Full Length Research Paper

An improved implementation of brain tumor detection using segmentation based on soft computing

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Image segmentation is an important and challenging factor in the medical image segmentation. This paper describes segmentation method consisting of two phases. In the first phase, the MRI brain image is acquired from patients' database, In that film, artifact and noise are removed after that HSom is applied for image segmentation. The HSom is the extension of the conventional self organizing map used to classify the image row by row. In this lowest level of weight vector, a higher value of tumor pixels, computation speed is achieved by the HSom with vector quantization.

Key words: Image analysis, segmentation, HSOM, tumor detection.

INTRODUCTION

Brain tumor is one of the major causes for the increase in mortality among children and adults. A tumor is a mass of tissue that grows out of control of the normal forces that regulates growth (Pal and Pal, 1993). The complex brain tumors can be separated into two general categories depending on the tumors origin, their growth pattern and malignancy. Primary brain tumors are tumors that arise from cells in the brain or from the covering of the brain. A secondary or metastatic brain tumor occurs when cancer cells spread to the brain from a primary cancer in another part of the body. Most Research in developed countries show that the number of people who develop brain tumors and die from them has increased perhaps as much as 300 over past three decades.

The National Brain Tumor Foundation (NBTF) for research in United States estimates that 29,000 people in the U.S are diagnosed with primary brain tumors each year, and nearly 13,000 people die. In children, brain tumors are the cause of one quarter of all cancer deaths. The overall annual incidence of primary brain tumors in the U.S is 11 - 12 per 100,000 people for primary malignant brain tumors, that rate is 6 - 7 per 1,00,000. In the UK, over 4,200 people are diagnosed with a brain tumor every year (2007 estimates). There are about 200 other types of tumors diagnosed in UK each year. About 16 out of every 1,000 cancers diagnosed in the UK are in the brain (or 1.6%). In India, totally 80,271 people are affected by various types of tumor (2007 estimates). "Artificial Neural Networks (ANNs) are mathematical analogues of biological neural systems, in the sense that they are made up of a parallel interconnected system of nodes, called neurons. The parallel action is a difference between von Neumann computers and ANNs. Combining ANN architectures with different learning schemes, results in a variety of ANN systems. The proper ANN is obtained by taking into consideration the requirements of the specific application, as each ANN topology does not yield satisfactory results in all practical cases. The evolution of digital computers as well as the development of modern theories for learning and information processing led to the emergence of Computational Intelligence (CI) engineering. Artificial Neural Networks (ANNs), Genetic Algorithms (GAs) and Fuzzy Logic are CI non-symbolic learning approaches for solving problems (Mantzaris et al., 2008). The huge mass of applications, which ANNs have been used with satisfactory results, has supported their rapid growth. Fields that ANNs were used are image processing (Gendy et al., 2001), environmental problems (Bandyopadhyay and Chattopadhyay, 2007; Chattopadhyay and Chattopadhyay, 2009), Climate study (Chattopadhyay, 2007), financial analysis (Papadourakis et al., 1993). In this paper, a new unsupervised learning Optimization algorithm such as SOM is implemented to extract the suspicious region in the Segmentation of MRI Brain tumor. The textural features can be extracted from

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the suspicious region to classify them into benign or malign.

RELATED WORK

The Segmentation of an image entails the division or separation of the image into regions of similar attribute. The ultimate aim in a large number of image processing applications is to extract important features from the image data, from which a description, interpretation, or understanding of the scene can be provided by the machine. The segmentation of brain tumor from magnetic resonance images is an important but time-consuming task performed by medical experts The digital image processing community has developed several segmentation methods[8], many of them ad hoc. Four of the most common methods are: 1.) amplitude thresholding, 2.) texture segmentation 3.) Template matching, and 4.) region-growing segmentation. It is very important for detecting tumors, edema and necrotic tissues. These types of algorithms are used for dividing the brain images into three categories (a) Pixel based (b) Region or Texture Based (c) Structural based. Several authors suggested various algorithms for segmentation (Hillips et al., 1995; Aidyanathan et al., 1995; Sai et al., 1995; HanShen et al., 2005; Livier et al., 2005).

Suchendra et al. (1997) suggested a multiscale image segmentation using a hierarchical self-organizing map; a high speed parallel fuzzy c-mean algorithm for brain tumor segmentation (Murugavalli and Rajamani, 2006); an improved implementation of brain tumor detection using segmentation based on neuro fuzzy technique (Murugavalli and Rajamani, 2007) while Chunyan et al. (2000) designed a method on 3D variational segmentation for processes due to the high diversity in appearance of tumor tissue from various patients.

Image acquisition

The development of intra-operative imaging systems has contributed to improving the course of intracranial neurosurgical procedures. Among these systems, the 0.5 T intra-operative magnetic resonance scanner of the Kovai Medical Center and Hospital (KMCH, Signa SP, GE Medical Systems) offers the possibility to acquire 256*256*58(0.86 mm, 0.86 mm, 2.5 mm) T1 weighted images with the fast spin echo protocol (TR = 400, TE = 16 ms, FOV = 220*220 mm) in 3 min and 40 s. The quality of every 256*256 slice acquired intra-operatively is fairly similar to images acquired with a 1.5 T conventional scanner, but the major drawback of the intra-operative image is that the slice remains thick (2.5 mm). Images do not show significant distortion, but can suffer from artifacts due to different factors (surgical instruments, hand movement, radio frequency noise from bipolar coagulation). Recent advances in acquisition protocol (Naylor and Li, 1988) however make it possible to acquire images with very limited artifacts during the course of a neurosurgical procedure. The choice of the number and frequency of image acquisitions during the procedure remains an open problem. Indeed, there is a trade-off between acquiring more images for accurate guidance and not increasing the time for imaging.

Images of a patient obtained by MRI scan is displayed as an array of pixels (a two dimensional unit based on the matrix size and the field of view) and stored in MATLAB 7.0. Here, grayscale or intensity images are displayed of default size 256 × 256. The following figure displayed a MRI brain image obtained in Mat lab 7.0.A grayscale image can be specified by giving a large matrix whose entries are numbers between 0 and 255, with 0 corresponding, say, to black, and 255 to white. A black and white image can also be specified by giving a large matrix with integer entries. The lowest entry corresponds to black, the highest to white. In routine, 21 male and female patients were examined. All patients with finding normal for age n = 20 were included in this study. The age of patients ranged from 20 - 50 years. All the MRI examinations were performed on a 1.5 T magneto vision scanner (Germany). The brain MR images are stored in the database in JPEG format.

Preprocessing

Noise presented in the image can reduce the capacity of region growing filter to grow large regions or may result as a fault edges. When faced with noisy images, it is usually convenient to preprocess the image by using weighted median filter.

Weighted Median (WM) filters have the robustness and edge preserving capability of the classical median filter. WM filters belong to the broad class of nonlinear filters called stack filters. This enables the use of the tools developed for the latter class in characterizing and analyzing the behavior and properties of WM filters, e.g. noise attenuation capability. The fact that WM filters are threshold functions allows the use of neural network training methods to obtain adaptive WM filters (Scherf and Roberts, 1990). A weighted median filter is implemented as follows:

W(x, y) =median {w1 x x1…wn x wn}
x1…..xn are the intensity values inside a window centered at (x,y) and w x n denotes replication of x, w times.

SOM AND HSOM IMAGE SEGEMENTATION

A self-organizing map (SOM) or self-organizing feature map (SOFM) is a type of artificial neural network for

unsupervised learning. SOMs operate in two modes: training and mapping, Training is a competitive process, also called vector quantization. Mapping automatically classifies a new input vector. Segmentation is an important process to extract information from complex medical images. Segmentation has wide application in medical field (Alirezaie et al., 1997; Haralick and Shapiro, 1985; Parra et al., 2003; Pal and Pal, 1993). The main objective of the image segmentation is to partition an image into mutually exclusive and exhausted regions such that each region of interest is spatially contiguous and the pixels within the region are homogeneous with respect to a predefined criterion. Widely used homogeneity criteria include values of intensity, texture, color, range, surface normal and surface curvatures. During the past many researchers in the field of medical imaging and soft computing have made significant survey in the field of image segmentation (Ahalt et al., 1990; Fu and Mui, 1981; Kohonen, 1988; Sahoo et al., 1988). Image segmentation techniques can be classified as based on edge detection, region or surface growing, threshold level, classifier such as Hierarchical Self Organizing Map (HSOM), and feature vector clustering or vector quantization.

The Trained Vector quantization has proved to be a very effective model for image segmentation process (Bilbro et al., 1987). Vector quantization is a process of portioning n-dimensional vector space into M regions so as to optimize a criterion function when all the points in each region are approximated by the representation vector Xi associated with that region. There are two processes involved in the vector quantization: one is the training process which determines the set of codebook vector according to the probability of the input data, the other is the encoding process which assigns input vectors to the code book vectors. Vector quantization process has been implemented in terms of the competitive learning neural network (CLNN) (DeSieno, 1988). Self Organizing Map (SOM) (Parra et al., 2003) is a member of the CLNNs and this can be the best choice when implementing vector quantization using neural network (Lin et al., 1991). The importance of SOM for vector quantization is primarily due to the similarity between the competitive learning process employed in the SOM and the vector quantization procedure. The main shortcoming of the SOM is that the number of neural units in the competitive layer needs to be approximately equal to the number of regions desired in the segmented image. It is not however, possible to determine a priory the correct number of regions M in the segmented image. This is the main limitation of the conventional SOM for image segmentation. The HSOM directly address the aforesaid shortcomings of the SOM. HSOM is the combination of self organization and graphic mapping technique. HSOM combine the idea of regarding the image segmentation process as one of data abstraction where the segmented image is the final domain independent abstraction of the input image. The hierarchical segmentation process for a

hierarchical structure is called abstraction tree. The abstraction tree bears some resemblance to the major familiar quad tree data structure (Naylor and Li, 1988; Samet, 1990) used in the several image processing and image analysis algorithms. The researchers in this field have used SOM or HSOM separately as one of the tool for the image segmentation of MRI brain for the tumor analysis. In this paper, we propose a hybrid technique combining the advantages of HSOM was implemented for the MRI image segmentation

Overview of proposed work

This paper describes the method of MRI brain image segmentation using Hierarchical self organizing map (Hsom). Figure 1 shows the flow of work in Hsom. In image acquisition process MR brain image is loaded into MATLAB 7.0. in the form of matrix.

Next initialize the variables sigma, weight vector and winning neuron .In that Calculate the neighborhood function, weight vector and winning neuron .Here neuron is the input and winning neuron is the output. In that we find the adaptive threshold if the (Current neuron >= winning neuron) then it is suspicious region other wise neglect it.

IMPLEMENTATION

A self-organizing map consists of components called nodes or neurons. Associated with each node is a weight vector of the same dimension as the input data vectors and a position in the map space. The usual arrangement of nodes is a regular spacing in a hexagonal or rectangular grid. The self-organizing map describes a mapping from a higher dimensional input space to a lower dimensional map space.

The procedure for placing a vector from data space onto the map is to find the node with the closest weight vector to the vector taken from data space and to assign the map coordinates of this node to our vector.

Euclidean distance to all weight vectors is computed. The neuron with weight vector most similar to the input is called the best matching unit (BMU). The weights of the BMU and neurons close to it in the SOM lattice are adjusted towards the input vector. The magnitude of the change decreases with time and with distance from the BMU. The update formula for a neuron with weight vector:

Wv(i) is Wv(i + 1) = Wi(i+1) = wi(i) + hci(I)*[(x(i) - w(i))] (1)

Here hci is neighborhood function to calculate it

h(i) = h(rc-r1)*a(i)*alpha   (2)

Here rc-r1=current neuron-next current neuron

a(i) = sigma 0 * exp(-i/nsm)   (3)
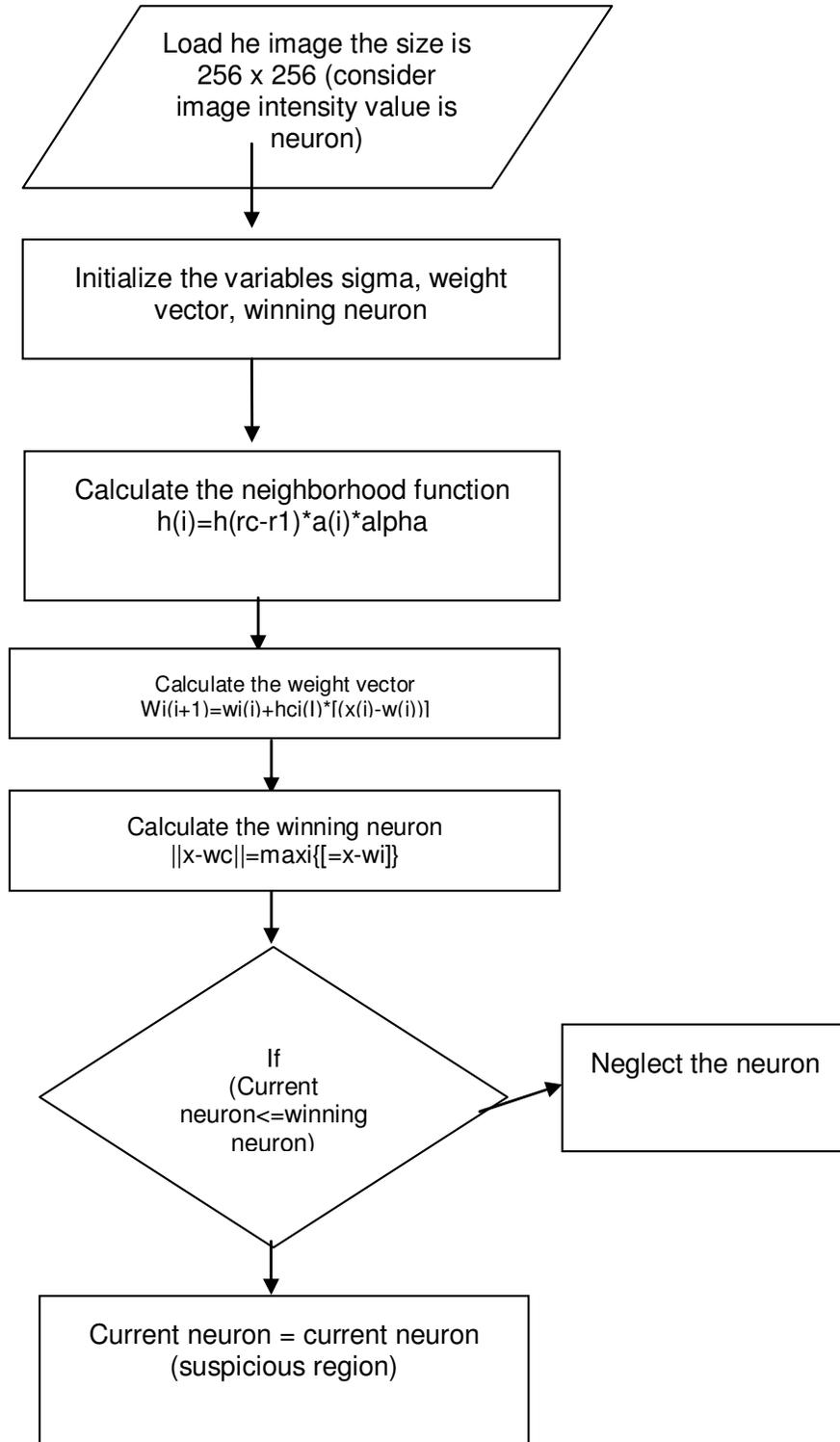
Figure 1. Flowdigram HSom for detection of brain tumor.

Initialize the variable:

Sigma = number of neighborhood pixels (8 or 24 or 48 or 80 or 120) if sliding window size (3*3 = 8), (5*5 = 24), (7*7 = 48),)

(9*9 = 80), (11*11=120)

Sigma N = Sigma 0 * exp(-i/taul)   (4)

Taul= total number of pixels / log (neighborhood number of pixel)

Similarly find the sigma value for each and every pixel.

```
Procedure seg (image)
/* load the input image*/
Im = imread(image);
/* initialize the variable*/
Sigma=number of neighborhood pixels(8 or 24 or 48 or 80 or 120)
/*if sliding windoe size(3*3 =8),(5*5=24),(7*7=48),)(9*9=80),(11*11=120)*/
Sigma N= Sigma 0 * exp(-i/taul)
Taul= total number of pixels / log(neighborhood number of pixel)
/*Similarly find the sigma value for each and every pixel */
/* find the neighborhood function */
Nf(i)=Img(i)-img(i+1)*sigma(i)
/*find the weight vector*/
Wi(i+1)=wi+Nf(i)*img(i)-w(i)
/*find the winning neuron*/
Wn=max(wn,img(i)-w(img(i))
/* segmentation of som*/
Img(i)>=wn then
img(i)=1
Else
Img(i)=img(i)
```

Figure 2. Pseudo code for tumor detection.

This process is repeated for each input vector for a (usually large) number of cycles λ. The network winds up associating output nodes with groups or patterns in the input data set. If these patterns can be named, the names can be attached to the associated nodes in the trained net.

The winning neuron formula is

$$||x-wc||=maxi\{[=x-wi]\} \qquad (5)$$

X is a neuron, wi is the weight vector

Pseudo code of Hierarchical self organizing map

Figure 2 shows the pseudo code of hierarchical self organizing map.

RESULT AND ANALYSES

Table 1 shows the result of image segmentation of Hsom .In any computer aided analysis, the execution time is one of the important parameters of medical image segmentation .In these result, we have calculated the number of tumor cells of different neighborhood pixel of 3×3, 5×5, 7×7, 9×9, 11×11 windows.

In that 3×3 window is chosen based on the high contrast than 5×5, 7×7, 9×9, and 11×11.

Figure 3 shows the tested segmented image with various neighborhood pixels, the original image of (256×256).

Performance analyses

It is very difficult to measure the performance of enhancement objectively. If the enhanced image can make observer perceive the region of interest better, then we can say that the original image has been improved.
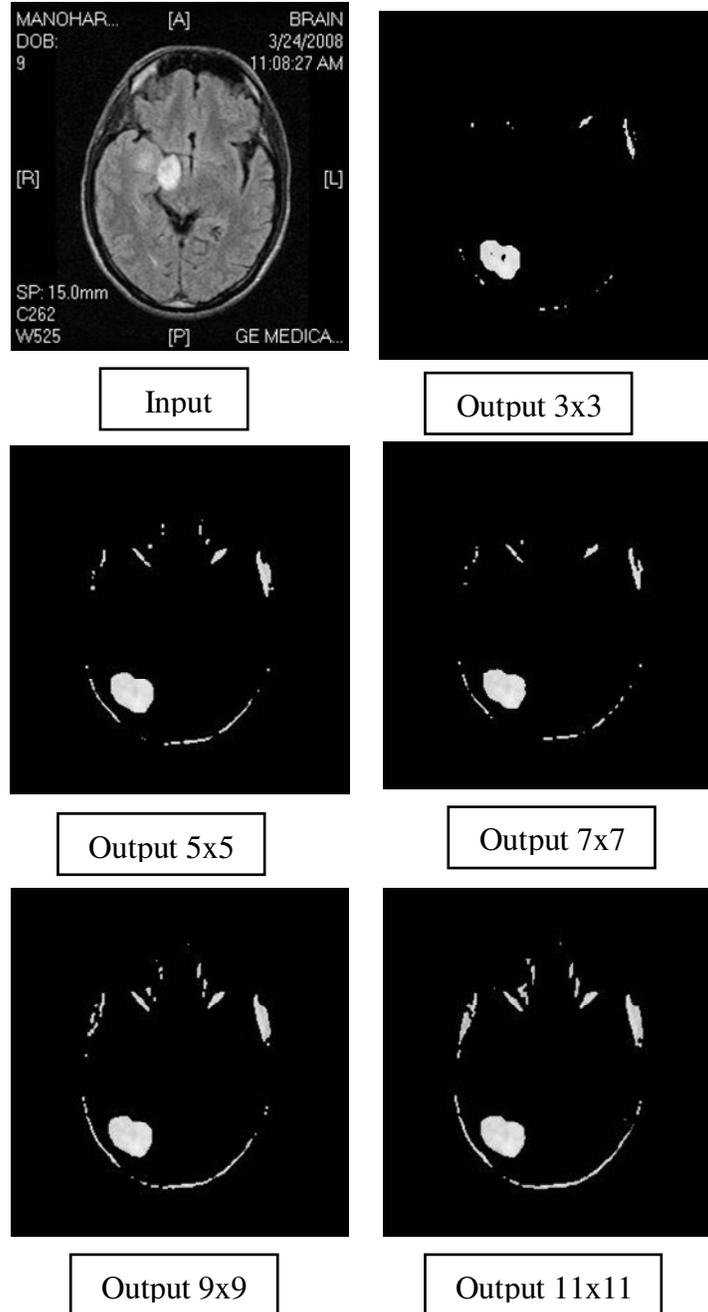
Here we are giving input image in that neighborhood pixel of 3×3, 5×5, 7×7, 9×9, 11×11 windows are analyzed. In that 3×3 window is chosen based on the high contrast than 5×5, 7×7, 9×9, and 11×11.

Figure 4c shows the weight vector for Hsom is 3×3 is 14, 5×5 is 8, 7×7 is 15, 9×9 is 23 and 11×11 is 32. Figure 4a shows the Execution time in Hsom of 3×3 is 13.76, 5×5 is 14.96, 7×7 is 15.20, 9×9 is 11.05 and 11×11 is 11.53. Figure 4b shows the number of segmented pixel in Hsom of 3×3 is 795, 5×5 is 1073, 7×7 is 1285, 9×9 is 1594 and 11×11 is1881. Figure 4c shows the wining neuron for Hsom is 3×3 is 209, 5×5 is 201, 7×7 is 194, 9×9 is 186 and 11×11 is 177.

The above 3×3, 5×5, 7×7, 9×9, 11×11 windows

Table 1. Winning neuron, number of segmented pixel, execution time, weight.

	Winning neuron	No. of seg. pixel	Exe. time	weight
3 × 3	209	795	13.76	14
5 × 5	201	1073	14.96	8
7 × 7	194	1285	15.20	15
9 × 9	186	1594	11.05	23
11 × 11	177	1881	11.53	32

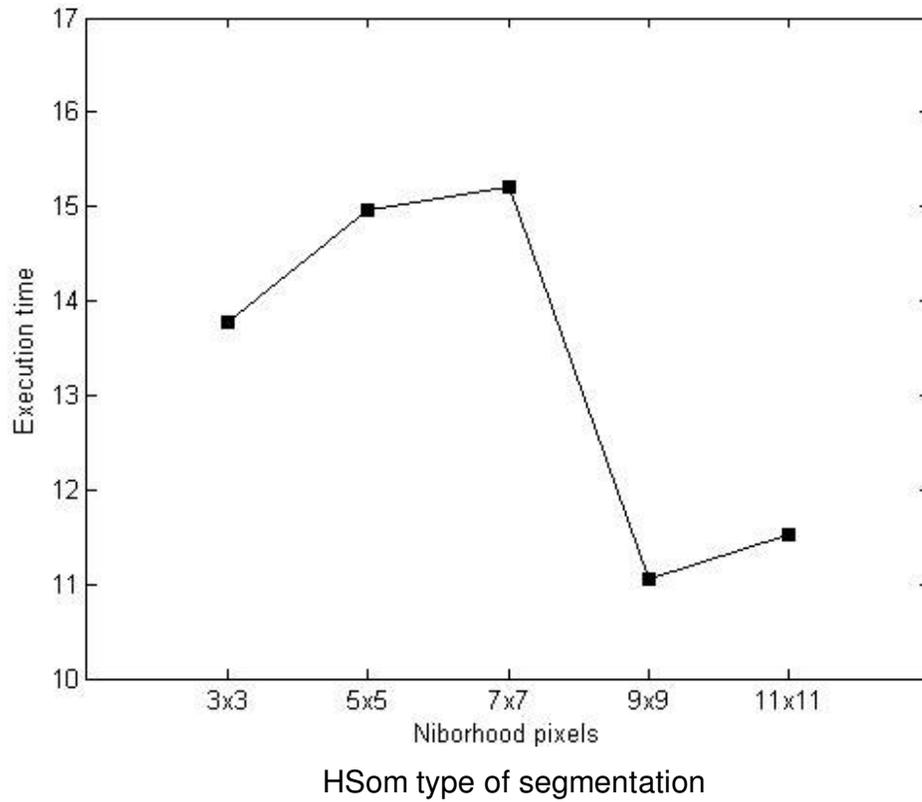**Figure 3.** A input image (256 × 256), Output 3 × 3, Output 5 × 5 Output 7 × 7 Output 9 × 9 Output 11 × 11.

HSom type of segmentation

Figure 4a. Relationship between execution time and neighborhood pixels.

HSom type of segmentation
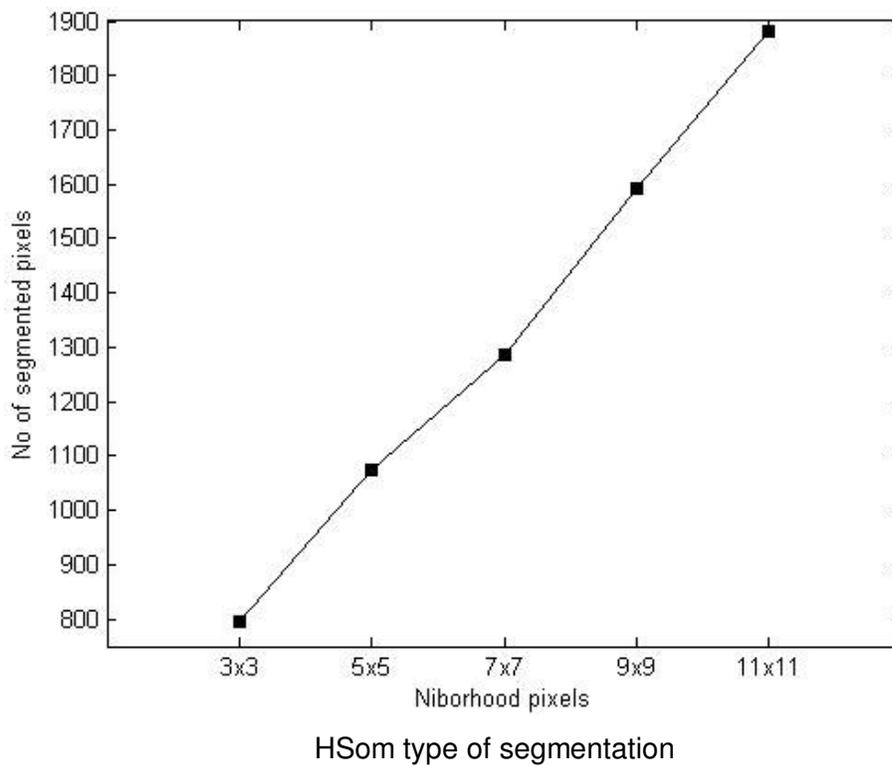
Figure 4b. Relationship between no of segmented pixel and neighborhood pixels.

HSom type of segmentation
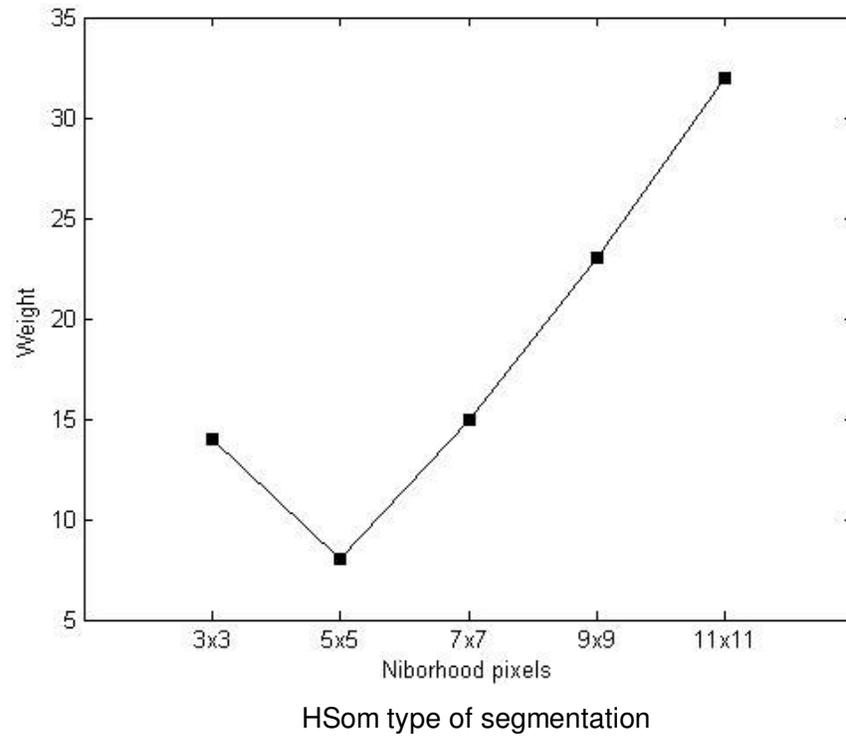
Figure 4c. Relationship between weight and neighborhood pixels.
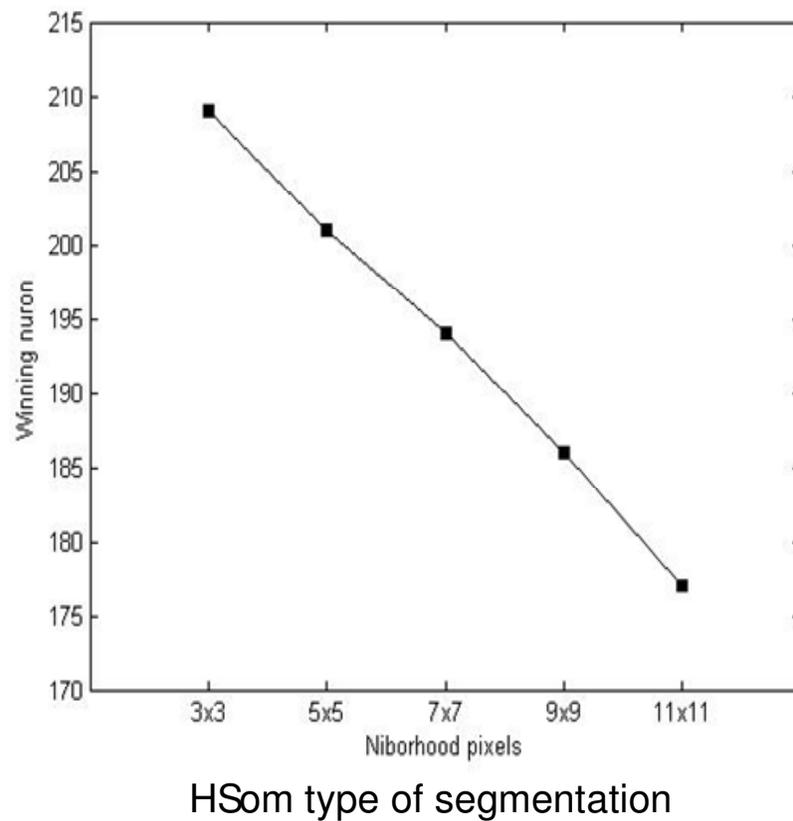

HSom type of segmentation

Figure 4d. Relationship winning neuron and neighborhood pixels.

are analyzed .In that 3 × 3 window is chosen based on the high contrast than 5 × 5, 7 × 7, 9 × 9, and 11 × 11.

Conclusion

Relevance of these techniques is the direct clinical application for segmentation. We studied the performance of the MRI image in terms of weight vector, execution time and tumor pixels detected. We have described several methods in medical image processing and discussed requirements and properties of techniques in brain tumor detection .This paper is used to give more information about brain tumor detection and segmentation. The target area is segmented and the evaluation of this tool from the doctor, whom the project is cooperated with, is positive and this tool helps the doctors in diagnosis, the treatment plan making and state of the tumor monitoring. In future, the system should be improved by adapting more segmentation algorithm to suit the different medical image segmentation.

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