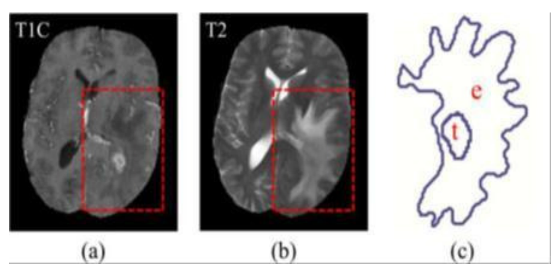

Fig. 1. Different modalities reveal different parts in the tumor area. The edge of the tumor area is visually vague. In addition, the brain structure is deformed because of the occurrence of edema. (a) T1C-weighted brain tumor MRI image. (b) T2-weighted brain tumor MRI image. (c) Contour of the actual brain tumor. "t" represents the combination of contrast-enhancing and necrotic parts, and "e" represents the edema part.

These methods include thresholding and morphological techniques, region growing approach, watershed method, atlas-based method, asymmetry analysis, contour/surface evolution method etc. Here in this review paper, we have made a comparative study of three approaches used for segmentation along with methods and results. To overcome the problems of segmentation an automatic tumor segmentation method proposed in [1]. Here tumor is treated as a classification problem along with the local independent projection based classification (LIPC) which classifies each pixel into different classes. Also the location of the tumor is an important issue in computing local independent projections for LIPC, Moreover, LIPC considers the data distribution of different classes by learning a softmax regression model, which can further improve classification performance. Another method proposed in [3] used hybrid segmentation technique to detect the selected region has a tumor or not. Here selection of multiple regions, with tumor or without tumor is done, Apply Segmentation technique like Adaptive Clustering technique and Level Set Method. Final output is tumor region and calculates tumor region area. Finally the third technique compared with the above mentioned is the pulse coupled neural network, mammalian visual cortex.

II. LITERATURE REVIEW AND RELATED WORK

A. LIPC Technique

The method for segmentation explained in [1], local independent projection-based classification, which is one of the recent works published The First method consists of four major steps, i.e., preprocessing, feature extraction, tumor segmentation using the LIPC method, and post processing. The flowchart of this method is illustrated in Fig. 2

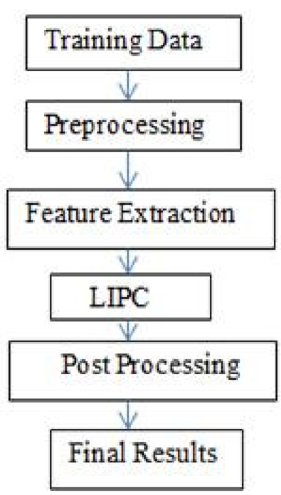

Fig 2. Flow chart for the local independent projection- Based classification

Basic Principle of LIPC:

Brain tumor segmentation can be considered as a multiclass classification problem. A one-versus-all (OvA) strategy can be used to solve this problem. Here, a classifier is trained per class to distinguish a class from all other classes. Therefore, N classifiers $f = \{f_i\}_{i-1}^{N}$ have to be determined in this study, where N represents the number of classes. Given a testing sample $x\epsilon R^M$, N real classification scores $y=\{y_i\}_{i-1}^{N}$ arecomputed using the learned classifiers f(x) ; where the sample x stands for the image feature in the current study y ϵ [0,1] stands for the probabilities that the sample belongs to the i^{th} class. The label of sample can be defined as follows $l=\arg\max f_i(x) =\arg$
$\max y_i$

The following assumptions considered as the basic for LIPC are some basic assumptions.

Assumption1: Samples from different classes are located on different non-linear sub manifolds, and a sample can be approximately represented as a linear combination of several nearest neighbors from its corresponding sub manifold.

For N-class classification, this assumption indicates that the samples are found on a manifold $\{M_i\}^N_{i=1}$ which consists of N sub manifolds; M_i represents the sub manifold associated with the ith class. For a dictionary $D=\{D_i\}^N_{i-1}$, which consists of N sub dictionaries $D_i= [d^1{}_i,d^2{}_i]$ consists of Ni typical samples from the ith sub manifold.

By this assumption, a testing sample x can be projected into each sub manifold the following linear representation is used

$$x=D_i\alpha_i + e_i = \sum_{i-1}^{N} a^{j} d^j{}_i + ei \qquad (1)$$

Although the reconstruction errors are used as the classification measure the testing sample is projected onto each sub manifold independently instead of the whole manifold for each sub manifold, therefore the projection calculation is independent. Hence if Assumption 1 is considered, the proposed method is more applicable. Next comes the LIPC implementation, performed by dictionary construction, locally linear representation, and classification score computation. The manually labeled original samples in a training set are used to construct D However, numerous original training samples possibly produce a large D, which dramatically increases computational and memory costs.

Feature Extraction

Prior to the extraction of image features the image heterogeneity correction and normalization should be performed because the image intensities in MRI images do not have a fixed meaning and widely vary within or between subjects.MRI image modalities are processed as follows, the bias field artifacts are removed from the images. Secondly intensity values at the 1% and 99% quantiles are computed for the brain region (including tumors, edema, and brain tissues), and then these two values are used to linearly scale the voxel intensities to the range [0,100]. Computational complexities are reduced by multi resolution frame.

Post-processing with Spatial Constraint

Connected component algorithm and mathematical morphology can be used to refine the classified edema regions since each edema region is located near tumor core regions. First, a binary image representing the classified edema regions is formed. Second, the binary image is used as an input for the connected component algorithm, and then some individual edema regions are generated. Third, each individual edema region is dilated with a small structuring element and compared against the classified tumor regions. Finally, the dilated edema regions that share at least a voxel with the classified tumor regions are considered valid. The edema regions from these valid regions are retained as the final edema classification results, whereas the other edema regions are discarded.

B. Level set Method

The second Technique discussed in this paper is the Brain Tumor image Segmentation using Adaptive clustering and Level set Method [3] Here the Algorithm follows the steps[2]

1. Preprocessing step,

2.Registration of Multi-modality MR images,

3. Generating an initial shape (surface or set of voxels) for the tumor to be segmented,

4. Segmentation of the tumor by applying an hybrid level-set segmenter.

The preprocessing involves the Non-brain tissue removal and the noise reduction (non-linear Filtering), which helps to reduce the computing time and to have more accurate segmentation. Appropriate filter, are used to smooth the extracted image because it contains various amounts of noise. Non-linear filters removes the high-frequency noise, preserve edge, and should not affect relevant major geometrical features followed by the registration steps based on free-form deformations, B-Spline deformable transform and normalized mutual information which is used as a voxel-based similarity measure. A level set segmentation process is applied to extract accurately brain tumor. As the evolution process can be guided by a combination of several information, [2] propose here an hybrid deformable model which is controlled by a new evolution speed function. This function is able to take into account simultaneously the local spatial context and the global one. Theoretically, this mechanism may lead the algorithm to a stable solution. The level set method, is an emerging method to represent shapes and track moving interfaces. The basic idea is to change the movement of a planar curve into the movement track of 3D surface. Theoretically, the level set boundary is defined as a zero level set of an implicit representation φ of an evolving front Γ(t). The implicit level set function φ can be evolved by solving the following PDE (partial differential equations):

$\partial\varphi/\partial t.=F.\ \nabla\varphi$ Where F is a scalar velocity (speed) function depending on the local geometric properties (i.e. curvature) and on the external parameters related to the input data (i.e. image gradient). ∇ denotes the gradient operator. The speed function F may be expressed as F = F(k), where k is the local mean curvature . At time t, the zero level set (= 0) describes the evolved of the front (desired boundary). Thereby, deforms iteratively according to its normal direction with the speed function F, and its position is given at each iteration step by the following equation : $\Gamma(x,y,z,t) = \{(x,y,z)/\varphi(x,y,z,t)\} = 0$

In Adaptive, Hybrid Level-set evolution, the speed function is designed to control movement of the curve (or surface). The deformable model contains both boundary and regional information. The design of the velocity F plays a major role in the evolutionary process. The performance of the level set function is improved by, changing the previous region-based speed function by an adaptive scheme which is better than the static one. The "non-homogeneous" tumor tissues aresegmented. by applying threshold updating parameter τ at the
(i+1)th iteration where τ is the threshold estimation for ith iteration
$\tau^{i+1} = m_T^i$ – sign (I)Kσ_T^i where m_T^i is the value of tumor region and σ_T^i is the standard deviation of the tumor region. At each iteration, the mean value and the standard deviation are updating according to the equations below

$$m_T^i = \frac{1}{n}\sum_{j=1}^{n} x_j \quad \sigma_T^i = \frac{1}{n-1}\sum_{j=1}^{n}(x_j - m_T^i)2 \qquad (2)$$

The convergence of the algorithm is related mainly to the choice of τ and k. Indeed, for a small value of k, the level set may never grow while for a relatively large value of k, convergence may not be possible.

Clustering can be termed here as a grouping of similar images in the database [5]. Clustering is done based on different attributes of an image such as size, color, texture etc [5]. Clustering use no training stages rather train themselves using available data Two methods mainly used for clustering based segmentation.

K-Means is one of the simplest unsupervised learning algorithms. In K means objects are classified as belonging to one of k groups exclusively, k is chosen priori .The main idea is to define k centroids, one for each cluster. These centroids should be placed in a cunning way because of different location causes different result Fuzzy C-Mean (FCM) is an unsupervised clustering algorithm that has been applied to wide range of problems involving feature analysis, clustering and classifier design .FCM has a wide domain of applications such as agricultural engineering, astronomy, chemistry, geology, image analysis, medical diagnosis shape analysis, and target recognition. Fuzzy C-means (FCM) algorithm is one of the most popular fuzzy clustering methods widely used in various tasks of pattern recognition, data mining, image processing, expression data Recognition etc.

C. Computer-aided detection (CAD)

The Third technique compared in this paper is the computer-aided detection (CAD) [4] has been developing fast in the last two decades. Improving inter- and intra-reader variability. The pulse coupled neural network PCNN is considered a very powerful front-end processor for an image recognition system. The pulse coupled neural network, is a biological model inspired of mammalian visual cortex, proposed by Eckhorn, Reitboeck, Arndt, and Dicke (1990). PCNN is considered as the third generation of neural network models, which increase the level of realism in a neural simulation. The PCNN is advisable to solve tasks as the feature generation for image, pattern recognition, edge extraction and image segmentation ROI can be viewed as a region growing method where seed pixels are identified by the neurons that fire during primary firing and the region growing is accomplished by capturing spatially connected The feedback PCNN (FPCNN) sends the output information in an inhibitory fashion back to the input in a similar manner to the rat's olfactory system For the case of the FPCNN the input experience feedback shunting that is not uniform for the entire input. This is the point where the PCNN and the FPCNN differ. For the FPCNN, the outputs are collected as a weighted time average,

A, in a fashion similar to the computation of h except for a the constant

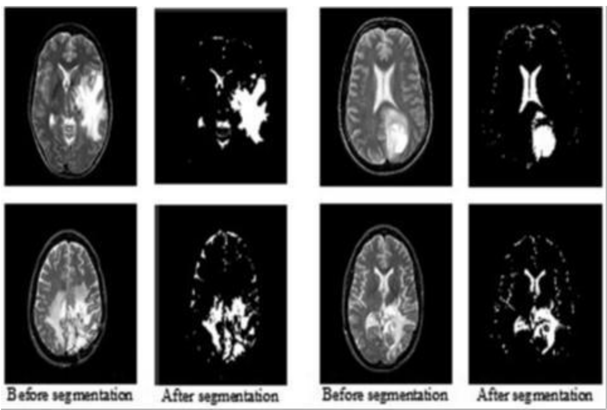

Fig 3 Sample of brain MRI from the database before and after segmentation using PCNN.

Classification using Neural Network

Neural networks are widely used in pattern classification since they do not need any information about the probability distribution and the a priori probabilities of different classes. A NN classification system mimics the human reasoning and in some cases, it gives the decision for more than one class to show the possibilities of other diseases. For brain MR image classification, as normal or abnormal, we used a Back-propagation neural network (BPNN) to classify inputs into the set of target categories (normal or abnormal)

based on feature selection parameters. BPNN is a supervised learning method which is a non-linear generalization of the squared error gradient descent learning rule for updating the weights of the artificial neurons in a single-layer perceptron, generalized to feed-forward networks (Haykin, 2008).

A Neural Network is a branch of artificial intelligence (AI). It can imitate the way in which a human brain works in processes such as studying, memorizing, reasoning and capable of performing massively parallel computations for data processing and knowledge representation. One advantage of the neural network approach is that most of the intense computation takes place during the training process. Once the ANN is trained for a particular task, operation is relatively fast and unknown samples can be identified. Generally, an ANN can be defined as a system or mathematical model that consists of many nonlinear artificial neurons running in parallel and may be generated as one-layered or multilayered. Most ANNs have three layers: input, output, and hidden. The function of the hidden layer is to intervene between the external input and the network output in some useful manner.

III. ANALYSIS PERFORMANCE

The template is used to format your paper and style the text. All margins, column widths, line spaces, and text fonts are prescribed; please do not alter them. You may note peculiarities. For example, the head margin in this template measures proportionately more than is customary. This measurement and others are deliberate, using specifications that anticipate your paper as one part of the entire proceedings, and not as an independent document. Please do not revise any of the current designations. noise level is high. LIPC selects almost 1000 neighbors which lead to increased computation costs. Now comparing these with the Level set method we can say that Adaptive Clustering technique and fuzzy clustering technique. we do not specify the cluster value k. Its directly appled to image and calculate the centroid of different clusters. Level set methods are applied for the smoothing of the tumor area. Finally calculate the tumor area by the approximate reasoning step the tumor using the binarization method. That is the image having only two values either black or white (0 or 1). The binary image can be represented as a summation of total number of white and black pixels .This paper reviews recent papers, the last compared technique was a hybrid technique for processing of MRI brain images. here first the feedback pulse-coupled neural network as a front-end processor for image segmentation and detecting the region of interest, and then employs the discrete wavelet transform to extract features from

MRI images. Moreover the principal component analysis is per-formed to reduce the dimensionality of the wavelet coefficients which results in a more efficient and accurate classifier. The reduced features are sent to back-propagation neural network to classify inputs into normal or abnormal based on feature selection parameters. Additionally, artifacts and noise in brain tumor images increase the difficulty when segmenting tumors. Thus, designing of a semi-automatic or automatic brain tumor segmentation approach is necessary to provide an acceptable performance.

IV. FUTURE SCOPE

We can apply the different steps to improve the limitations of computational cost and to detect the grade of the tumor. Other contextual features may be added in future studies to further improve the classification accuracy obtained in this study, which can also be useful for computer guided surgery.

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b Egyptian E-Learning University, 33 El-mesah St., El-Dokki, Postal code 12611 Giza, Egypt

c Faculty of Computers and Information Technology, Future University, Cairo, Egypt d The School of Computer Science, University of Westminster, London HA1 3TP, UK

e Faculty of Informatics and Computer Science, British University of Egypt, Cairo, Egypt

f Faculty of Computer and Information Science, Ain Shams

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