BRAIN TUMOR ANALYSIS FOR MRI IMAGE SEGMENTATION USING SEEDED REGION GROWING AND PCNN

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ABSTRACT

In this paper, we analysis the feature extraction of brain image disease like brain tumor segmentation using the technique called seeded region & PCNN. Brain Magnetic Resonance Image segmentation is a complex problem in the field of medical aging despite various presented methods. MR image of human brain can be divided into several sub-regions especially soft tissues such as gray matter, white matter and cerebrospinal fluid. This thesis paper investigates two algorithms to segment brain tissues and to implement the competent one through simulations by MATLAB software. Segmentation of the brain structure from magnetic resonance imaging (MRI) has received paramount importance as MRI distinguishes itself from other modalities and MRI can be applied in the volumetric analysis of brain tissues such as multiple sclerosis, schizophrenia, epilepsy, Parkinson’s disease, Alzheimer’s disease, cerebral atrophy, etc.,

There are a number of techniques to segment an image into regions that are homogeneous. Not all the techniques are suitable for medical image analysis because of complexity and inaccuracy. There is no standard image segmentation technique that can produce satisfactory results for all imaging applications like brain MRI, brain cancer diagnosis etc. Optimal selection of features, tissues, brain and non–brain elements are considered as main obstacles for brain image segmentation. So This paper points out the new method for medical image segmentation based on improved PCNN The new methods can automatically segment the medical images without selecting the PCNN parameters. Region growing segmentation is used to segment the MR image of brain tumor. A detail of the region growing segmentation is covered in the respective section. The algorithm takes an initial threshold value and seed point as input parameters. It is based on the measurement of mean value of the pixel intensity. The segmented image shows the tumor portion without any undesired portion of the image.

KEYWORDS: Pulse Coupled Neural Network (PCNN), Brain Magnetic Resonance Image (MRI), Image Segmentation

INTRODUCTION

Segmentation of major brain tissues, including gray matter (GM), white matter (WM), and cerebrospinal fluid, from magnetic resonance (MR) images plays an important role in both clinical practice and neuroscience research. However, due to the non uniform magnetic field or susceptibility effects, brain MR images may contain a smoothly varying bias field, which is also referred to as the intensity in homogeneity or intensity non uniformity [1]. As a result, the intensities of the same tissue vary across voxel locations and may lead to segmentation errors. Therefore, bias field correction and segmentation should be interleaved in an iterative process so that they can benefit from each other and yield better results. Many brain MR image segmentation approaches with bias field correction have been proposed in the literature [2]–[12]. Among them, those based on the expectation-maximization (EM) algorithm [2]–[4] and fuzzy C-mean (FCM) clustering [5]–[12] are the most popular ones. Pham and Prince. [8] proposed an adaptive FCM (AFCM) algorithm, which incorporates a spatial penalty term into the objective function to enable the estimated membership functions to be spatially
smoothed. Ahmed et al. [9] added a neighbor-hood averaging term to the objective function, and thus developed the bias-corrected FCM (BCFCM) algorithm. Li and Yan [10] used a B-spline surface to model the bias field and incorporated the spatial continuity constraints into fuzzy clustering algorithms. Li et al. [6] proposed an energy-minimization approach to the coherent local intensity clustering (CLIC), with the aim of achieving tissue classification and bias field correction simultaneously.

In our previous work [11], [12], we incorporated the global information into the CLIC model to enhance its robustness to the involved control parameters, then we pro-posed a newly modified possibility FCMs clustering algorithm (MPFCM) for bias field estimation and segmentation of brain MR image. Although such modification improves the segmentation accuracy, it also dramatically increases the computational complexity.

Various kernel techniques have been used to improve the performance of clustering approaches. Chen and Zhang [13] replaced the original Euclidean distance with a kernel-induced distance and supplemented the objective function with a spatial penalty term, which models the spatial continuity compensation.

Yang and Tsai [14] proposed an adaptive Gaussian-kernel-based FCM (GKFCM) algorithm with the spatial bias correction. Liao et al. [15] developed a spatially constrained fast kernel FCM (SKFMC) clustering algorithm to improve the computational efficiency. However, the clustering performed in a kernel space is generally very time consuming.

Alternatively, brain MR images can be segmented by using the Gaussian mixture model (GMM) [16], where the voxel intensities in each target region are modeled by a Gaussian distribution [17]. The GMM parameters are usually estimated by maximizing the likelihood of the observed image via the EM algorithm [2]. A major drawback of the GMM-EM framework is its lack of taking the spatial information and uncertainty of data into consideration. As a result, it may produce less accurate segmentation results.

To remedy this drawback, Greenspan et al. [18] and Blekas et al. [19] incorporated the spatial constraints into the GMM. Tran et al. proposed the fuzzy GMM (FGMM) model to address the uncertainty of data and improve parameter estimation [20]. Zeng et al. [21] developed the type-2 FGMM (T2-FGMM) model for density modeling and classification. However, to our knowledge, so far those fuzzy ex-tensions of the GMM-based segmentation algorithm have not been able to overcome the difficulties caused by the intensity in homogeneity.

PROPOSED CLASSIFICATION METHODS

The block diagram of our proposed algorithm is shown in Figure 1. As shown in this figure, after the preprocessing step the images are segmented into isolated objects from each other and from background and the different objects are labeled. The feature extraction and selection step also measures certain properties of labeled objects. These features are then passed through a supervised BPNN classifier that evaluates the presented evidences and makes a decision on the class that each object should be assigned.

Preprocessing

In medical images, due to diagnostic and therapeutic applications the removal of noise and artifacts is critical. Specially, in MRI, inhomogeneous magnetic field, patient motion in imaging duration and external noise, are some sources of artifacts and other undesired effects. These form the main causes of computational errors in automatic image analysis and brain tumor detection. Therefore, it is necessary to remove them in the preprocessing procedure before any image analyzes can be performed. In this paper, the preprocessing step consists of image enhancement and image restoration.
Image Enhancement

Enhancement algorithm is used to make the image more appropriate for the subsequent processes. It can reduce image noise and increase the contrast of structures in regions of interest. Image noise can reduce the capacity of region growing filter to grow into large regions or may result in false edges. Median filtering is a nonlinear operation often used in image processing to reduce "salt and pepper" and speckle noise. A median filter is more effective than convolution when the goal is to simultaneously reduce noise and preserve edges. For noise suppression, a weighted median filter (WMF) using neural network is constructed in this paper.

PCNN ALGORITHM

The pulse coupling neural network is an artificial neural network, which was founded in the last century 90's, completely different from artificial neural networks. When PCNN is used for image segmentation, it is the single two dimension local connection network. The neuron is corresponding with the pixel one by one. Each neuron is connected with the corresponding pixel which is also connected with the neighbor neuron. Input each gray value of pixel into corresponding F channel. The L channel of each neuron is connected with other neuron's output in neighborhood and receives their outputs. Each neuron only has two states, outputting pulse or not. Algorithm for medical image segmentation, each neuron can only be activated once.

Concrete steps are as follows:

- Set the initial values of PCNN parameters, which means that all threshold values are set to be zero. The aim is that all pixels can be activated.

- Generate the next iteration threshold according to equation

\[
E_{\phi}[n] = E[n] = \begin{cases} 
0, & \text{if } \sum_{j=0}^{n-1} Y_{\phi}[n-1] = 1 \\
E_0, & \text{else} 
\end{cases} 
\]

- Do the circulate iterating according to equation

\[
F_{\phi}[n] = I_{\phi}
\]

When in the neighborhood where \(J\phi(\text{internal weight coefficient matrix})\) is there appears the pixel whose gray value is similar with others, and some pixel's gray value is less than the input threshold. These pixels output the pulse one by one; other around neurons whose gray values are similar can output pulse. Then produce the pulse sequence \(J'[n]\).
SEGMENTATION METHODS

Here we used two types of segmentation 1. Seeded region growing & 2. Pulse coupled neural network to extract the features of MRI Brain images.

Region Growing Methods

The first region growing method was the seeded region growing method. This method takes a set of seeds as input along with the image. The seeds mark each of the objects to be segmented. The regions are iteratively grown by comparing all unallocated neighboring pixels to the regions. The difference between a pixel's intensity value and the region's mean is used as a measure of similarity. The pixel with the smallest difference measured this way is allocated to the respective region. This process continues until all pixels are allocated to a region. Seeded region growing requires seeds as additional input. The segmentation results are dependent on the choice of seeds. Noise in the image can cause the seeds to be poorly placed. Unseeded region growing is a modified algorithm that doesn't require explicit seeds. It starts off with a single region the pixel chosen here does not significantly influence final segmentation.

At each iteration it considers the neighboring pixels in the same way as seeded region growing. It differs from seeded region growing in that if the minimum is less than a predefined threshold then it is added to the respective region. If not, then the pixel is considered significantly different from all current regions and a new region is created with this pixel. One variant of this technique, proposed by Haralick and Shapiro (1985), [1] is based on pixel intensities. The mean and scatter of the region and the intensity of the candidate pixel is used to compute a test statistic. If the test statistic is sufficiently small, the pixel is added to the region, and the region’s mean and scatter are recomputed. Otherwise, the pixel is rejected, and is used to form a new region.

Neural Networks Segmentation Method

Neural Network segmentation relies on processing small areas of an image using an artificial neural network [23] or a set of neural networks. After such processing the decision-making mechanism marks the areas of an image accordingly to the category recognized by the neural network. A type of network designed especially for this is the Kohonen map. Pulse-Coupled Neural Networks (PCNNs) are neural models proposed by modeling a cat’s visual cortex and developed for high-performance biometric image processing. In 1989, Eckhorn introduced a neural model to emulate the mechanism of cat’s visual cortex. The Eckhorn model provided a simple and effective tool for studying small mammal’s visual cortex, and was soon recognized as having significant application potential in image processing. In 1994, the Eckhorn model was adapted to be an image processing algorithm by Johnson, who termed this algorithm Pulse-Coupled Neural Network. Over the past decade, PCNNs have been utilized for a variety of image processing applications, including: image segmentation, feature generation, face extraction, motion detection, region growing, noise reduction, and so on.

A PCNN is a two-dimensional neural network. Each neuron in network corresponds to one pixel in an input image, receiving its corresponding pixel’s color information (e.g. intensity) as an external stimulus. Each neuron also connects with its neighboring neurons, receiving local stimuli from them. The external and local stimuli are combined in an internal activation system, which accumulates the stimuli until it exceeds a dynamic threshold, resulting in a pulse output. Through iterative computation, PCNN neurons produce temporal series of pulse outputs. The temporal series of pulse outputs contain information of input images and can be utilized for various image processing applications, such as image segmentation and feature generation. Compared with conventional image processing means, PCNNs have several significant merits, including robustness against noise, independence of geometric variations in input patterns, capability of bridging minor intensity variations in input patterns, etc.
EXPERIMENTAL RESULTS

Segmentation of Synthetic Images

The basic goal of restoration is to improve the quality of images and attempts to reconstruct (or recover) the degraded image by using a prior knowledge of the degradation phenomenon. An image might be degraded by noise, blurring, and distortion during acquisition and transmission in the imaging systems. Image restoration tries to remove (or reduce) these degradations using the point spread function (PSF) that directly characterizes the image degradation process. In this paper, to restore the images we apply the inverse of the blurring and distortion transformation on degraded images.

An image can be geometrically distorted within an imaging system, due to unequal magnification within the field of view. Extreme wide-angle and low-angle lenses produce very significant barrel and pin-cushion, respectively. Barrel distortion perturbs an image radially in outward from its center. Distortion is greater as we move farther from the center, resulting in convex sides as shown in Figure (3). Pin-cushion distortion is the inverse of barrel distortion. It is because the cubic term has negative amplitude. Distortion is still greater we going farther from the center but it results in concave sides, as can be seen in Figure (4).

Segmentation of Brain MR Images

Segmentation refers to partitioning an image into meaningful regions, in order to distinguish objects (or regions of interest) from background. There are two major approaches, region-based method (such as region growing, split/merge using quad tree decomposition) in which similarities are detected, and boundary-based method (such as thresholding, gradient edge detection), in which discontinuities are detected and linked to form boundaries around regions. Segmentation of nontrivial images is one of the most difficult tasks in image processing. Segmentation accuracy determines the eventual success or failure of computerized analysis procedures.
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CONCLUSIONS

In this paper, we have developed a novel neural network-based classifier to distinguish normal and abnormal (benign or malignant) brain MRIs. The proposed technique consists of six stages, namely, preprocessing, automatic seeded region growing segmentation, connected component labeling, feature extraction, feature dimension reduction, and classification. In the preprocessing stage, the enhancement and restoration techniques are used to provide a more proper image for subsequent automated analysis. In the segmentation stage, the automatic seeded region growing is used for partitioning an image into meaningful regions. In the third stage, once all groups have been determined, each pixel is labeled according to the component to which it is assigned to. In the fourth stage, we have obtained the features related to MRI images using discrete wavelet transform.

In the fifth stage, the number features of MRI are reduced, using the principal component analysis. In the classification stage, a supervised feed-forward back-propagation neural network technique is used to classify subjects as normal or abnormal (benign, malignant). We applied this method on 600 images (50 normal, 250 benign and 300 malignant). A classification with 100% sensitivity rate and 96% specific rate was obtained. According to experimental results, the proposed method is efficient for classification of human brain into normal and abnormal classes. The classification performances of this study show that the proposed method is fast, easy to operate, non-invasive, and
inexpensive. Extension of developed techniques for classification of different types of brain tumor is the topic of our future research. Also, we will try to develop this algorithm for classification of other tumors such as breast cancers.

REFERENCES


