Advances in Natural and Applied Sciences, 8(10) Special 2014, Pages: 126-132

AENSI Journals
Advances in Natural and Applied Sciences
ISSN:1995-0772 EISSN: 1998-1090
Journal home page: www.aensiweb.com/ANAS/

Automatic Tumor Classification in Brain MRI Images Using Genetic Algorithm and Artificial Neural Network

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ARTICLE INFO
Article history:
Received 25 June 2014
Received in revised form
1 July 2014
Accepted 31 August 2014
Available online 15 September 2014

Keywords:
brain tumor, segmentation, Zernike, Genetic Algorithm, classification, ANN.

ABSTRACT
Brain tumor is one the main causes of death among people. In the recent studies, there are different automatic and semi-automatic methods for brain tumor detection. Semi-automatic tumor detection methods lead to less fluctuation in results reported by specialists, but using them in greater clinics is time consuming and there would be a lot of differences between evaluation criteria. So it is essential to develop the automatic system to help the specialists in tumor detection. Here in this article an automatic system is presented to detect brain tumors. First some pre-processing operations are done on the brain images. Then a threshold-based method is used for brain tissue segmentation. After segmentation some features, such as Zernike are extracted and the important features are selected by Genetic Algorithm. At last, Artificial Neural Network (ANN) is used in order to classify the images under tumor existence or its absence. In this paper 1410 healthy pictures (without tumor) and 423 pictures with tumors (which are caused by different diseases) are chosen. The results show that the accuracy of proposed method is improved in comparison with some of the most related methods, in literatures.

To Cite This Article: SoodehNaderi and Mehdi Jafari Shahbaz Zadeh., Automatic Tumor Classification in Brain MRI Images Using Genetic Algorithm and Artificial Neural Network. **Adv. in Nat. Appl. Sci.,** *8(10): 126-132, 2014*

INTRODUCTION

Brain is one of the most important organs of human body and its segmentation is very helpful for science development, especially in medical (diagnostic and treatment) and engineering (modeling) fields. If we visually detect abnormal tissue, we can be wrong about the location of unwanted tissue in brain, since there are human errors which are related to visual fatigue, therefore it is very important to detect tumors in early growth stages. Brain tissue segmentation is about differentiation between different tissues such as tumors (active or solid tumor or dead tissues) and normal brain tissues, such as GM (gray matter), WM (white matter) and CSF (Cerebrospinal Fluid). In many cases it is easy to detect abnormal tissues but its detachment from normal tissues is difficult.

In resent year, different approaches are introduced for brain tissue segmentation. In addition to manual methods which are performed by professionals, there are also semi-automatic and automatic methods. It is possible that semi-automatic methods (or interactive methods) stay popular for a while, especially in applications in which we can delete incorrect interpretations (Gordillo *et al*., 2013). In recent years, scientists are focused on MR images. They have reasonable quality and they facilitate the process of finding tumor locations (Jafari *et al*., 2011).Whit respect to MRI (magnetic resonance imaging) advantages, compared to other imaging methods, this paper presents novel brain tissue segmentation algorithm based on MRI. These images have different weights such as T1 and T2. In this paper we use MRI with T2, since the resolution of concentrated tissues such as tumors is higher in T2 images. This can improve the quality of automatic tumor detection. Different researches were done about tumor detection. Many papers use different and innovative methods, such as wavelet transform (Jafari *et al*., 2011) and (El-Sayed Ahmed El-Dahshan *et al*., 2010), Fourier transform (Lashkari, 2010), Gabor filter (Lashkari, 2010), image histograms (MamataS.Kalas, 2010) and methods, which are based on static brain properties and its symmetric features (Lashkari, 2010) and (MamataS.Kalas, 2010). Methods such as PCA (Principle Component Analysis) (Song-yunXie *et al*., 2009) and GA (Genetic Algorithm) (Velthuizen *et al*., 1996) are also performed.

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In this paper we will first explore methods which are based on brain tissue segmentation and then we will make some improvements in these methods. We can detect tumors and brain tissue whit the help of: location, size, shape, tissue boundaries (edges), structure distortion and contrast. CAD systems (Computer Assisted Diagnosis) is a set of automatic and semi-automatic methods which are developed in order to assist radiologists, they can be used for diagnosis, anomaly segmentation, treatment process control or surgery (Grimaud *et al*., 1996). Nowadays, automatic brain tissue detection in MRI Images is very important in diagnosis programs. In early researches about tissue detection, available algorithms used classic imaging methods such as Edge Detection, Region Growing and Watershed. In recent years these techniques are combined whit ANN (artificial Neural Networks), Genetic Algorithms m Fuzzy Logic and Markov Model. In this article we will use a fully automatic system for brain tissue classification and segmentation in MRI images and finally we will use ANN, with higher speed and lower error.

Proposed method:

2.1 Pre-processing:

Today MRI brain cancer or tumor detection is very important role for worldwide to save the life. Doctors can miss the abnormality due to inexperience in the field of cancer or tumor detection. The pre-processing is the most important step in MRI brain image analysis due to poor captured image quality. In this phase image is enhanced in the way that finer details are improved and noise is removed from the image. Most commonly used enhancement and noise reduction techniques are implemented that can give best possible results. Enhancement will result in more prominent edges and a sharpened image is obtained, noise will be reduced thus reducing the blurring effect from the image. In addition to enhancement, image segmentation will also be applied. This improved and enhanced image will help in detecting edges and improving the quality of the overall image. Edge detection will lead to finding the exact location of tumor. Different types of filtering techniques are available for pre-processing. We have used median filter for MRI brain image pre-processing.

The aim of this stage is to improve the quality of images, such as noise reduction and resolution improvement. Pre-processing has 3 steps:

1. Images are converted to gray level.
2. Image Enhancement, using histogram equalization.
3. Employ median filter on MRI images, this filter is used for image quality improvement and noise reduction.

Following steps will be followed in the pre-processing stage:

2.1.1 Histogram Equalization:

Histogram equalization is a technique that allows us to improve the contrast of images with such narrow histograms and it has been found to be a powerful technique in image enhancement (Volker Schatz, 2011). This technique does not change the values contained in the matrix x (m, n) that represents the image. Instead, it modifies the color mapping associated with the values of the matrix x (m, n), so that this tends is uses to evenly every color in the full dynamic range [black to white]. The histogram of an image represents the relative frequency of occurrence of the various gray levels in the image (Johnson *et al*., 1999). In MRI pictures we use histogram equalization for contrast improvement. Pre-processing, between a tumor and its surrounding can cause light differences, this will improve segmentation process. Histogram equalization is illustrated in figure (1):

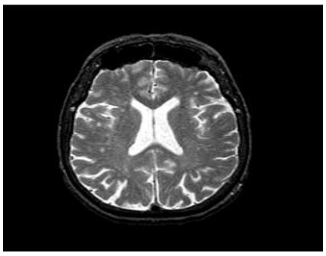

Fig. 1: Histogram equalization.

2.1.2 Median Filter:

Median Filter remove the noise with high frequency components from MRI without disturbing the edges and it is used to reduce ’salt and pepper’ noise. This technique calculates the median values i.e. set median value pixels values of the surrounding pixels to determine the new de-noised value of the pixel (Selvanayaki *et al*., 2012). A median is calculated by sorting all pixel values by their size, then selecting the median value as the new value for the pixel. The basic function for median image is written below in equation (1), where f(x,y) output median and g(s,t) is the original values. In figure (2) we can see median filter application.

$$f(X.Y) = median_{(s,t)\epsilon Sxy}\{g(s,t)\} \qquad (1)$$

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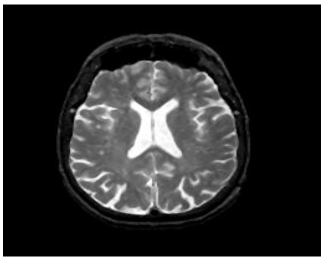

Fig. 2: An image after median filter application.

2.2 Segmentation based on threshold method:

Segmentation is a very commonly used and important step in medical image analysis and computer vision. The aim of image segmentation is to decompose an image domain into a number of disjoint regions so that the features within each region have visual similarity, strong statistical correlation and reasonably good homogeneity. Brain tumor segmentation from MRI images is an interesting but challenging task in the field of medical imaging. Image Segmentation partitions an image into set of regions. The region represents meaningful areas in an image or be the set of border pixels grouped into structures such as line segments, edges etc. The segmentation has two objectives: (i) to decompose an image into regions for further analysis, (ii) to perform a change of representation of an image for faster analysis (Vipul Singh, 2013). Different types of segmentation techniques are used for segmentation. Based on the application, a single or a combination of segmentation techniques can be applied to solve the problem effectively. Segmentation algorithm is based on the properties of gray level values of pixels. The different types of segmentation techniques are: (a) Edge based segmentation (b) Threshold Based Segmentation (c) Region Based Segmentation (d) Clustering (e) Matching. In this paper, a threshold-based method is used for brain tissue segmentation. Threshold is one of the aged procedures for image segmentation. Threshold techniques identify a region based on the pixels with similar intensity values. This technique provides boundaries in images that contain solid objects on a contrast background (Jayaraman *et al.*, 2009). Threshold technique gives a binary output image from a gray scale image. This method of segmentation applies a single fixed criterion to all pixels in the image simultaneously (Jayaraman *et al.*, 2009). In this stage various parts of the white and gray matter and cerebrospinal fluid are extracted from MRI image for tumor detection. For this intention a possible framework is built which makes possible the image recording, tissue classification and bias correction for the new image segmentation. Some image samples after segmenting different areas of white and gray matter and cerebrospinal fluid are shown in figure (3):

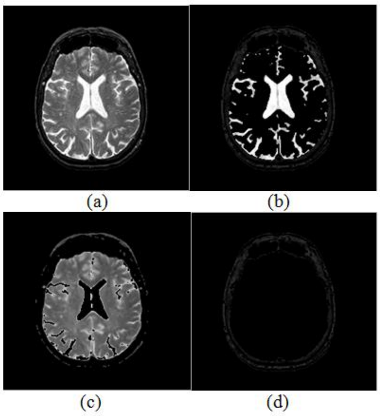

Fig. 3: Results of brain segmentation in four different levels of the brain: a) The total area of the brain, b) white matter , c) gray matter, d)cerebrospinal fluid.

2.3 Feature Extraction:

After segmentation of tumor area for their account in images, we need to extract important features from the tumors. Here 43 intensity, shape and tissue features are extracted from tumors. These features have very important role in tissue segmentation. Some equations related to these extracted features are presented below (Ramos *et al.*, 2012):

$$mean = \sum_{i=0}^{L-1} z_i p(z_i) \qquad (2)$$

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$$Skewness = \sum_{i=0}^{L-1} (z_i - m)^3 \, p(z_i) \tag{3}$$

$$Entropy = -\sum_{i=0}^{L-1} p(z_i) Log_2 \, p(z_i) \tag{4}$$

$$Kurtosis = \frac{E(x-\mu)^4}{\sigma^4} \tag{5}$$

$$Energy = \sum_{i=1}^{n}\sum_{j=1}^{m} x_{ij}^2 \tag{6}$$

$$smoothness = 1 - {}^{1}/_{(1+\sigma^2)} \tag{7}$$

In all these equations $z_i$is intensity random variable, $p(z_i)$isz_i intensity frequency in image, L the number of possible intensity levels, x image matrix, μ average, σ image standard deviation,$E(t)$ expected value of *t* quantity, and m, n are image dimensions.

2.3.1 Zernike:

These moments are an image projection to a set of Zernike complex polynomials. Zernike moment calculation for an input image is performed in 3 steps:

1. Radial polynomial calculation
2. Zernike basic function calculation
3. Zernike moment calculation which is performed by image matrix projection on Zernike basic functions (Wang *et al.*, 2009).

A discrete form of Zernike moments for each $N \times N$ pixel is offered as below (Tahmasbi *et al.*, 2011):

$$Z_{n,m} = \frac{n+1}{\lambda_N}\sum_{c=0}^{N-1}\sum_{r=0}^{N-1} f(x,y)\, V_{n,m}(x,y) = \frac{n+1}{\lambda_N}\sum_{c=0}^{N-1}\sum_{r=0}^{N-1} f(x,y) R_{n,m}(p_{xy}) e^{-jm\theta_{cr}} \tag{8}$$

In this equation $0 \leq p_{xy} \leq 1$ and λ_N is the normalization factor. n is a nonnegative integer that shows the order of radial polynomial. m is a integer that fits in the condition of equation (9) and shows angle repeat, $R_{n,m}$ radial polynomial and $V_{n,m}$ is the base 2-dimentional Zernike function.

$$n - |m| = an\ even\ number\ and\ |m| \leq n \tag{9}$$

Zernike moment with high order has high calculative complexities but is sensitive toward noise. Any way they give better descriptions from tumors' shape and density compared to Zernike moment with lower orders.

2.4 Feature selection:

In this stage in order to decrease the computational complexity and increase the speed of tumor detection algorithm, only features that are of higher importance in classification stage are selected by genetic algorithm.

2.5 GA for feature selection:

Genetic algorithm is a numeric search tool which uses genetic evolution as a problem solving model and searches for a maximum or minimum value of an objective function defined according to the problem in solution space. After segmentation, some features, such as shape and intensity features, are extracted. In here, genetic algorithm will chose some of them, which are more important for differentiability. For each area which is segmented by the algorithm (white and gray matter and CSF and the whole brain), we will chose 18 features are selected with the biggest priorities. For example in figure (4), we can see GA procedure for white matter feature extraction. As it is shown, fitness function will be improved as the number of iteration grows and the algorithm is stopped at 19th iteration. The best value for fitness function is -0/27486, in this point, 18 features which are selected by GA, will be transferred to classification step, as the best features.

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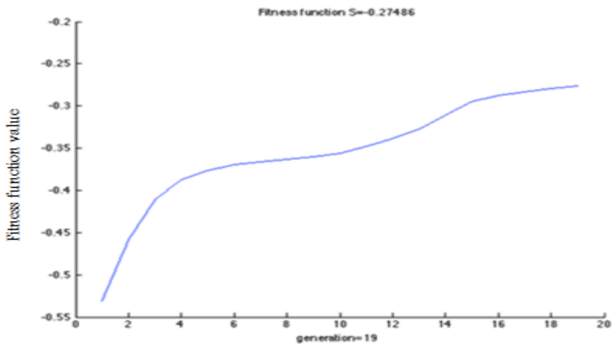

Fig. 4: Fitness function increasing trend for white matter feature selection.

2.6 Classification with neural network:

Artificial Neural Networks (ANN) are inspired from human brain process system. In mathematical model, ANN consists of a set of attached neurons. Each neuron is a processing unit that is considered as the base of ANN. For more survey, we will use neural network for classification procedure. Our neural network is a single layer network with 18 inputs (features which are selected by GA) and we have 3 neurons in hidden layer and 1 neuron in output layer for tumor detection in brain. In figure (5) we can see neural network procedure for tumor detection. This procedure is stopped at 14th iteration, this is where the network has learned enough and network weights are saved for testing. If we stop the algorithm in some point, less that 14th iteration, learning wound not be enough and if we go beyond the 14th iteration, over learning occurs.

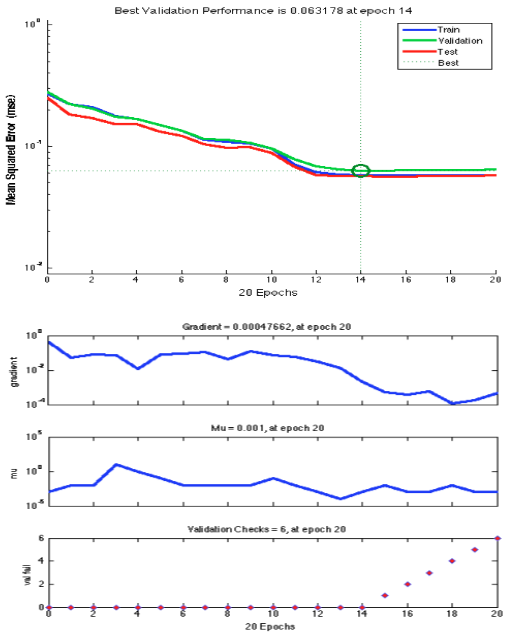

Fig. 5: ANN learning result (whit respect to GA results for 43 features).

In figure (6) the area under the ROC curve is shown for tumor detection in different areas. The more area under this curve tells us that samples which are selected correctly for classification are greater. These curves represent promising results.

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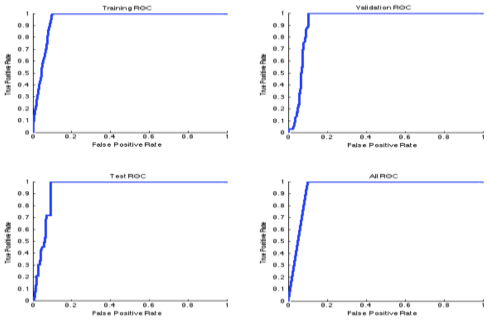

Fig. 6: ROC curve for brain tumor detection (based on GA results for 43 features).

Network learning trend with GA results are the same for other brain areas.

3. Experiment results:

Table 1: A comparison between proposed and available methods for brain tumor detection.

Method	Classifier	Sensitivity(%)	Specificity(%)	Accuracy(%)
proposed method	ANN	100	89.9	92.3
Reference (Aguilar *et al*., 2013) method	ANN	80.2	90	84.9
Reference (Aguilar *et al*., 2013) method	SVM	81	86.4	83.6

Based on extracted features from segmented MRI images, it a tumor's existence or absence can be specified. Since tumors appear with a higher intensity than other areas of the image, this intensity difference will influence extracted features. As we can see in table (1), our proposed method is better respect to the previous approaches in different perspectives: sensitivity, specificity and accuracy are improved for tumor detection, compared to the same criteria which is used by (Aguilar *et al*., 2013).

4. Conclusion:

After different studies on brain area segmentation and tumor detection with different methods, we can see that our proposed method in this article made some improvement. After pre-processing, we performed segmentation with a model which is based on a threshold method. Then, with respect to extracted tissues in segmentation step, we exploited meaningful features, such as shape and features of tissues. Finally in order to perform image classification, we used artificial neural network. With respect to our analysis, the proposed algorithm accuracy for tumor detection in different brain areas such as white matter, gray matter, CSF and the whole brain was improved.

REFERENCES

AmirEhsanLashkari, 2010. A Neural Network based Method for Brain Abnormality Detection in MR Images Using Gabor Wavelets, International Journal of Computer Applications (0975 – 8887), 4-7.

Aguilar, C., E. Westman, J. Muehlboeck, P. Mecocci, B. Vellas, M. Tsolaki, L.O. Wahlund, 2013. Different multivariate techniques for automated classification of MRI data in Alzheimer's disease and mild cognitive impairment.*Psychiatry Research: Neuroimaging*, pp. 89-98.

Dr.Vipul Singh, 2013. Digital Image Processing with M ATLAB and Lab VIEW; ELSEVIER.

El-Sayed Ahmed El-Dahshan,Tamer Hosny,Abdel-Badeeh M. Salem, 2010, Hybrid intelligent techniques for MRI brain images classification, Elsevier, Digital Signal Processing, pp: 433-441.

Grimaud, J., M. Lai, J. Thorpe, P. Adeleine, L. Wang, G.J. Barker, D.H. Miller, 1996. Quantification of MRI lesion load in multiple sclerosis: a comparison of three computer-assisted techniques. *Magnetic resonance imaging*, *14*(5): 495-505.

Gordillo, N., E. Montseny, P. Sobrevilla, 2013. State of the art survey on MRI brain tumor segmentation. Magnetic Resonance Imaging.

Johnson, J.L, M.L. Padgett, 1999. "PCNN models and applications". IEEE Transactions on Neural Networks, 10(3): 480-498.

Selvanayaki, K,. Dr. P. Kalugasalam, 2012. "Pre-Processing And Enhancement Of Brain Magnetic Resonance Image (Mri)" Ijrcm, 2-10.

Mehdi Jafari, ShohrehKasaei, 2011. Automatic Brain TissueDetection in Mri Images Using Seeded Region Growing Segmentation and Neural Network Classification Australian Journal of Basic and Applied Sciences, 5(8): 1066-1079, ISSN 1991-8178.

Advances in Natural and Applied Sciences, 8(10) Special 2014, Pages: 126-132

Mrs.Mamata, S., Kalas, *2010. An Artificial Neural Network for Detection of Biological Early Brain Cancer,* International Journal of Computer Applications (0975 – 8887), 1.

Ramos, R.P., M.Z.D. Nascimento, D.C. Pereira, 2012. Texture extraction: An evaluation of ridgelet, wavelet and co-occurrence based methods applied to mammograms. *Expert Systems with Applications*, *39*(12): 11036-11047.

Robert, P., Velthuizen,LawrenceHallt,LaurenceP.Clarke, 1996. *Mri Feature Extraction Using Genetic Algorithms*,18th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, Amsterdam.

Jayaraman, S., S. Esakkirajan, T. Veerakumar, 2009. Digital Image Processing, Tata M cGraw Hill Education Private Limited.

Song-yunXie,RangGuo,Ning-feiLi,GeWang,Hai-tao Zhao, 2009. *Brain fMRI Processing and Classification Based on Combination of PCA and SVM* , Proceedings of International Joint Conference on Neural Networks, Atlanta, Georgia, USA, June 14-19.

Tahmasbi, A., F. Saki, H. Aghapanah, S.B. Shokouhi, 2011. A novel breast mass diagnosis system based on Zernike moments as shape and density descriptors. In *Biomedical Engineering (ICBME), 2011 18th Iranian Conference of* , 100-104.

Volker Schatz, 2011.”Low-latency histogram equalization for infrared image sequences - a hardware implementation”, Journal of Real- Time Image Processing, June.

Wang, W., J.E. Mottershead, C. Mares, 2009. Mode-shape recognition and finite element model updating using the Zernike moment descriptor.*Mechanical Systems and Signal Processing*, *23*(7): 2088-2112.