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An Image Segmentation Technique for Mri Brain Tumor Image Using Modified fcm Algorithm

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ABSTRACT

Magnetic Resonance Imaging (MRI) is one of the best technologies currently being used for diagnosing brain tumor. Brain tumor is diagnosed at advanced stages with the help of the MRI image. Segmentation is an important process to extract distrustful region from complex medical images. MRI Brain tumor images with spatial information can be analyzed for diagnosis purpose. A conventional FCM algorithm does not fully utilize the spatial information in the image. Fuzzy C Means is a data clustering technique wherein each data point belongs to a cluster to some degree that is specified by a membership grade. In this modified FCM, spatial information is utilized for clustering. A new fuzzy level s *et al*gorithm is proposed for MRI brain tumor image segmentation. It begins with spatial fuzzy clustering, whose results are utilized to initiate level set segmentation. The advantage of the method is that it is less sensitive to noise than other techniques. Then features are extracted from the segmented region using GLCM. The neural network is trained with the features extracted from the normal and abnormal images. Neural network employing feed forward back propagation training algorithm is used and performance of the network is analyzed by giving unknown test data. The results of the work will aid physicians in early diagnosis of tumor thereby increases the chances of survival.

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INTRODUCTION

Medical Image processing plays a vital role for the analysis and diagnosis of data obtained from various imaging modalities. This helps doctors for ease interpretation of the information in medical images and better diagnosis. Brain tumor is a group of abnormal cells that grows inside of the brain or around the brain. Tumors can directly destroy all healthy brain cells. It can also indirectly damage healthy cells by crowding other parts of the brain and causing inflammation, brain swelling and pressure within the skull. Over the last 20 years, the overall incidence of cancer, including brain cancer, has increased by more than 10percentage, as reported in the National Cancer Institute statistics (NCIS). Brain tumor pathologies are the most common fatality in the current scenario of healthcare society. People of different age groups are prone to be affected by cancer which is mainly due to brain tumor. This causes arrest of blood supply to brain resulting in problems related to cerebral disfunctioning. The prime objective is to analyze magnetic resonance imaging of brain tumor. The analysis is therefore carried out in the brain as a step towards early diagnosis of high risk disease like tumor.

Literature survey:

Magnetic Resonance imaging is one of the clinical diagnostic procedures, it is a safe and painless test that can provide detailed pictures of organs and other structures inside your body. MR Imaging uses a strong magnetic field and radio waves to create pictures, on a computer, of tissues, organs and other structures inside your body. Normally Magnetic Resonance images have some noise. Hence it is possible for the efficient and experienced physicians to extract the diagnostic details from the image. Eventhough manual segmentation differs from one physician to other and it is impractical when large number of brain tumor images are to be analyzed which is a time consuming task. Many researchers attempt to develop different methods for automatic diagnosis of brain tumor.

Indah Soesanti, AdhiSusanto, Thomas Sri Widodo and Maesadji Tjokrongoroetal (2011)

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presented analgorithm that incorporates spatial information into the membership function for clustering. This method is less sensitive to noise than other techniques. This technique is a powerful method for noisy images.

Jianghua Huang, Junying Zhang *et al* (2011) proposed an efficient distributed clustering algorithm based on FCM by incorporating the neighborhood sensor spatial information into the FCM algorithm (FCMS) to meet sensor data correlation increasing with decreasing spatial separation.

Bing Nan Li, Chee Kong Chui, Stephen Chang and S.H. Ong (2011)presented a new fuzzy level algorithm to facilitate medical image segmentation. The controlling parameters of level set evolution are also estimated from the results of fuzzy clustering.

V.Sivakrithika B.Shanthi, etal(2011) presented a comparative study of two classification methods: One which utilize the texture features extracted from the images by directly feeding to the Neural Network based classifier stage to classify the images into benign or malign and in the other hybrid method, those texture features are made to undergo fuzzy discretization before feeding to the Neural Network classifier for the classification.

Description Of The Project:

The principal aim is to segment the brain image and to classify the image as normal or abnormal. The objective is to automatically segment magnetic resonance brain image which is used for identifying brain tumor. The various steps involved are

- First acquiring the image using magnetic resonance imaging
- Secondly preprocessing the image to remove the noises in the image
- Segmentation of the image to extract the diagnostic details without any user interaction
- Classifying segmented brain image using neural networks
- Finding the image is normal or abnormal

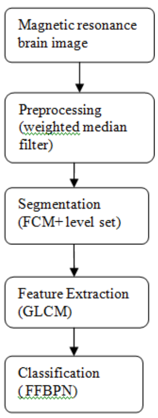

Fig. 3.1: Block Diagram for Segmentation.

3.1 ***Acquisition Of The Image:***

Magnetic Resonance Imaging uses magnetization and radio waves, rather than x-rays to make very detailed, cross-sectional pictures of the brain. MRI, or magnetic resonance imaging, is a means of "seeing" inside of the body in order for doctors to find certain diseases or abnormal conditions. The MRI examination requires specialized equipment that uses a powerful, constant magnetic field, rapidly changing local magnetic fields, radio frequency energy, and dedicated equipment including a powerful computer to create very clear pictures of internal body structures. During the MRI examination, the patient is placed within the MR system or scanner. The powerful, constant magnetic field aligns a tiny fraction of subatomic particles called protons that are present in most of the body's tissues. Radio frequency energy is applied to cause these protons to produce signals that are picked up by a receiver within the scanner. The signals are specially characterized using the rapidly changing, local magnetic field and computer-processed to produce images of the body part of interest.

3.2 ***Image Preprocessing:***

The preprocessing module is implemented for noise suppression, image smoothing and boundary enhancement. Magnetic Resonance imaging is a widely used medical imaging procedure because it provides high spatial resolution and excellent discrimination of soft tissues. But, one of its main shortcomings is the raw MR images normally consist of many artifacts such as intensity in-homogeneities, extra cranial tissues, etc. which reduces the overall accuracy and so filtering is used to enhance the image.

In order to extract diagnostic information from a Magnetic Resonance image, we need many kinds of image processing techniques. Among them, preprocessing is indispensable, and is particularly important to extract diagnostic information. Various kinds of smoothing techniques may eliminate noise effectively. The main challenge in noise removal consists of suppressing the corrupted information while preserving the integrity of fine medical image structures. Several and well-established techniques, such as weighted median filtering are successfully used in gray scale imaging.

3.2.1 Weighted Median Filter:

Weighted median filtering approach is particularly adapted for impulsive noise suppression. The advantages of weighted median filter ear robustness and edge preserving capability. Weighted median filtering performs well for images corrupted by impulse noise. This is same as median filter but only difference is the mask is not empty, it has some weight. It is nonlinear filter.

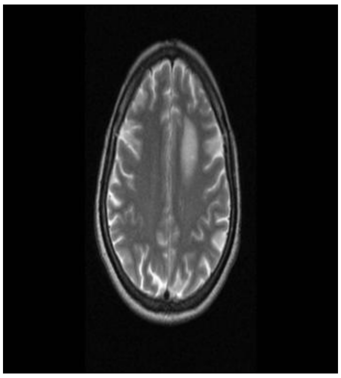

Fig. 3.3: Original Image.

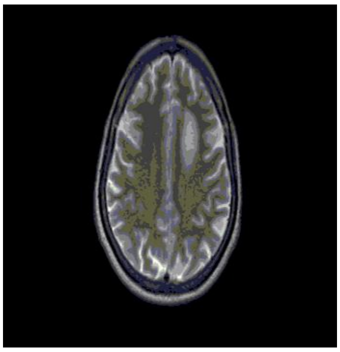

Fig. 3.4: Preprocessed Image.

Image Segmentation:

Image segmentation is the fundamental task in image processing and segmentation of medical images is a challenging problem due to the complexity of images. Automated segmentation methods are of considerable importance to the effective use of medical images in clinical and surgical setting. Segmentation of medical images is needed for applications involving estimation of the boundary of an object, classification of tissue abnormalities, shape analysis, contour detection and texture segmentation. Despite the existence of several techniques, segmentation of specific medical images still remains a crucial problem due to complex nature of the most of the medical images. In the present work the desired region of interest is segmented using modified FCM (spatial FCM+ level set) algorithm.

4.1 Modified Fcm Algorithm:

Both FCM algorithms and Level set methods are general purpose computational models that can be applied to problems of any dimension. However if we constrain them to medical image segmentation it is possible to take advantage of the specific circumstances for better performance. A modified FCM algorithm is thereby proposed for automated medical image segmentation. It begins with spatial fuzzy clustering, whose results are utilized to initiate level set segmentation, estimate controlling parameters and regularize level set evolution.

The modified FCM algorithm automates the initialization and parameter configuration of the level set segmentation using spatial fuzzy clustering. It employs an FCM with spatial restrictions to determine the approximate contours of interest in a medical image.

4.1.1 Spatial Fuzzy C-Means Algorithm:

Fuzzy C-means is one of the most popular algorithms in fuzzy clustering, has been widely applied to medical problems. The classical FCM algorithm originates from the K-means algorithm. In K-means clustering, every object is limited to one of K clusters. In contrast FCM utilizes a membership function $\mu_{mn}$to indicate the degree of membership of n th object to the m th cluster, which is justifiable for medical image segmentation. The cost function in an FCM is

$$J = \sum_{n=1}^{n}\sum_{m=1}^{c} \mu_{mn}^{l} \| i_n - v_m \|^2 \qquad (4.1)$$

Where (l>1) is a parameter controlling the fuzziness of the segmentation. The membership functions are subject to the following constrains:

$$\left.\begin{array}{l} \sum_{m=1}^{C} \mu_{mn} = 1; \\ 0 \leq \mu_{mn} \leq 1; \\ \sum_{n=1}^{N} \mu_{mn} > 0; \end{array}\right\} \qquad (4.2)$$

The membership functions μ_{mn} and the centroids v_m are updated iteratively

$$\mu_{mn} = \frac{\| i_n - v_m \|^{-\frac{2}{l-1}}}{\sum_{k=1}^{C} \| i_n - v_k \|^{-2/(l-1)}} \qquad (4.3)$$

$$v_i = \sum_{n=1}^{N} \mu_{mn}^{l} i_n / \sum_{n=1}^{N} \mu_{mn}^{l} \qquad (4.4)$$

The standard FCM algorithm is optimized when pixels close to their centroid are assigned high membership values, while those that are far away are assigned low values. One of the problems in FCM is lack of spatial information. Since image noise and artifacts often impair the performance of an FCM segmentation, it would be attractive to incorporate spatial information into an FCM. The membership function for spatial FCM is

$$\mu_i' = \frac{\mu_{ij}^{p} h_{ij}}{\sum_{k-1}^{c} \mu_{ij}^{p}} \mu_{ij}^{q} \qquad (4.5)$$

where p and q are parameters controlling the respective contribution. The variable h_{mn} includes spatial information by

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$$h_{mn} = \sum_{k \in Nn} \mu_{nk} \qquad (4.6)$$

where N_n denotes a local window centered around the image pixel n.

4.1.2 Level Set Segmentation:

In contrast to FCM using pixel classification, level set methods utilize dynamic variational boundaries for an image segmentation. Segmenting images by means of active contours is a well known approach, but instead of parametric characterization of active contours, level set methods embed them into a time dependant PDE function Φ(t,x,y). It is then possible to approximate the evolution of active contours implicitly by tracking the zero level set Γ(t).

$$\left.\begin{array}{ll} \Phi(t, x, y) < 0 & (x, y) \text{ is inside } \Gamma(t) \\ \Phi(t, x, y) = 0 & (x, y) \text{ is at } \Gamma(t) \\ \Phi(t, x, y) > 0 & (x, y) \text{ is outside } \Gamma(t). \end{array}\right\} \qquad (4.7)$$

The implicit interface Γ may be comprised of a single or a series of zero isocontours. The issue of an image segmentation is therefore converted to

$$U_{sk}U_{f}=1 \qquad (4.8)$$

The inclusion of the time variable t leads to a higher dimensional level set function Φ, which incurs an additional computation but has many practical advantages. For example the interface Γ can be easily determined by checking the values of the level set function Φ which accommodates topological changes of the implicit interface Γ naturally. In particular, the evolution of Φ is totally determined by the numerical level set equation

$$\partial\Phi/\partial t + F|\nabla\Phi| = 0 \qquad (4.9)$$

$$\Phi(0,x,y) = \Phi_0(x,y) \qquad (4.10)$$

Where |▼Φ| denotes the normal direction, $\Phi_0(x,y)$ is the initial contour and F represents the comprehensive forces, including the internal force from the interface geometry (eg,mean curvature, contour length and area) and the external force from image gradient and/or artificial momentums.

The advancing force F has to be regularized by an edge indication function g inorder to stop level set evolution near the optimal solution

$$g = 1 / 1+|\nabla(G\sigma*I)|^2 \qquad (4.11)$$

where Gσ*I stands for the convolution of the image I with a smoothing Gaussian kernel Gσ, and ▼ denotes the operation for an image gradient. The function g is near zero in variational boundaries, but positive otherwise. A popular formulation for level set segmentation is

$$\partial\Phi / \partial t = g|\nabla\Phi| \, (\mathrm{div}\,(\nabla\Phi/|\nabla\Phi|) + \nu) \qquad (4.12)$$

Where div (▼Φ/|▼Φ|) approximates mean curvature k and v is a customable balloon force.

Level set methods have been shown to be versatile, robust, accurate, and efficient techniques for a wide class of problems in etching, deposition, and photolithography development.

The modified FCM algorithm automates the initialization and parameter configuration of the level set segmentation using spatial fuzzy clustering. It employs an FCM with spatial restrictions to determine the approximate contours of interest in a medical image.

Thus the desired region of interest is extracted using modified FCM algorithm and the results of segmentation are shown below.

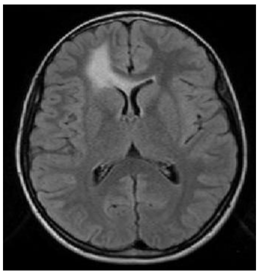

Fig. 4.1: Original Image.

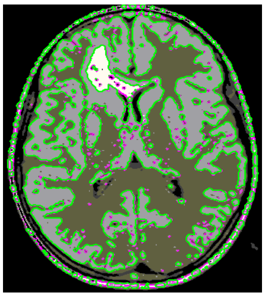

Fig. 4.2: Segmented Image.

Feature Extraction:

The features will be extracted, once the region of tumor is segmented using modified FCM(level set+ FCM) segmentation and the segmented region can be classified as normal or abnormal using neural networks. Feature extraction is the technique of extracting specific features from the pre-processed image in such a way that within –class similarity is maximized and between-class similarity is minimized. The textural features like contrast, energy, entropy, homogeneity, correlation etc. can be given as input to train the network to categorize normal or abnormal.

5.1 ***Statistics Based Features:***

Statistics based features characterize the image as a function of spatial variations in pixel intensities. It provide sin formation about the local variability of the intensity values of pixels in an image.

- Mean
- Standard deviation

5.2 ***Glcm Based Features:***

In this features are calculated from the gray level co-occurrence matrix. It is based on repeated occurrence of some gray-level configuration in the texture of the image. This configuration varies rapidly in fine textures, more slowly in coarse

textures. Such occurrence of gray-level configuration may be described by matrices of relative frequencies, called co-occurrence matrices.
GLCM based features are:

- Energy
- Contrast
- Correlation
- Entropy
- Homogeneity

Classification:

Artificial Neural Networks (ANN) is an information processing system having large number of processing elements. It finds its application in many areas. It arrives at an output or performs an automated classification based on the described rules which helps in making decisions. More training algorithms are developed to improve the performance of the network. In the proposed work the brain image is classified as normal or abnormal using neural networks. In this work, the neural network is trained with the features extracted from the normal and abnormal images. Neural network employing feed forward backpropagation training algorithm is used.

6.1 ***Feed Forward Back Propagation Neural Networks:***

Neural network consists of a layer of input neurons, a layer of output neurons and one or more hidden layers which is determined by trial and error. All the processing elements are connected to each others by means of associated weight vectors. The network is trained by giving a set of training vectors as input each with an associated target vector. The weights are adjusted accordingly to the learning algorithm. Feed Forward Back Propagation training algorithm involves feed forward of the input vector, calculation of error and back propagate to reduce the error by adjusting the weights. Once the network is trained test vectors are given to the network for automated classification and the performance of the network is evaluated.

6.1.1 ***Architecture Of Feed Forward Back Propagation Neural Networks:***

Seven features are given as input to the network and the network has a hidden layer with 20 nodes and an output with 2 nodes i.e. normal and abnormal. The network is trained using feedforward function which can adaptively train the input data by propagating backwards. Once the network is trained with the training data, it can be put for validation to identify whether the test image is normal or abnormal.

Table 6.1: Network Parameters.

PARAMETERS	NETWORK ARCHITECTURE
Number of nodes in input layer	7
Number of nodes in output layer	2
Number of hidden layers	1
Number of nodes in hidden layer	20

RESULTS AND DISCUSSIONS

In this work, the proposed methods are carried out on 24 images wherein 13 images are used for training the networks. Then the remaining 11 images are used for testing in which 6 images are normal and 5 images are abnormal Figure 7.1(a) shows the Magnetic Resonance image of normal brain. Figure 7.1(b) shows the corresponding segmented image. Figure 7.2(a) shows the Magnetic Resonance image of abnormal brain. Figure 7.2(b) show the segmented image. Figure 7.3 show the training of the network and its performance.

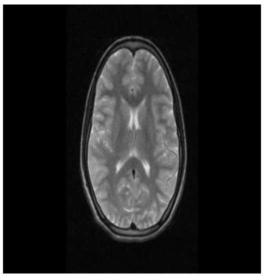

Fig. 7.1: (a) Normal image.

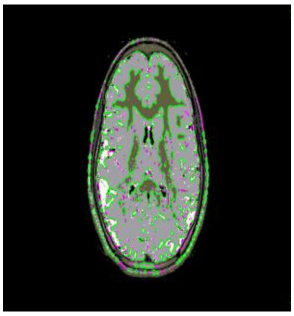

Fig. 7.1: (b) Segmented image.

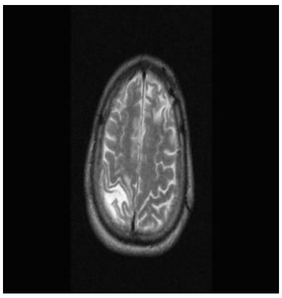

Fig. 7.2: (a) Brain tumour image.

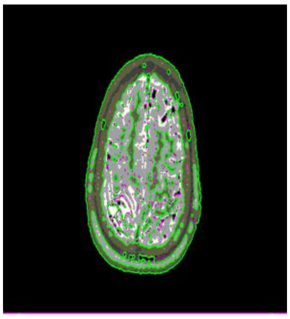

Fig. 7.2: (b) Segmented image.

Once the desired region of interest is segmented, then features are extracted from 24 images (out of which 13 are normal and 11 are abnormal).

7.1. *Training Of Backpropagation Neural Networks:*

Neural networks employed with back propagation training algorithm is trained with features extracted from 13 images.

7.2 *Performance Analysis:*

From the above table it is shown that Feed Forward Back Propagation neural networks offers better results for identifying the brain is normal or abnormal due to the presence of tumour and thus best suited for classification.

Future Work:

In the proposed work Magnetic Resonance images of brain are acquired and analysed to identify the nature of brain which could help in early diagnosis of tumor. This helps doctors to give treatment in advance thereby saving patient's lives. The performance of the networks are analyzed from the following parameters

- **Sensitivity** – is a measure of performance of the network and this parameter evaluates the ability of the classifier to identify the abnormal brain.

Sensitivity = {TP/(TP+FN)}*100‰ (7.1)

where TP - abnormal correctly classified as abnormal

FN – abnormal wrongly classified as normal

- **Specificity**– this parameter quantifies the ability of the networks to identify the normal brain.

Specificity = {TN/(TN+FP)}*100‰ (7.2)

Where TN - normal correctly classified as normal

FP – normal wrongly classified as abnormal

- **Accuracy-** this parameter measures the probability or proportion of images correctly classified.

Accuracy={TP+TN/(TP+TN+FP+FN)}*100 (7.3)

where TN - normal correctly classified as normal

FP – normal wrongly classified as abnormal

Table 7.2 shows the performance of the networks. In this work parameters like sensitivity, specificity and accuracy are found and the results are tabulated as shown below.

In this work images are preprocessed using weighted median filter to improve the image quality for easy diagnosis. The desired region of interest is segmented automatically using modified FCM algorithm. Further automatic classification is done using Neural networks from the features extracted. As an end result different networks are trained and a comparative study is done to analyze the performance of the networks. This work could be extended in future for other brain abnormalities like multiple sclerosis, stroke etc. and improving classification with large number of datas.

Table 7.2: Performance Analysis of the networks.

Neural Networks	Sensitivity	Specificity	Accuracy
Feed Forward BPN	100	83.33	90.90
Radial Basis Function	80	66.67	72.63

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