Diagnosis of Brain Tumor using PNN Neural Networks

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Abstract

Cells grow and then need a very neat method to create new cells that work properly to maintain the health of the body. When the ability to control the growth of the cells is lost, they are unconsidered and often divided without order. Exemplified cells form a tissue mass called the tumor. In fact, brain tumors are abnormal and uncontrolled cell proliferations. A segmentation method is used in biomedical image processing and examines the methods used for better segmentation. Critical assessment of the current state of the automated and automated methods, have the benefits and disadvantages for categorizing anatomical medical pictures with emphasis on. In this project, we recognize brain tumors and classify tumor stages using database testing and training. Segmentation is used for testing purpose by FCM space. Neural networks are also used for its segmentation, which yields acceptable results in PNN neural networks.

Keywords: Brain MR, image segmentation, learning vector quantization, self-organizing feature map, stationary wavelet transform.

1- Introduction

The Magnetic Resonance Imaging (MRI) technique provides a complete report on the characteristics of brain tumors, cellular structure and body and vessel tissues, and it is an important tool for more accurate diagnosis, treatment and control of diseases. MRI (Imaging) (MRI) is a safe medical image that helps doctors diagnose greatly in order to be effective. The MRI uses a strong magnetic field, a radio frequency pulse, and a computer for accurate imaging of organs, soft tissue, bone, and almost all other body structures. After that, you can view the images on a computer screen or print it or copy it to a CD. MRI imaging does not use ionizing radiation (x-rays). Precise MR images allow doctors to examine different parts of the body and determine the presence of certain diseases.

Detecting and accurately determining the location, size, and type of brain tumor automatically from MRI images is one of the most complex tasks in today's modern medical imaging research. This automatic diagnosis requires the division of the brain image, which is the process of splitting the image into distinct areas, one of the most important aspects of the clinical computer diagnostic tools. The noise in the MRI brain, multiple sounds and the reduction of these sounds is a difficult task. The anatomical details of the minute should be eliminated clinically by the process of noise removal. These processes make the fragmentation of brain images a challenge. However, the precise breakdown of MRI images is important and important for accurate diagnosis with computerized clinical tools.

Many algorithms have been developed to vary the MRI images. Scheduling for surgery, post-surgical evaluation and analysis, diagnosis of a disorder, and many other medical programs require the sharing of medical images. Despite the large number of automatic and semi-automatic image segmentation techniques, in many cases they often fail because of unknown and irregular noise, homogeneity, poor contrast, and weak boundaries inherent in medical images.

Magnetic resonance imaging (MRI) is done for many reasons. It is used to find problems such as tumors, bleeding, injury, blood vessel diseases, or infection. MRI also may be done to provide more information about a problem seen on an X-ray, ultrasound scan, or CT scan. Contrast material may be used during **MRI** to show abnormal tissue more clearly. A brain tumor is any intracranial tumor created by abnormal and uncontrolled cell division, normally either found in or around the brain itself, or spread from cancers primarily located in other organs (metastatic tumors). Primary (true) brain tumors are commonly located in the posterior cranial fossa in children and in the anterior two-thirds of the cerebral hemispheres in adults, although they can affect any part of the brain.

In the United States in the year 2000, it was estimated that there were 16,500 new cases of brain tumors, which accounted for 1.4 percent of all cancers, 2.4 percent of all cancer deaths, and 20-25 percent of pediatric cancers. Ultimately, it is estimated that there are 13,000 deaths/year as a result of brain tumors. Magnetic resonance imaging **(MRI)** is a noninvasive medical test that helps physicians diagnose and treat medical conditions.MRI uses a powerful magnetic field, radio frequency pulses and a computer to produce detailed pictures of organs, soft tissues, bone and virtually all other internal body structures. The images can then be examined on a computer monitor, transmitted electronically, printed or copied to a CD. MRI does not use ionizing radiation (x-rays). Detailed MR images allow physicians to evaluate various parts of the body and determine the presence of certain diseases.

2- Classification Separation Methods

Preprocessing is the image name for operations in images at the lowest abstraction level, the purpose of which is to improve image data that suppress undesirable distortions or increase some of the important visual features for further processing. This operation does not increase the content of the image information. Its methods are remarkable

2-2-Redundancy in pictures.

In realistic images, the neighboring pixels of an object have a same or similar brightness value, and if you can remove a distorted pixel from the image, it can be reconstructed as the average value of neighboring pixels. The image preprocessing tool created in Matlab understands many brightness changes and local preprocessing methods. In fact, the purpose of the preprocessing operation is to improve the image data that distorts the image unwanted, or improves some of the visual features associated with processing and further analysis. Image pre-processing uses image redundancy. Neighbor pixels belonging to a real object have the same brightness or similar magnitude. If a distorted pixel can be taken from the image, it can be reconstructed as the average value of neighboring pixels. The pre-processing image processing methods can be categorized according to the size of the pixel range used to calculate the new pixel brightness.

2-2-Medium filters

In image processing, common filters are widely used, because some of the important details of the image, for example, with the preservation of the edges, were implemented by the filters, so that noise can be effectively eliminated. Weighted average filters (WMs) are another natural type of medium filter set that uses not only ordered information but also spatial information of the input signal. In the middle filter, the neighboring pixels are ranked according to the brightness (intensity), and the average value becomes the new value for the central pixel. Medium filters can do great things to exclude certain types of noise, especially "shot" or shock noise, in which some individual pixels have severe amounts. In practice, the average filtering, pixel values in the neighborhood window are ranked according to severity and the mean value (average) is converted to the output value for the pixel under evaluation.

The median filter are nonlinear. The median is, in a sense, a more robust "average" than the mean, as it is not affected by outliers (extreme values). Since the output pixel value is one of the neighboring values, new "unrealistic" values are not created near edges. Since edges are minimally degraded, median filters can be applied repeatedly, if necessary.

2-3-Wavelet Transform Converter (SWT)

Removing the noise from the image remains a major problem in the field of image processing. Using wavelet transforms, various algorithms were introduced for detection in wavelet domain. Due to their own characteristics, such as multiple resolution, the wavelets have improved visual performance. The problem of estimating an image that has been added through an increase in Gaussian noise has been considered for practical and theoretical reasons. Nonlinear methods, especially wavelet-based ones, have become popular due to their advantages over linear methods. An enhanced image resolution technique based on the interpolation of high-frequency images obtained by digital wavelet transform (DWT) and input image. Edges increase with the introduction of a moderate stage using constant wavelet transform (SWT). The DWT is applied to decompress an input image under different sub bands. Then the high frequency sub bands as well as the input image are interpolated. The estimated high frequency sub bands are being modified by using high frequency sub band obtained through SWT. Then all these sub bands are combined to generate a new high resolution image by using inverse DWT (IDWT). The

Stationary wavelet transform (SWT) is a wavelet transform algorithm designed to overcome the lack of translation-invariance of the discrete wavelet transform (DWT). Translation-invariance is achieved by removing the down samplers and up samplers in the DWT and up sampling the filter coefficients by a factor of 2(j-l) in the j th level of the algorithm. The SWT is an inherently redundant scheme as the output of each level of SWT contains the same number of samples as the input so for a decomposition ofN levels there is a redundancy ofN in the wavelet coefficients.

2-4-Segmentaition

Segmentation is the process of dividing an image into regions with similar characteristics, such as gray level, color, texture, brightness and contrast. The role of division is to divide the objects into an image; if the division of the medical image is the goal:

• Anatomy structure study

• Identify the examined area, which is the same brain tumor, determine lesion and other disorders Diagnosis of tissue volume size to measure tumor growth (also reducing tumor size with treatment). Helping to plan treatment before radiation; calculate radiation dose. The automatic division of medical images is difficult because medical images are complex in nature and rarely have a simple linear feature. In addition, the output of the segmentation algorithm is due to the effect of minor volumes, the intensity of homogeneity, the presence of artifacts, the close proximity to gray levels of different soft tissues. The artifacts contained in MR and CT images can be divided into three categories based on the image processing technique needed to correct them: (i) Artifacts that require appropriate filter technology. For example, artificial noise, the sensitivity characteristic, and the presence of non-warp edges in an artificial image (ii) requiring appropriate techniques for image restoration, for example, artifacts, and (iii) artificial ones requiring a particular algorithm; volume Partial, non-deviation of intensity.

Although a large number of algorithms have been proposed in the field of medical image categorization, the division of the medical image remains a complex and challenging and attractive problem. Different scholars have done the classification of division techniques in a different way. Now, from our medical image processing perspective, we have categorized categorization methods based on techniques based on gray-level techniques and specific tissues. Additionally, artificial intelligence is considered as a tool to optimize these early techniques for achieving accurate segmentation results.

2-5-spatial FCM

In this paper, the spatial-based FCM approach for image segmentation as one of the best visual clustering methods using fuzzy C-means local information is often used to segment the image. Noise effects are avoided using spatial relationships between pixels, but often create border areas for mixed pixels around the edges. This letter provides an image spatial clustering method called fuzzy C-means with edge and local information (FELICM) that performs edge degradation by entering pixel weights in adjacent local windows. This method can be directly applied to the image without any filter pre-processing, and empirical results over remote sensing images show that FELICM not only effectively solves the problem of separate and random distribution of pixels within the regions, But to get the top alignment of the edge. In order to create stronger clustering, many spatial clustering techniques that can withstand the original image without filtering are suggested.

2-6- Fuzzy C-means (FCM) (BCFCM)

In the BCFCM, a pixel label is filtered by both the spectral properties of the pixels and its neighbors and determines a neighboring control parameter. Tarabalka et al. A spectral-spatial approach for hypertensive images was proposed. Homogeneous regions are obtained by combining the results of support vector and clustering using the majority vote. To exploit spatial information, aThespatial function is defined as:

$$h_{ij} = \sum_{k\in} U_{ik} NB(x_j) \tag{1}$$

In this equation, NB (xj) represents a square window in the spatial domain in pixel xj. a 3×3 window was used during this task. Like the membership function, the Spatial function hij represents the probability that the pixel xj belongs to the cluster i. A spatial function is a pixel for a large cluster if the majority of its neighborhood belongs to a cluster. The spatial function in membership function is as follows:

$$u_{ij} = \frac{{u_{ij}}^{p} {h_{ij}}^{q}}{\sum_{j=1}^{c} {u_{ij}}^{p} {h_{ij}}^{q}} \tag{2}$$

Here p and q are parameters. The task of these two parameters is to control the relative importance of both functions. In a homogeneous region, spatial functions amplify the original membership, and the clustering result remains unchanged. However, for a noisy pixel, this formula reduces the weight of a noisy cluster with the label of its neighboring pixels. As a result, unclassified pixels from noisy areas or fake bubbles can easily be corrected.As one of the best methods, Krinidis and Chatzis presented a robust image clustering method called fuzzy local information C-means (FLICM). FLICM is a noise insensitive method without a priori knowledge.

The clustering is based on spatial and spatial information that collaborates with a fuzzy agent. However, this method assumes that the label is a pixel associated with the labels of its spatial neighbors. Therefore, incorrect cluster tags may be assigned to pixels around the edges of the areas and thus the edges will be removed. This letter offers a visual spatial clustering method called FCM with edge and local information (FELICM) that delivers edge degradation by importing pixel weights in local neighbor windows

2-7- probabilistic Neural Network (PNN)

One of the relevance based neural networks used in this study is a probabilistic neural network in the previous work of the neural network mask probability probabilistic. The probabilistic neural network algorithm (PNN) represents the probability function algorithm of a data class as the sum of the same, different variables. In practice, the PNN is often an excellent algorithm classification, which is more than other categories, including reimbursement. However, due to changes in feature space, it is not strong, and this can lead to poor performance in particular data. We called a PNN format called Weighted PNN (WPNN) that compensates for unnecessary Gaussians, Gaussians, whose covariance does not have multiple identity matrices. The covariance is optimized using a genetic algorithm, some of its interesting features are its logarithmic and exclusive coding and the size of the large PNN population, its lack and stability due to changes in the space of the attribute Probabilistic neural networks can be used to solve classification problems. When an input is provided, the first layer calculates the distances from the input vector to the instruction input vectors, and generates a vector that shows the elements that are close to entering the entry of a learning input. The second layer generates this contribution for each class of inputs as the net output of a probability vector. Finally, a transfer function of competition in the second layer output selects the maximum of these probabilities and generates one class for that class and another 0 class. To correct this, a PNN format is called WPNN, which suggests anisotropic curves for isotropic Gaussians that are used by the PNN. Given the assumption that Covariance Gaussian is diagonal, we have described how to use a genetic algorithm to optimize covariance for optimal performance in the training set. With SVM, we can only understand that the MR image as natural or abnormal, but with the help of PNN, we can obtain three results that the brain status are normal or have amalignant or benign tumor . So using PNN, we can more accurately predict or classify the MR image.

3- Custom Block Design

In this section we present materials, brain image MRI data and methods used for MR brain segmentation algorithm. The general flowchart of the algorithm used in this paper, which includes both the learning and testing process, is given in Figure 1.The details of implementing the algorithm steps are discussed below.

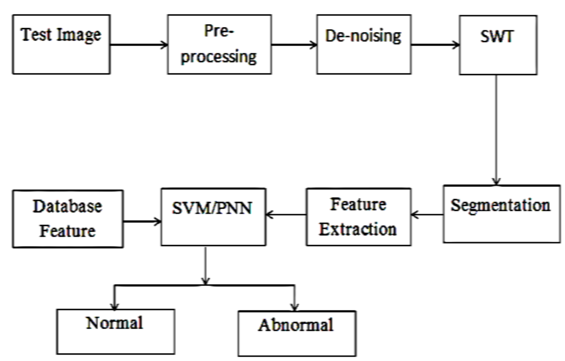

Fig.1. Block diagram

A. Images tested

We worked with a data set of 15 patients who had glial brain tumors and according to the site's source, these patients were under no surgical procedure. We downloaded the data from the medical image database of the Physiognomy website. The whole database of this section was searched for images of the MR brain with a tumor report.

B. Preprocessing

We restricted the intensity range of the images to [0 1] and normalized by dividing all the intensity values into maximum intensity. To improve and increase the signal-to-noise ratio, we used an exclusive broadcast filter for images as a preprocessing stage. This powerful filter is defined as a propagation process [2].

C. Destruction and SWT

To determine the image in this paper, common filters and SWT method are used.

D. Segmentation

Segmentation is the process of dividing an image into areas with similar properties like gray level, color, texture, brightness and contrast.

E. Feature extraction

We used SWT to extract the features of MR images used as inputs for NNs. SWT is not something that can be translated or extracted, and is known as a special name. The SWT tolerance will not change even with the signal shift [4, 5].

F. SVM / PNN

In this paper, we used the FCM space for segmentation.

4- Experimental Results

In the following, Figure 3 shows the results for converting from color to gray image and middle filter. Since a color image is the original image, the gray image is Right to the original image, salt and pepper noise is underneath the original image, and another is the Median Filter image.

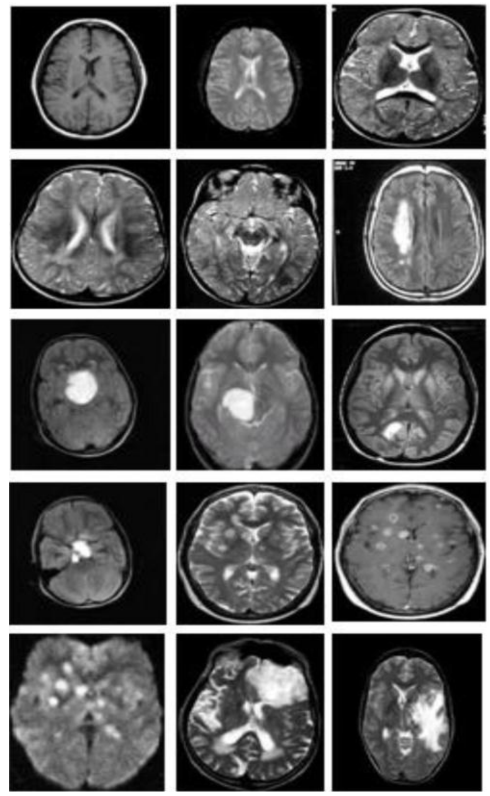

Fig.2. Different Database Test Images

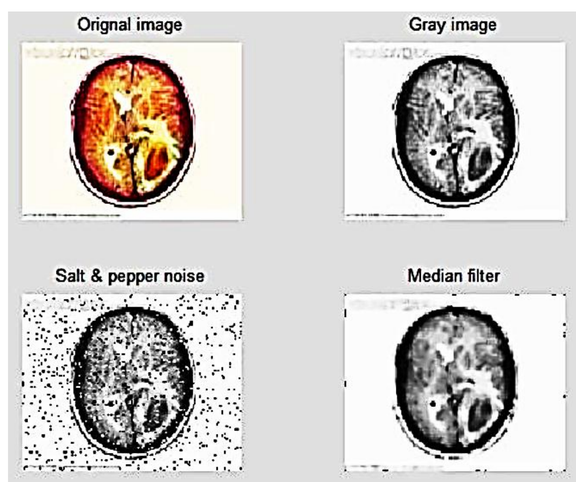

Fig.3. Result for color to gray & De-noised by median filter image

Following figure 4 shows Clustering by special FCM. Out of which upper left is cluster 1 image, upper right is cluster 2 image, cluster 3 is below cluster 1 & cluster 4 is below cluster 2.

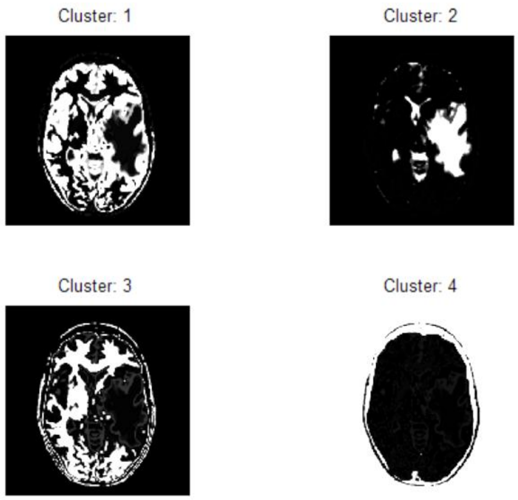

Fig.4. Clustering by spatial FCM

5- Conclusion

The proposed algorithms for diagnosing a brain tumor based on MRI images have higher accuracy and low error rates. Statistical analysis of empirical results shows that the developed algorithm can split the brain's MR images accurately. We find ways to identify these tumors more quickly to improve survival. Various neural network based algorithms are also available for accurate and accurate categorization. However, most of these neural network algorithms have a wide range of oversight and monitoring functions, and their function depends on the training method and the data used in the training. Finally, medical image categorization algorithms and classification algorithms are required to have the following characteristics: a) accuracy, b) reliability, c) repeatability, d) reliability, and a) least dependence on the operator.

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