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MRI Brain Image Segmentation Using Combined Fuzzy Logic and Neural Networks for Tumor Detection

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Abstract

Considering that brain tumor is one of the diseases which threaten members of a society and unless it is not diagnosed at the right time it can lead to people's death, its diagnosis is of too much importance. In most cases individual develops tumor lesion but since it is very small, it cannot be detected by first medical images such as CT and MRI and it may postpone diagnosis and may also lead to an irreparable lesion. During the past decade in order to help radiologists and specialized physicians, most experts have tended to pay more attention to computer algorithms for the diagnosis of this phenomenon. In this case they can use computer to analyze medical images taken from brain more precisely and tumor detection can be done. Using this method may lead to reduce the risk of tumor diagnosis.

In this article we extract candidate abnormal areas by the use of morphological operations and then combination of artificial neural networks and fuzzy logic that refers to NeuroFuzzy is used to classify tumor region from non tumor candidate areas. After localization of the tumor region Whole brain tumor boundary was extracted by the use of traditional level set method. The evaluation result with brain MRI tumor images shows that our proposed method is more precise and robust for brain tumor segmentation.

Keywords: Brain tumor, Magnetic Resonance Imaging, Level Set, Neural Networks, Fuzzy logic.

I. Introduction

Brain is responsible for controlling memory, learning, the senses, and emotions. Moreover, it controls body parts including muscles, organs, and blood vessels [Salle *et al.*, 2003].

As we all know, human body consists of different cell types each of which performs a specific duty. These body cells grow in such a way as to be able to produce new cells through cell division. Cell division is vital and necessary for correct functioning of the body. Therefore, if cells failed to properly control their growth, limitations arising from such failure in cell division would impair blood circulation. That is why tumors are produced [Upson M,2003]. Brain tumor is the term used for an unnatural growth in the form of a lump which might be benign or malignant. It should be noted that a benign tumor can cause as much disability as a malignant one unless it is properly treated [Upson M, 2003].

1. Preprocessing

Many MRI images become noisy and therefore unusable because most of the patients carry metal objects such as watches, bracelets, etc. during the MRI imaging. Therefore, it's necessary to

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apply a series of initial processing procedures on the image before any image processing for special purposes. This set of operations is called the preprocessing. This is a necessary stage for improving the image quality and removing the noise. The improved image will then be scanned in order to find the important areas. Since the brain images are more sensitive than other medical images, they should be of minimum noise and maximum quality.
We first try to remove noise, background and other specific signs from the image, and then find the range of skull and brain in it, and finally improve its quality. Some other people may try to improve the whole image quality.
Each MRI image of the brain includes the following parts:

1. *The range of brain*
2. *Background*
3. *Signs and labels (May be present)*

Because in most MRI images, a large volume of the image is occupied by a dark background which is unnecessary and may be a source of error in image processing due to its coloring similarity to the tumor; we try to remove this part from the images. Removing the background decreases the amount of the memory used which in turn increases the processing speed.
The following four phases are commonly used for the application of preprocessing and removing the additional parts of the image:

1. *Creating the mask image*
2. *Using the Canny edge detector operator*
3. *Using the morphological operators*

2. Extracting the candidate areas

Tumor segmentation and separation in MRI images using the image of a brain is based on this fact that the pixels inside the tumor have different behavior than the other pixels. These behaviors include the pixel's brightness and color. Since the tumors are created in various shapes, the apparent shape of a tumor is rarely used in its separation.
Segmentation is generally done in two ways: With or without an observer.
In segmentation with an observer, the system has a series of previous information which uses them for segmentation. In segmentation without an observer though, the image is divided into different areas considering a series of common properties including gray colored surfaces, texture and color.

3. Labeling

After separating candidate points, we number each connected pixels in the extracted candidate matrix so that each connected candidate pixels got same label. In order to better classify the detection of diseases, each connected areas will be labeled so the properties of each label will be delivered to the classifier.

4. Extracting the properties

After finding the candidate areas and labeling them, it's time for extracting the properties. This stage has a special importance because selecting the appropriate properties may greatly facilitate the correct diagnosis of the disease. Different areas in an image create properties based on different behaviors. Image processing properties are placed into four categories [Sonka et al. 2008].

I. *Brightness*
II. *Differentiate*
III. *Texture*
IV. *Shape*

5. Classification Methods

After selecting the appropriate properties form the available sample, an appropriate classifier will be used to classify them.

I. *Fuzzy Methods*
II. *Artificial neural network Methods[Schalkoff, 1997]*
III. *Neuro-fuzzy Methods[Robert Full, 2000]*

5.1. Neuro-fuzzy Methods

Fuzzy interpreter systems and neuron systems are each other's counterpart in designing and making intelligent systems. Artificial neuron networks (ANN) has the ability of learning (through changing weighted coefficient if inter layers connections) which makes this method unique.

Fuzzy interpreter systems (FIS) work based in the theory of fuzzy series and logic. The main characteristic of these systems is the use of linguistic verbs instead of numbers which is similar to humans' control and processing function.

As Neuro-fuzzy systems benefit from both neuron network and fuzzy processing, it become favored. In simple words, a neuro-fuzzy system is defined as a fuzzy interpreter (FIS) which is taught by learning methods of neuron network. In this teaching method the fuzzy system parameters are adjusted and makes the system function improve.

There are miscellaneous methods for making artificial intelligence in machines. In recent years, neuro-fuzzy methods show outstanding efficiency the precious characteristics of neuron system is the ability of learning which expands its generalization and right reactions towards unfamiliar inputs.

While fuzzy systems use some kinds of linguistic verbs instead of numbers and makes outputs by the help of simple conditional rules (if x and y then z). In fact, there happens a kind of non-linear mapping in fuzzy systems in which inputs are transported from numerical to the fuzzy area and finally outputs brought back from fuzzy area to numerical area. The main advantageous of fuzzy methods are: natural stability, not having high sensitivity towards noise and the ability of applying human experience in different processing steps.

Considering the above mentioned characteristics, the combination of these two methods has been welcomed very much. There are miscellaneous techniques for incorporating fuzzy method and neural network which are used based on the type of application.

I. *Neuro- Fuzzy Systems (FIS)*
II. *Mamdani Neuro-Fuzzy system*
III. *Takagi-Sugeno Neurofuzzy System*

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6. Extraction of the tumor boundary

After generating the area classification results output, if there will be tumor area among the candidate areas; the central pixel is usually determined and grows until it reaches the edge. When it reaches the edge of the desired area, it can be said that the tumor boundary is identified. If the classifier was not able to detect the tumor location among the candidate locations, it can be concluded that the image does not have any tumor. Contours are usually used to identify tumor areas.

7. The proposed method

As mentioned in earlier chapters, this study plans to examine MRI digital images of brain. In this study, we search MRI images to find brain tumors, in other words, the images of patients are processed by the system to detect a brain tumor scope in more precise.

To achieve this goal, several steps have been proposed.

The overall procedure of the work is reviewed as follows:

1. Pre-processing
2. Extraction of candidate region
3. Classification
4. Whole tumor region boundary extraction.

7.1. Preprocessing

Before any processing for tumor extraction, it is necessary to standardize the photos.

7.1.1. Mask of Image

It is important to distinguish between background and foreground, because most of the algorithms only need to consider the foreground pixels .for Mask Of Image used Canny Edge detector , Dilate result , Fill the holes AND Negated mask image.

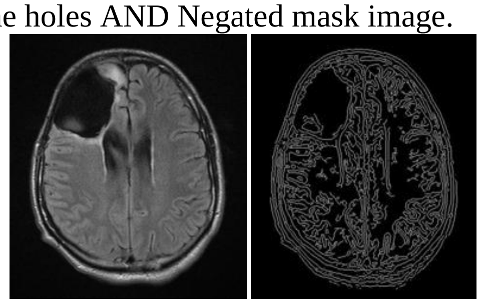

Figure1.Left:, Original Image, Right: Extracted Edges

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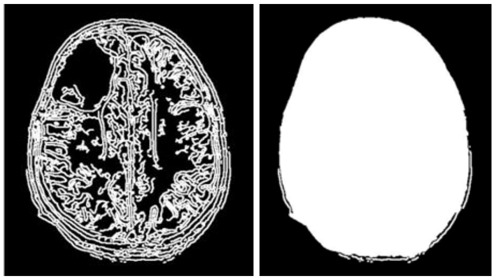

Figure 2: Left: Dilated Image, Right: Filled Image

The dataset we used in experiment is www.bic.mni.mcgill.ca/brainweb of we used is hypointense model in t1-wighted

7.2. Segmentation of Candidate Pixels

After separation of the background image from the main image (ROI), Image is segmented and the characteristic of each piece is examined to extract tumor position. To identify candidate points that are likely tumor's locations, the images became negative so that the dark spots of tumors become bright. To aim this goal the average of image was calculated and subtracted from the image extent and then the result was compared with number 25 that is the scale of darkness. All points that are less than 25 took into account as the candidate points, and their extent was supposed 1as shown in figure 3.3. (i.e. the point become bright).

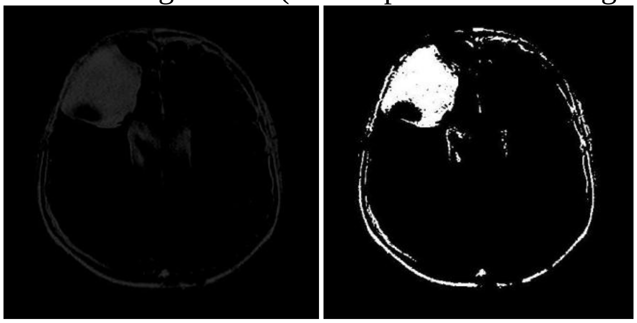

Figure 3: Extraction of candidate regions.

7.3. Labeling

After separating candidate points, we number each connected pixels in the extracted candidate matrix so that each connected candidate pixels got same label. In order to better classify the detection of diseases, each connected areas as shown in figure 3.4 will be labeled so the properties of each label will be delivered to the classifier.

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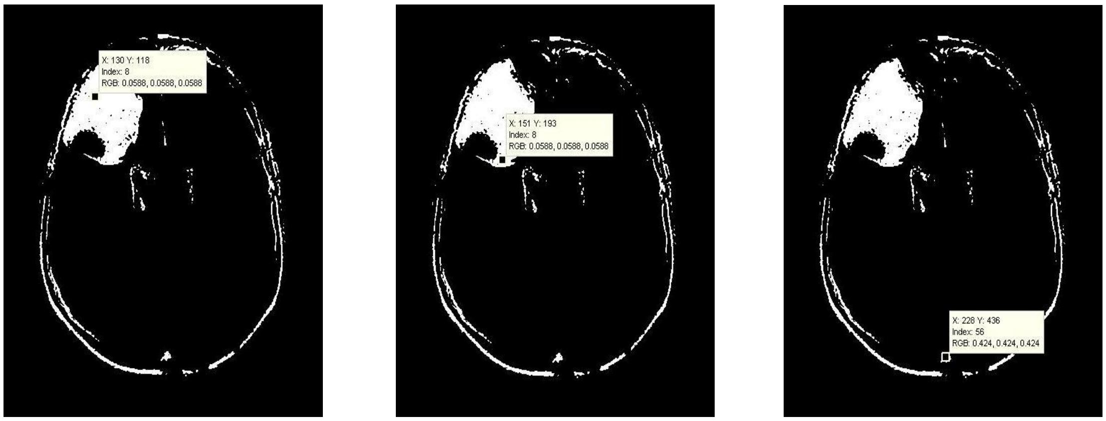

Figure 4: Labeling candidate areas

7.4. Feature extraction

In this part, characteristics of candidate's area are extracted from data. The goal of choosing these characterizations is better tumor distinguishing. By comparing extracted data with the amount of following characteristics, we can recognize the tumor location more precisely.

- *Average intensity*:
- *Standard deviation*:
- *Maximum intensity:*
- *Minimum intensity:*
- *Summation of intensity*
- *Entropy of intensity*
- *Summation of absolute Gradient of candidate region.*

for increasing the speed and decreasing the volume of the matrix of assumed attributes, the number of attributes, which due to their separation possibility, are 12 in mlp and other systems is restricted to the above attributes which results in decreasing the volume of matrix and as a result faster extraction of the tumor area.

7.5. Neuron fuzzy based classification

As mentioned before neuro-fuzzy refers to combinations of artificial neural networks and fuzzy logic in the field of artificial intelligence. Neuro-fuzzy was proposed by J. S. R. Jang(Jang, J.-S. R. et al. 1995). Neuro-fuzzy crossbreeding results in a hybrid intelligent system that synergizes these two techniques by combining the connectionist structure of neural networks with the human-like reasoning style of fuzzy systems. Neuro-fuzzy hybridization is widely termed as Fuzzy Neural Network (FNN) or Neuro-Fuzzy System (NFS) in the literature. Neuro-fuzzy system incorporates the human-like reasoning style of fuzzy systems through the use of fuzzy sets and a linguistic model consisting of a set of IF-THEN fuzzy rules. The principle power of neuro-fuzzy systems is that they are universal approximators with the ability to interpretable IF-THEN rules.

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So the neuro-fuzzy based approach is used for MRI brain tumor region detection from other candidate regions. Actually, this tool is like a fuzzy inference system, but the difference is in the use of a back propagation algorithm for minimizing the error [Pejman T. et. al 2010].
For every candidate regions eight mentioned features in previous sections are calculated.
We used integrated neuro fuzzy Takagi-Sugeno classifier. Its rules, parameters and membership functions will be optimized during the learning process with the use of Back Propagation algorithm. Learning in this process is supervised. Although all the rules and parameters are optimized automatically by the way we can set them manually that this characteristic is one of the best character of neuro-fuzzy systems.
The first step in this regard is to define the primary structure of the system. This primary structure combines the inputs, outputs, fuzzy rules, and the shape of membership functions. The number of inputs is the number of selected features, and the number of outputs is one that means we consider one neuron in outer layer and we learn the system so that the output of this neuron show the class of regions in classification procedure. If the candidate region be tumor region the output of this neuron will be one, otherwise it will be zero.
Among the different types in the shape of membership functions such as trapezoidal, Gaussian, triangular, and etc. We selected Gaussian shape membership function with normal distribution that give best results in our examinations.
The block diagram of the system is illustrated in figure 3-5.

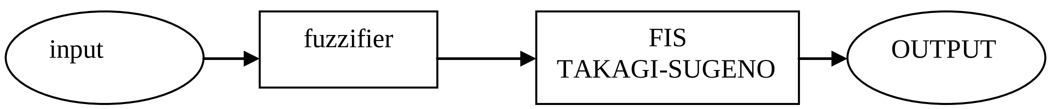

Figure 5: The block diagram of proposed neuro fuzzy system

The precise structure of this system is shown in figure below:

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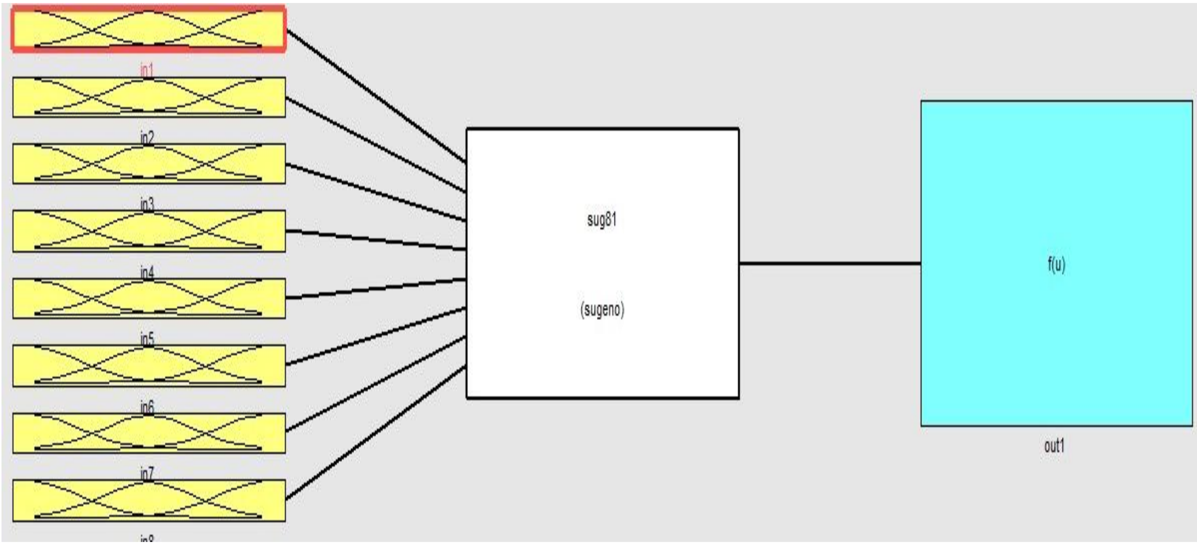

Figure6: The precise structure of the proposed system.

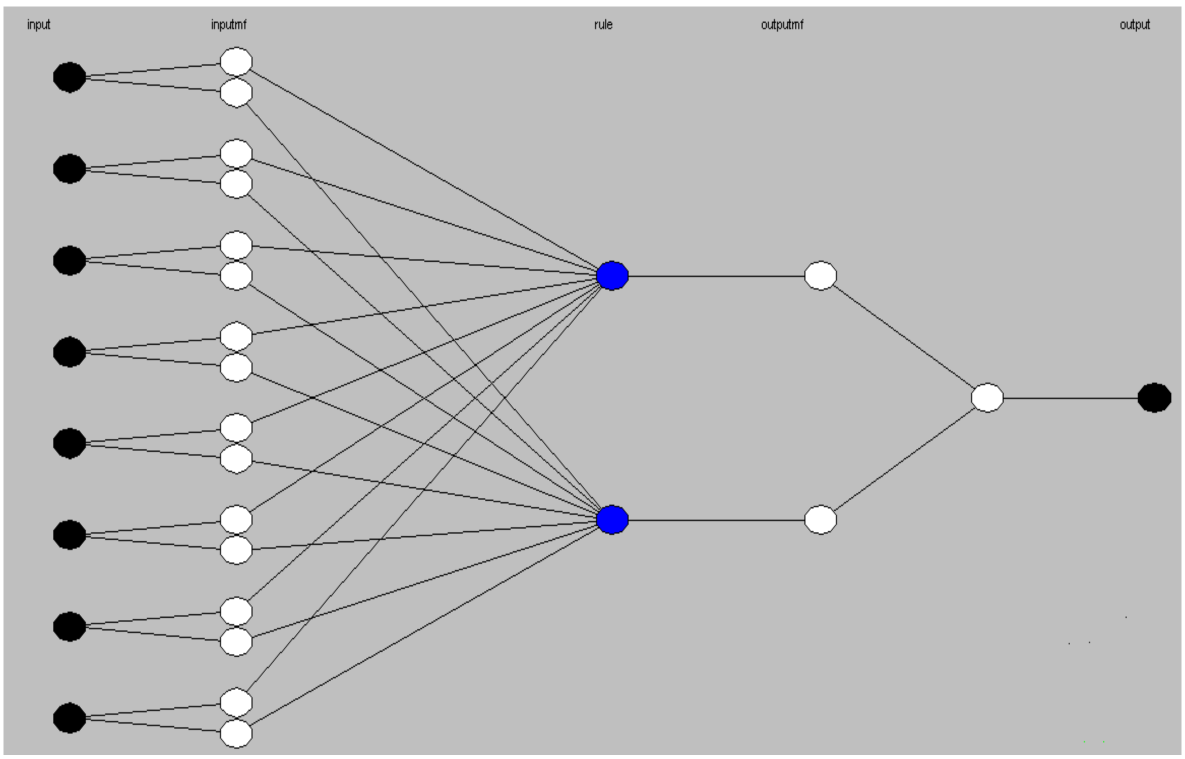

Figure 7: The proposed ANFIS model structure

7.6. training and testing

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Considering the high learning potentiality of neuro-fuzzy systems and for decreasing the learning time, we only used two-third of the whole data and used the rest as test data. In addition, we increased the learning time 14 times more than that of Mamdani model because of using Takagi-Sugeno model and its structure for classification.

We used from the half of the extracted data to train the proposed system and MLP network. Epochs to reach the target shows how the system in training phase that in each train try to reach the desired target. In other words this parameter shows the number of modification and regularization of parameters in pack propagation error of the process.

This parameter selected such that the root mean square (RMS) error get minimized. By increasing the epochs the time of training process will increase exponentially.

The membership function of the system after training process are shown in figure 3-8.

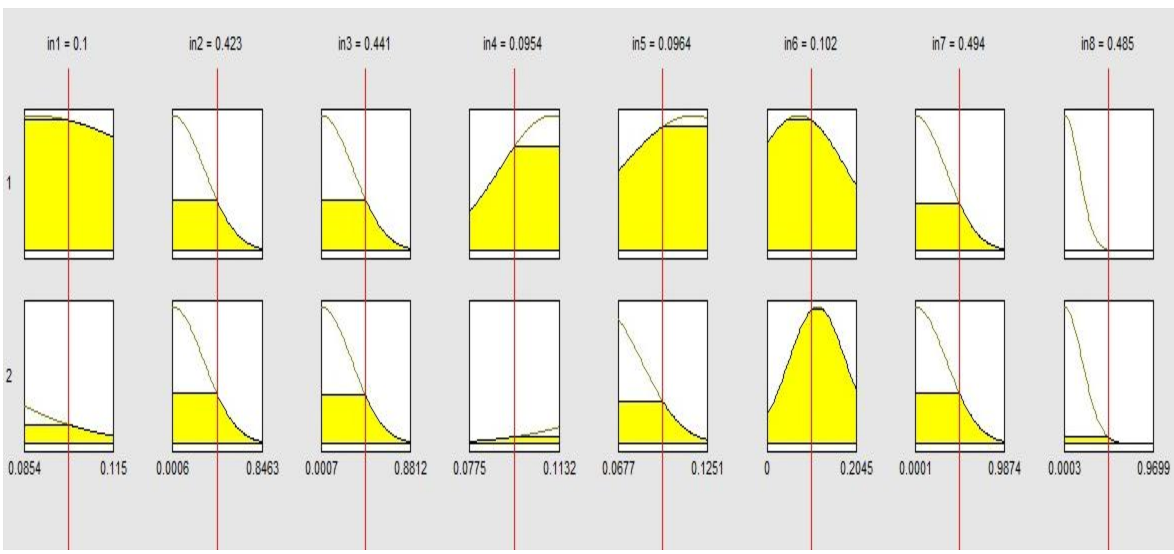

Figure8: Member ship functions of the system after training phase with tow rules.

According to research conducted for the detection of brain tumor in mri images or fuzzy neural networks or genetic algorithms are used., But we have to recognize this phenomenon more The combination of neural networks and fuzzy logic as used neru-fuzzy

For our result don't used of process average but in neruo –fuzzy we used training Artificial Neural Network for process image but in ANN we should 100 times but in neruo-fuzzy training is 10 times.

7.7. Extraction of whole tumor region boundary

As described in section 3-6 after detection of tumor region, the boundary of tumor is determined by using level set deformable model. For this purpose:

- The initial level set contour ϕ is defined around the detected tumor region.

For each iteration:

- The steepest descent gradient flow is computed to minimize total energy function of the contour:

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$$\frac{\partial \phi}{\partial t} = \mu\left[\nabla \phi - div\left(\frac{\nabla \phi}{|\nabla \phi|}\right)\right] + \lambda\delta(\phi)div\left(g\frac{\nabla \phi}{|\nabla \phi|}\right) + vg\delta(\phi)$$

(3-1)

- where ∇ is the Laplacian operator , δ is the univariate Dirac function, g is the edge indicator function defined by:

$$g = \frac{1}{1+|\nabla(G_\sigma * I)|^2}$$

(3-2)

$G_\sigma * I$ is the convolution of the original image I with a Gaussian kernel with standard deviation σ,

μ > 0 is a parameter controlling the effect of penalizing the deviation of φ from a signed distance function and v, λ are constants.

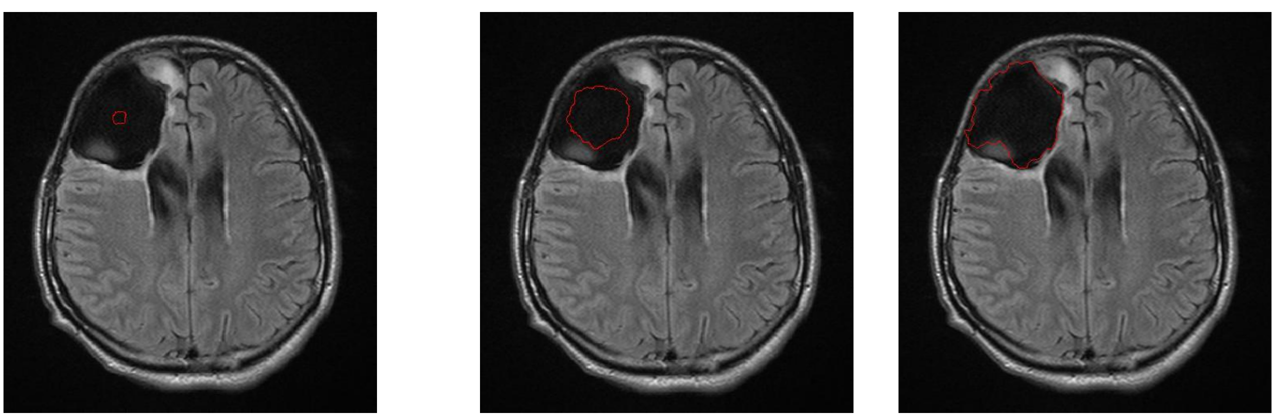
-The contour ϕ starts deforming in each iteration $(\phi = \phi + \frac{\partial \phi}{\partial t})$ and moving towards the tumor boundary.

The Dirac function δ(x) in equation (3-10) is smoothed as the following function $\delta_\varepsilon(x)$ with ε = 1.5, and defined by:

$$\delta_\varepsilon(x) = \begin{cases} 0 & |x| > \varepsilon \\ \frac{1}{2\varepsilon}[1+\cos(\frac{\pi x}{\varepsilon})] & |x| \le \varepsilon \end{cases}$$

(3-3)

Figure 3-18 shows the ground-truth image and resulted tumor region boundary obtained by variational level set models with $\sigma = 1, \lambda = 8, v = 2, \mu = .1$ after approximately 200 iterations.



8. Conclusions and results

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8-1- Validation of proposed method

The validation of the segmentation results is very important, especially for medical images. The reason is because any significant disagreement between the detected results and the real targets might lead to severe damages in clinical activities.

The first parameter to be considered in performance evaluation of a Computer aided diagnosis system is the specificity, i.e., the number of correct answers disregarding of their being negative or positive. This method has certain limitations including two parameters representing positive and negative cases called sensitivity and specificity respectively, which are defined as follows:

Sensitivity: Percentage of true positive diagnoses (TPF) or:

$$\text{Sens} = \frac{\text{Number of true positive Marks}}{\text{Number of Lesions}} \qquad (4\text{-}1)$$

Specificity: Percentage of true negative diagnoses (TNF) or:

$$\text{Spec} = \frac{\text{Number of true Negative Marks}}{\text{Number of Normal tissues}} \qquad (4\text{-}2)$$

We also have:

False Negative Percentage: FNF=1-TPF (4-3)

False Positive Percentage: FPF=1-TNF (4-4)

Performance of a system is often evaluated on the basis of (TPF-TNF) or (FNF-FPF) groups (see Figure 4-1). However, a more exact method for errors is required for better understanding how the system works. This problem is more prevalent in medicine since every doctor adopts a different method for diagnosis based on his/her own knowledge and experience.

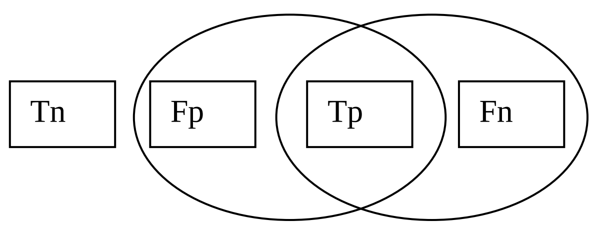

Figure 10: Validation of algorithm based on comparison of extracted region and Gold standard

The accuracy of computer-assisted segmentation of medical images is difficult to quantify in the absence of a ground truth. Traditionally, there are two mechanisms for validation, if no ground truth data are provided (Fan, 2003)

I. Create synthetic images with known size and shapes, segment them with the proposed method, and contrast the values to those used when generating the image.

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II. Train some human operators to segment a set of defined volumes (most of the time it is necessary to repeat the segmentation in order to evaluate their variability), then compare the segmentations results using proposed method with their manual segmentations.

In order to quantitatively assess the quality of an automatic binary segmentation in comparison to a manual binary segmentation produced by the above method, we chose to use the Jaccard measure for the abnormal class (where M is the set of manually defined tumor pixels, and A is the set pixels classified as tumor by the automatic method):

$$J(A,M) = \frac{A\cap M}{A\cup M} = \frac{t_p}{t_p+f_p+f_n} \qquad (4\text{-}5)$$

The Jaccard measure provides a single easily interpretable measuring the similarity between the two segmentations. This score will be 1 if the segmentations are identical, while it will approach 0 for completely dissimilar segmentations.

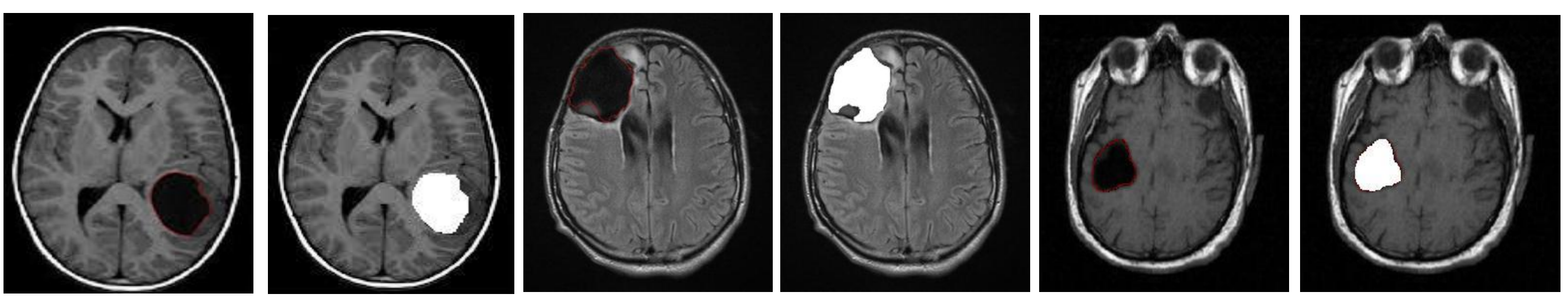
The evaluation of segmentation performance is also carried out quantitatively by employing false positive function (FPF), false negative function (FNF).

The false positive function (FPF) represents the error due to the misclassification in class i and the false negative function (FNF) represents the error due to the loss of desired pixels of class i they are defined as follows:

Lower value of FPF, FNF gives better segmentation result.

$$FPF = \frac{B-(A\cap B)}{A} \qquad (4\text{-}6)$$

$$FNF = \frac{A-(A\cap B)}{A} \qquad (4\text{-}7)$$



Ae Ag Be Bg Ce Cg

Figure 11: Extracted region and Gold standard of three images (A,B,C) of our data base, Left column: Extracted region Right Column: Gold standard

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TableI: The Validation of Our Propose Algorithm on Three Images of Our Database

MRI Image	FPF(%)	FNF(%)	Sensitivity	Specificity	J(%)
Image A	0.4	0.6	.94	.92	91
Image B	0.6	0.7	.91	.91	89
Image C	0.4	0.3	.98	.97	93

An average Jaccard index of our method in 20 images that are collected is 89.1% that is, the overlap degree between our segmentation result and the manual segmentation is higher. The average FPF and FNF values are equal to 0.56% and 0.68%. It shows misclassification and loss of desired tumor pixels is reduced in great degree.

The quantitative result of our method in these collected images for localization of tumor region is also 100%.The experimental result shows that the proposed algorithm is robust to variable appearance of MRI brain images and can give the sufficiently accurate location of tumor.

TABLE II COMPARES THE PERFORMANCE OF FINAL TUMOR BOUNDARY EXTRACTION OF OUR PROPOSED METHOD THAT USE OF NEURO-FUZZY CLASSIFIED WITH OTHER TRADITIONAL CLASSIFIERS SUCH AS FUZZY C-MEANS AND MULTILAYER PERCEPTRON NEURAL NETWORK.

TABLE II. COMPARISON BETWEEN PERFORMANCE OF OUR ALGORITHM AND OTHER TRADITIONAL CLASSIFIERS

	total samples	classifier	FPF(%)	FNF(%)	J(%)
MRI Brain Images	20	Fcm	0.72	0.83	79.8
	20	mlp	0.96	0.83	82. 3
	20	Nf	0.56	0.68	89.1

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TABLE III. COMPARISON OF CLASSIFICATION PERFORMANCE FOR THE PROPOSED TECHNIQUE AND RECENTLY OTHER WORK (SHARMA1 M., ET AL. 2012)

MRI Brain Images	Classifier	Sensitivity	Specificity
	Fcm(Yang.Y et al. 2005)	0.92	0.91
	Fluid Vector Flow+ Support vector machine (Vijayakumar B.et al. 2012)	0. 81	0.9
	Proposed Algorithm	0.94	0.93

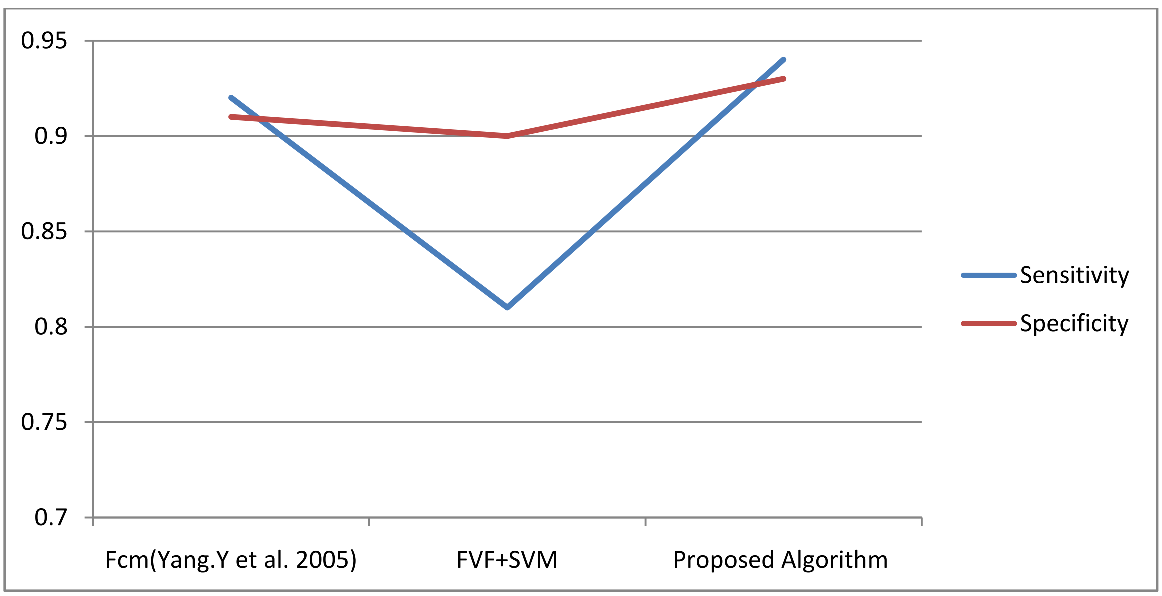

Figure 12: Comparative analysis graph

8.2 Conclusions

We have presented in this paper a tumor segmented method which combines both Neural Network and fuzzy clustering method and extraction of boundary based on level set deformable model .We verified our proposed method with brain tumor MRI images. The obtained results are quantitatively verified with other existing method shows that our proposed method provides better result. The proposed methodology of this research has been able to increase correctness of the process of diagnosis and isolation of tumor dramatically. The automatic procedure was compared with tumor segmentation by manual outlining.

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Following this way and in order to further improve the achievements, the following tasks can be reviewed:

- The use of other neuro-fuzzy systems or a combination of them.
- To increase the number and variety of educational samples by rising the volume of the database of the applied images.
- To find new features (frequency, morphological or statistical), with the ability of better isolation.
- To find solutions for reducing the dimensions of the vector of the features of image If we are able to reduce the dimensions of the attribute vector, the complexity of the neuro-fuzzy system will decrease, and the speed and efficiency of the procedure will increase.
- To apply preprocessing methods on the image before extraction of features

Nonlinear preprocessing methods such as thresholding increases separability of different areas of image; therefore, one can predict that applying them before feature extraction stage may improve the achievements

- To employ a processing method on the image and to combine its achievement with the main method.

A processing method such as boundary detection can be used in parallel with the main method, and in the end the achievements will be combined together.

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