International Journal of Computer and Communication Technology

Volume 3 | Issue 2 Article 1

April 2012

Feature Extraction and Texture Classification in MRI

Jayashri Joshi
Marathwada Mitra Mandal's College of Engineering, Pune, kjayashri@rediffmail.com

.A. C. Phadke
Maharashtra Institute of Technology, Pune, anu_phadke@yahoo.com

Recommended Citation

Joshi, Jayashri and Phadke, .A. C. (2012) "Feature Extraction and Texture Classification in MRI," *International Journal of Computer and Communication Technology*: Vol. 3 : Iss. 2 , Article 1.
DOI: 10.47893/IJCCT.2012.1118
Available at: https://www.interscience.in/ijcct/vol3/iss2/1

Feature Extraction and Texture Classification in MRI

Jayashri Joshi[1], Mrs.A.C.Phadke[2]
1. Marathwada Mitra Mandal's College of Engineering, Pune.
2. Maharashtra Institute of Technology, Pune
1. kjayashri@rediffmail.com
2. anu_phadke@yahoo.com

Abstract--**Automated MRI (Magnetic resonance Imaging) brain tumor segmentation is a difficult task due to the variance and complexity of tumors. In this paper, a statistical structure analysis based tumor segmentation scheme is presented, which focuses on the structural analysis on both tumorous and normal tissues. The basic concept is that local textures in the images can reveal the typical 'regularities' of biological structures. Thus, textural features have been extracted using co-occurrence matrix approach. By the analysis of level of correlation we can reduce the number of features to the only significant component .An artificial neural network and fuzzy c-means are used for classification. This approach is designed to investigate the differences of texture features among macroscopic lesion white matter (LWM), normal appearing white matter (NAWM) in magnetic resonance images (MRI) from patients with tumor and normal white matter (NWM).**

Keywords: MRI; Texture Analysis; Feature Selection; Texture Classification; Fuzzy c-means

1. INTRODUCTION

Texture analysis is an important task in many computer applications of Computer image analysis for classification, detection or segmentation of images based on local spatial patterns of intensity. Textures are replications, symmetries and combinations of various basic patterns, usually with some random variation. The major task in texture analysis is the texture segmentation of an image, that is, to partition the image space into a set of sub regions each of which is homogeneously textured. Automated MRI brain tumor segmentation provides useful information for medical diagnosis and surgical planning. However, it is a difficult task due to the large variance and complexity of tumor characteristics in images, such as sizes, shapes, locations and intensities. So in practice, segmentation of brain tumor continues to depend on manual tracing and delineating. Many image processing techniques have been proposed for MRI brain tumor segmentation.

1.1 Prior Work

Most of the previously-reported work falls into the category of pattern recognition methods. The key issue of successful pattern recognition methods is to extract effective features. Intensity-based statistical features are the most straightforward and have been widely used. But due to the complexity of the pathology in human brain and the high quality required by clinical diagnosis, only intensity features can not achieve acceptable result. Thus many texture features have been presented for tumor segmentation. Co-occurrence matrix and wavelet-based texture features are often used and achieve promising results. The problem in most previous work is the lack of effective feature selection strategies. Texture features are usually in large dimensions, but not each dimension can provide useful information for the segmentation.

1.2 Proposed work

In this paper, a statistical structure analysis method is presented and applied to MRI brain tumor segmentation. Firstly, MR images are divided into small structure elements, and then different kinds of features are extracted from each element, which quantify the intensity, symmetry, and texture properties of different tissues. The basic assumption is that different local textures in images can describe different physical characteristics corresponding to different local textures in image can describe different physical characteristics corresponding to different objects. We used gray level co-occurrence matrix approach introduced by Haralick [7] which is well-known statistical method for extracting second-order texture information for images. The assumption is that local texture of tumor cells is highly different from local texture of other biological tissues. Thus texture measurements in the image could be part of an effective discrimination technique between healthy tissues and possible tumor areas. The association between local texture measures and recognized tumor area is executed using artificial neural network and fuzzy c-means. Image segmentation techniques can be classified as based on edge detection, region or surface growing, threshold level, classifier such as Artificial Neural Network (ANN), and feature vector clustering or vector quantization.

In this paper, we propose ANN and Fuzzy C-means implementation for the MRI image segmentation process shown in fig1 to detect various tissues like white matter, gray matter, csf and tumor. The attention focused extracting only a small number of suitable features. A correlation analysis of the feature matrix permitted to decrease the quantity of input information to the only significant data.

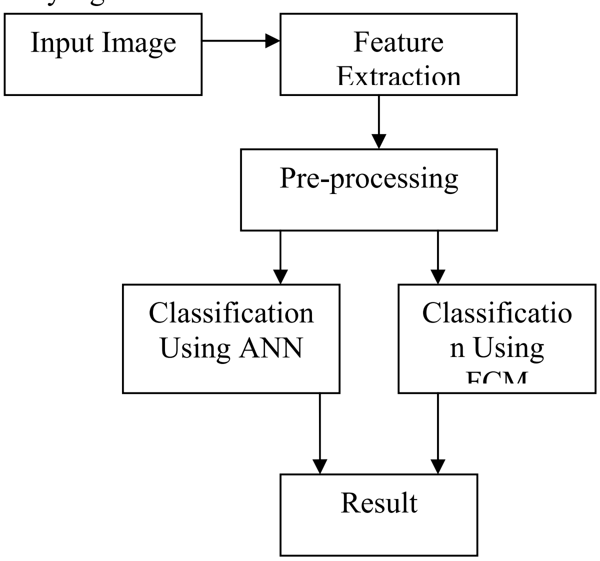

Fig-1 Detailed description of proposed work

2. Methodology

2.1Textural Features

Texture is a commonly used feature in the analysis and interpretation of images. Texture is characterized by a set of local statistical properties of pixel intensities. We base our texture feature extraction on the spatial gray level co-occurrence-matrix (SGLCM). The GLCM method considers the spatial relationship between pixels of different gray levels. The method calculates a GLCM [7] by calculating how often a pixel with a certain intensity i occurs in relation with another pixel j at a certain distance d and orientation θ. For instance, if the value of a pixel is 1 the method looks, for instance, the number of times this pixel has 2 in the right side. Each element (i, j) in the GLCM is the sum of the number of times that the pixel with value i occurred in the specified relationship to a pixel with value j in the raw image. Once the GLCM[3] is calculated several second-order texture statistics can be computed as illustrated in Table 1 where $P_{d,\theta}$ (i, j) is the GLCM between i and j. Co-occurrence matrices are calculated for four directions: 0^0, 45^0, 90^0 and 135^0degrees. The eight Haralick texture descriptors are extracted from each co-occurrence matrices which are computed in each of four angles.

Table 1 Computation of Texture Features

Feature	Formula
Energy	$\sum_{i,j=0}^{G-1}(P_{d,\theta}(i,j))^2$
Inertia	$\sum_{i,j=0}^{G-1}(i-j)^2 P_{d,\theta}(i,j)$
Entropy	$\sum_{i,j=0}^{G-1}P_{d,\theta}(i,j)\log_2[P_{d,\theta}(i,j)]$
Homogeneity	$\sum_{i,j=0}^{G-1}\frac{P_{d,\theta}(i,j)}{1+(i-j)^2}$
Maximum Probability	max $_{i,j}$ $P_{d,\theta}(i,j)$
Contrast	$\sum_{i,j=0}^{G-1}(i-j)^2\sum_{i,j=0}^{G-1}P_{d,\theta}(i,j)$
Inverse	$\sum_{i,j=0}^{G-1}\frac{P_{d,\theta}(i,j)}{(i-j)^2}$
Correlation	$\frac{\sum_{i,j=0}^{G-1}ijP_{d,\theta}(i,j)-\mu_x\mu_y}{\sigma_x\sigma_y}$

2.2 Artificial Neural Network

The Neural networks [3] developed from the theories of how the human brain works. Many modern scientists believe the human brain is a large collection of interconnected neurons. These neurons are connected to both sensory and motor nerves. Scientists believe, that neurons in the brain fire by emitting an electrical impulse across the synapse to other neurons, which then fire or don't depending on certain conditions. Structure of a neuron is given in Figure 2.

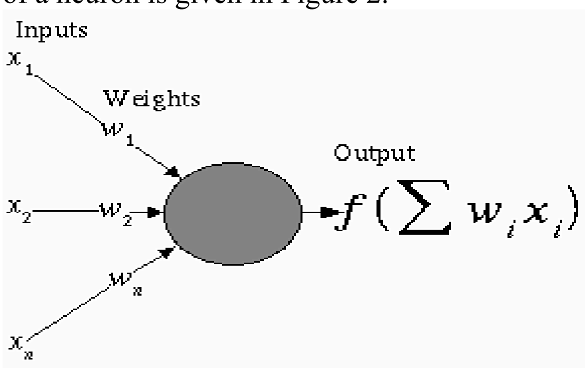

Fig-2 Structure and functioning of a single neuron

The Artificial neural network [3] is basically having three layers namely input layer, hidden layer and output layer. There will be one or more hidden layers depending upon the number of dimensions of the training samples. Neural network structure used in our experiment is consist of only two hidden layers having 7 neurons in the input layer and 1 neuron in the output layer as shown in Figure 3.

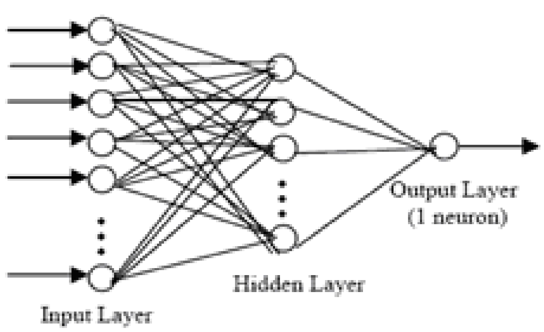

Fig-3 Simple Neural network Structure

A learning problem with binary outputs (yes / no or 1 / 0) is referred to as binary classification problem whose output layer has only one neuron. A learning problem with finite number of outputs is referred to multi-class classification problem whose output layer has more than one neuron. The examples of input data set (or sets) are referred to as the training data. The algorithm which takes the training data as input and gives the output by selecting best one among hypothetical planes from hypothetical space is referred to as the learning algorithm.

The approach of using examples to synthesize programs is known as the learning methodology. When the input data set is represented by its class membership, it is called supervised learning and when the data is not represented by class membership, the learning is known as unsupervised learning. There are two different styles of training i.e., Incremental Training and Batch training. In incremental training the weights and biases of the network are updated each time an input is presented to the network. In batch training the weights and biases are only updated after all of the inputs are presented.

In this experimental work; back propagation algorithm is applied for learning the samples, Tan-sigmoid and log-sigmoid functions are applied in hidden layer and output layer respectively, Gradient descent is used for adjusting the weights as training methodology.

In this paper, each pixel together with a small square neighborhood is defined as a structure element, which is called 'block'. Further steps are all based on the blocks. For training process, firstly different features are extracted block by block in one image. When a new image comes, only those selected features are extracted and the trained classifier is used to categorize the tumor in the image. The training and detection process flow of the proposed method is shown in figure 4. It should be noticed that the input images are preprocessed beforehand, including skull stripping which eliminates the skull from the brain image and scale normalization to adjust the intensity scale of the input images.

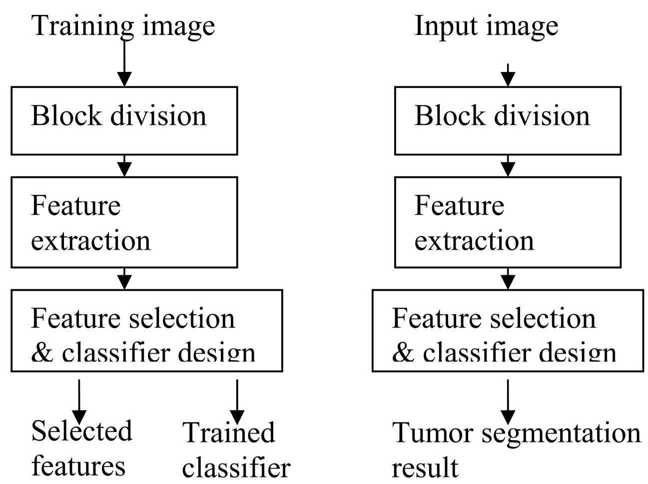

Fig-4 (Left) the training process flow
(Right)The tumor segmentation process flow

2.3 Fuzzy C-Means Algorithm

Fuzzy C-Means algorithm based on the concept of fuzzy C partition [2] which was introduced by various researchers in this field, developed by Dunn and generalized by Bezdek. The aim of fuzzy C-means is to find cluster centers (centroids) that minimize dissimilarity functions. In order to accommodate the fuzzy partitioning technique, the membership matrix (U) is randomly initialized as

$$\sum_{i=1}^{c} Uij = 1, \forall j = 1,...,n \qquad (1)$$

where, *i* is the number of cluster and *j* is the image data points .The dissimilarity function can be computed as

$$J(U,c_1,c_2,...,c_n)\sum_{i=1}^{c} J_i = \sum_{i=1}^{c}\sum_{j=1}^{n} u_{ij}^{\ m} d_{ij}^{\ 2} \qquad (2)$$

where, Uij is between 0 and 1, c_i is the centroid of cluster i, dij is the Euclidian distance between ith centroid (ci) and jth data point, m is a weighting exponent and the value is greater than one. The minimum of dissimilarity function can be computed as

$$U_{ij} = \frac{1}{\sum_{k=1}^{c}\left(\frac{d_{ij}}{dkj}\right)^{2/(m-1)}} \qquad (3)$$

where, dij=||xi-cj||, dkj =||xi-ck||, xi is the i th of d dimensional data, cj is the d-dimension center of the cluster and ||*|| is any norm expressing the similarity between any measured data and center. This iteration will stop when Max_{ij} {|uij (k+1)-uij (k)|} < ε, where ε is a termination criterion between 0 and 1, whereas *k* are the iteration steps. The steps of the fuzzy C-means algorithm [2] has been listed as follows

1. Initialize U= [u_{ij}] matrix, U (0).
2. At k-step: Initialize centers vectors C (k) = [c_j] taken clustering algorithm.
3. Update U (k), U (k+1), then compute the dissimilarity function.

$$U_{ij} = \frac{1}{\sum_{k=1}^{c}\left(\frac{d_{ij}}{dkj}\right)^{2/(m-1)}}$$

If || U (k+1) – U (k) ||< ε then STOP; otherwise return to step3.

In the first step, the algorithm selects the initial cluster centers clustering algorithm. In the first step, the algorithm selects the initial cluster centers from clustering algorithm. Then, in later steps after several iterations of the algorithm, the final result converges to actual cluster center. Therefore a good set of initial cluster is achieved and it is very important for an FCM algorithm. If a good set of initial cluster centers is chosen, the algorithm make less iterations to find the actual cluster centers. The winning neural units and their corresponding weight vectors from each layer result in a hierarchical structure termed as an abstraction tree. Each node in the abstraction tree represents the region of the image at a specified level of abstraction. A segmented image is generated on demand by traversing the abstraction tree in the breadth first manner starting from the root node until some criterion is met. The size of the abstraction tree (weight vector) is expanded if the sum of the variances of weight vector divided by size of the weight vector is less than element of weight vector. Otherwise the node is labeled as a closed node and none of its descendants are visited. Regions corresponding to the closed nodes constitute a segmented image and the resulting segmented image usually contains the regions from different abstraction levels.

2.4 Performance measures

All classification result could have an error rate and on occasion will either fail to identify an abnormality, or identify an abnormality which is not present. It is common to describe this error rate by the terms true and false positive and true and false negative as follows: [8]

True Positive (TP): the classification result is positive in the presence of the clinical abnormality.

True Negative (TN): the classification result is negative in the absence of the clinical abnormality.

False Positive (FP): the classification result is positive in the absence of the clinical abnormality.

False Negative (FN): the classification result is negative in the presence of the clinical abnormality.

Table 2 is the contingency table which defines various terms used to describe the clinical efficiency of a classification based on the terms above and

Sensitivity = TP/ (TP+FN) *100%

Specificity = TN/ (TN+FP) *100%

Accuracy = (TP+TN)/ (TP+TN+FP+FN)*100 %

are used to measure the performance of the classifier [8]

Table 2: Contingency table

Actual group	**Predicted group**	
	Normal	**Abnormal**
Normal	TN	FP
Abnormal	FN	TP

3. IMPLEMENTATION AND RESULTS

Images acquired were in DICOM (Digital Imaging and Communications in Medicine) format. The system was implemented using the functions available in MATLAB. We have conducted experiments on 25-MR images of different patient. Firstly the images are divided into different blocks and features are extracted

from each block. Artificial neural network and fuzzy C-means applied on each block of the image. Results of ANN are as shown in figure 5 to 11.

Sensitivity, specificity, and accuracy are calculated for ANN classification. These terms are used to describe the clinical efficiency of a classification in table 3.

Table 3: Clinical Efficiency Defined By ANN

Image Number	Sensitivity (%)	Specificity (%)	Precision (%)	Accuracy (%)
Image1	95.40	99.26	51.96	99.23
Image2	88.19	98.23	61.23	97.97
Image3	91.18	99.63	52.95	99.59
Image4	79.13	99.47	53.05	99.44
Image5	74.30	99.68	54.18	99.56
Image6	90.67	99.53	62.47	99.46

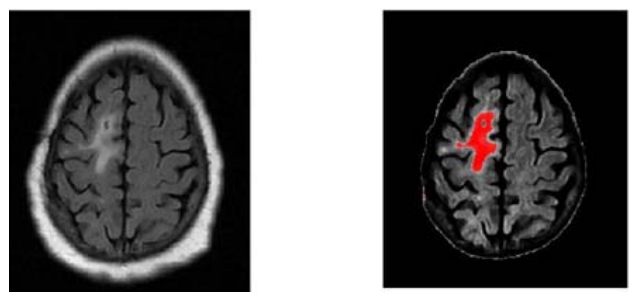

Fig-5 ANN Result (segmentation and classification, image1)

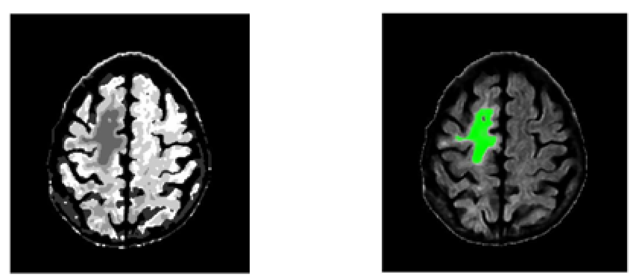

Fig-6 Fuzzy C-means Result (segmentation and classification)

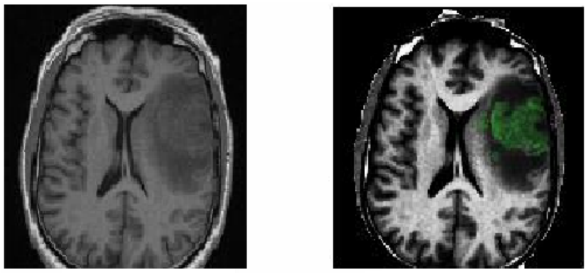

Fig-7 ANN Result (image 2)

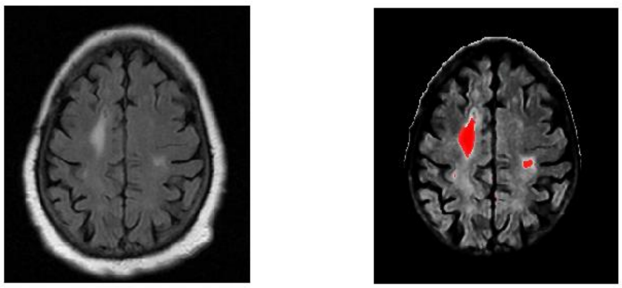

Fig-8 ANN Result (image 3)

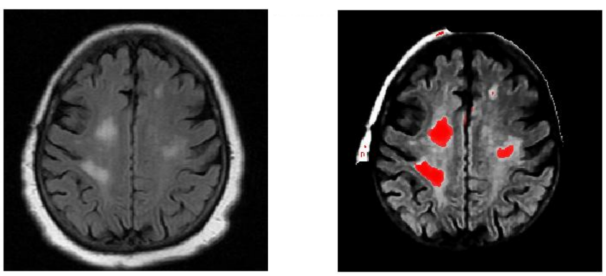

Fig- 9 ANN Result (image 4)

4. CONCLUSION AND DISCUSSION

This result is considered satisfying for a computer system providing semi-automatic tumor recognition in MRI. The main characteristics of system are summarized here. It is designed and developed to recognize typical feature in brain based on the concept that local texture of the images can reveal typical ‘regularities’ of the biological structures. Thus textural feature have been extracted using a co-occurrence matrix approach. The analysis of level of correlation has permitted to decrease the number of features to the only significant components.

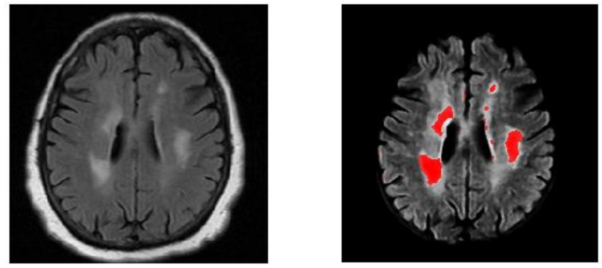

Fig-10 ANN Result (image 5)

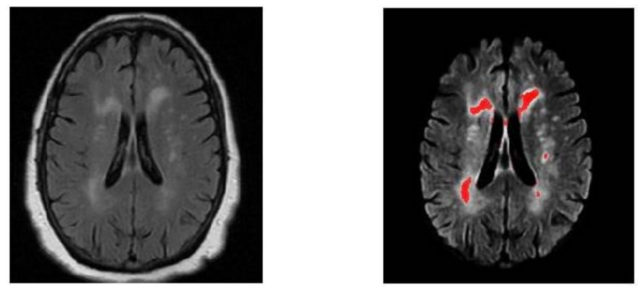

Fig-11 ANN Result (image 6)

An artificial neural network and fuzzy c-means has been proposed for texture analysis and classification. ANN analysis has been implemented and we are working on Fuzzy c-means algorithm.

Our efforts are now addressed to improve the system performance considering following modifications: 1) improvement of feature functions to obtain well separated data; 2) segmentation of low contrast MRI;

3) Comparison of Fuzzy C-means and ANN.

REFERENCES:

[1] Michael Barnathan, Jingjing Zhang, “A Texture-Based Methodology for Identifying Tissue Type in Magnetic Resonance Images”, Proceedings of the IEEE International Symposium on Biomedical Imaging, pp(s) 464-467, 2008.

[2] Xiao Xuan, Qingmin Liao, “Statistical Structure Analysis in MRI Brain Tumor Segmentation”, Proceedings Of fourth International Conference on Image and Graphics, pp(s)421-426, 2007.

[3] Devendram V, Hemalatha Thiagarajan, "Texture based Scene Categorization using Artificial Neural Networks and Support Vector Machines: A Comparative Study", ICGST-GVIP, ISSN 1687-398X, Volume (8), Issue (IV), December 2008.

[4] S.Murugavalli, V. Rajamani, "An Improved Implementation of Brain Tumor Detection Using Segmentation Based on Neuro Fuzzy Technique", Journal of Computer Science 3 (11), pp(s) 841-846, 2007.

[5] Weifang Liu, "Texture Analysis of MRI in patient with Multiple Sclerosis Based on the Gray-level difference Statistics", IEEE, International Workshop on Education Technology & Computer Science-pp(s) 771-774, 2009.

[6] Jing Zhang, Lei Wang, "Feature Reduction and Texture Classification in MRI-Texture Analysis of Multiple Sclerosis", IEEE/ICME International Conference on Complex Medical Engineering-pp(s) 752-757, 2007.

[7] Haralick, Robert M.; Shanmugam, K., "Dinstein, Textural Features for Image Classification", IEEE Transactions on Systems, Man and Cybernetics, Vol. No. 3, Issue 6, pp(s)610 – 621, 1973.

[8] H. Selvaraj, S.Thamarai Selvi; "Brain MRI Slices Classification Using Least Squares Support Vector Machine", IC-MED, Vol. 1, No. 1, Issue 1, Page: 21-33, 2007.

[9] http://www.fp.ucalgary.ca/mhallbey/tutorial.htm Bayer Mryka Hall, 2007.GLCM Tutorial.