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Optimized Feature Parameter Extraction of Brain Tumor MRI

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Abstract- This study aimed to extract optimized feature parameters for PET-MRI fusion imaging, a state-of-the-art medical imaging technique that has been the focus of much recent research. The medical images obtained from this technique are characterized by high resolution and low exposure dose.

A neural network was trained by inputting extracted feature values. As a result of the experiment, it was found that the R-value of the segmented image is closer to 1 than the original image. The reason is that the images obtained by segmenting the areas of the weighted parts already have similarities. Also, it was found that the similarity between T1 and T2 weighted images is high in the same combination, and the similarity is relatively low in different weighted images. The most important issue in medical imaging is ensuring the confidence of radiologists using artificial intelligence. To solve this problem, it is of utmost importance that the algorithm developer and radiological technologist work together to provide a solution that is integrated with the radiologist's workflow.

Key word: MRI, Image Processing, Discrete Wavelet Transform, Segmentation

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I. Introduction

Noninvasive imaging at the molecular level is an emerging field in biomedical research. PET-MRI fusion image is a new technology synergizing two leading imaging methodologies: positron emission tomography (PET) and magnetic resonance imaging (MRI). Although the value of PET lies in its high-sensitivity tracking of biomarkers in vivo, it lacks

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resolving morphology. MRI has lower sensitivity, but produces high soft-tissue contrast and provides spectroscopic information and functional MRI (fMRI). PET-MRI provides a powerful tool for

studying biology and pathology in preclinical research and has great potential for clinical applications. Combining fMRI and spectroscopy with PET paves the way for a new perspective in molecular imaging.[1] With the increasing use of direct digital imaging systems for medical diagnostics, digital image processing becomes more and more important in health care. In addition to originally digital methods, such as Computed Tomography (CT) or Magnetic Resonance Imaging (MRI), initially analog imaging modalities such as endoscopy or radiography are nowadays equipped with digital sensors. Digital images are composed of individual pixels, to which discrete brightness or color values are assigned. They can be efficiently processed, objectively evaluated, and made available at many places at the same time by means of appropriate communication networks and protocols, such as Picture Archiving and Communication Systems (PACS) and the Digital Imaging and Communications in Medicine (DICOM) protocol, respectively. Based on digital imaging techniques, the entire spectrum of digital image processing is now applicable in medicine.[2] Histogram equalization is widely used for medical image processing because of its simple features and effects. In this paper, we enhance the image by histogram equalization. Brain image segmentation is one of the most important parts of clinical diagnostic tools. Brain images mostly contain noise, inhomogeneity and sometimes deviation. Therefore, accurate segmentation of brain images is a very difficult task. However, the process of accurate segmentation of these images is very important and crucial for a correct diagnosis by clinical tools[3]. Segmented the brain image by setting the appropriate threshold in images with various pixel values[4]. We propose a method of extracting optimal feature values after decomposing a segmented image by DWT. The extracted feature values may be useful for image analysis and treatment planning.

II. Materials and methods

1. Medical image processing by MATLAB

MATLAB is a data analysis and visualization tool that has been designed with powerful support for matrices and matrix operations[5]. As well as this, MATLAB has excellent graphics capabilities and its own powerful programming language. One of the reasons that MATLAB has become such an important tool is through the use of sets of MATLAB programs designed to support a particular task. These sets of programs are called toolboxes, and the particular toolbox of interest to us is the image processing toolbox. In this paper, we used the image toolbox for medical image processing[5]. We shall introduce functions, commands, and techniques as required. A MATLAB function is a keyword that accepts various parameters and produces some sort of output: for example a matrix, a string, a graph or figure[5]. Examples of such functions are sin, imread, imclose. There are many functions in MATLAB, it is very easy to write our own. MATLAB, we can combine functions and commands, or put multiple commands on a single input line. MATLAB's standard data type is the matrix—all data are considered to be matrices of some sort. Images, of course, are matrices whose elements are the grey values of its pixels[6]. It is single values are considered by MATLAB to be 1 X 1matrices, while a string is merely a 1 x n matrix of characters.

2. Image segmentation

In digital image processing, image segmentation is the process of dividing a digital image into segments. The goal of segmentation is to simplify or change the representation of the image to something more meaningful and easier to analyze.[7][8] Image segmentation is commonly used to find objects and boundaries (lines, curves, etc.) in an image. More precisely, image segmentation is the process of assigning a label to every pixel in an image so that pixels with the same label share specific characteristics. The result of the image segmentation is a set of segments that collectively covered with a set of contours extracted from the whole image or the image.[9][10] Each pixel in the area is similar in terms of some characteristics or calculated properties, such as intensity. The adjacent region varies considerably concerning for the same characteristics.[11] The simplest method of image segmentation is called the threshold method. This method converts grayscale images to binary images based on the clip level. The key to this method is to choose a threshold. In this paper, we segmented the image in the following way;

BW= imsegfmm(W,mask,thresh)

BW=imsegfmm(W,mask,thresh) returns a segmented image BW, which is computed using the Fast Marching Method. The array W specifies weights for each pixel. mask is a logical array that specifies seed locations. thresh is a non-negative scalar in the range [0 1] that specifies the threshold level.

3. Discrete Wavelet Transform(DWT)

Wavelet transform was proposed in the mid-1980s, and it has been used in various fields such as signal processing, image processing, computer vision, image compression, biochemistry medicine, etc.[12] For image processing, it provides an extremely flexible multi-resolution image and can decompose an original image into different subband images including low- and high-frequencies. Therefore people can choose the specific resolution data or subband images upon their demands.[13] A 2-D DWT of an image is illustrated in Figure 3(a). When the original image is decomposed into four-subband images, it has to deal with row and column directions separately. First, the high-pass filter G and the low-pass filter H are exploited for each row data, and then are down-sampled by 2 to get high- and low-frequency components of the row. Next, the high- and the low-pass filters are applied again for each high- and low-frequency components of the column, and then are down-sampled by 2.[14] By way of the above processing, the four-subband images are generated: HH, HL, LH, and LL. Each subband image has its feature, such as the low-frequency information is preserved in the LL-band and the high-frequency information is almost preserved in the HH-, HL-, and LH-bands. The LL-subband image can be further decomposed in the same way for the second level subband image.[15] By using 2-D DWT, an image can be decomposed into any level of subband images, as shown in Figure 3(b).

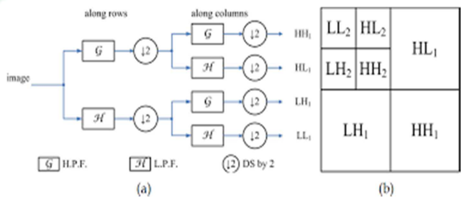

Figure 1. Diagrams of DWT image decomposition: (a) the 1-L 2-D analysis DWT image decomposition process, (b) the 2-L 2-D analysis DWT subband.[11]

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4. Neural Networks

Artificial intelligence (AI) has led to many medical advancements, from AI-based software for the management of medical records to diagnosing and recognizing conditions.[16] Most of the new work on artificial intelligence in the medical field is related to diagnostic technology, and AI systems are trained to recognize the characteristics of various conditions.[17][18] Through 'machine learning' (ML), AI provides techniques that uncover complex associations that cannot easily be reduced to an equation.[19] For example, neural networks represent data through vast numbers of interconnected neurons in a similar fashion to the human brain. This allows ML systems to approach complex problem solving just as a clinician might by carefully weighing evidence to reach reasoned conclusions.[20] However, unlike a single clinician, these systems can simultaneously observe and rapidly process an almost limitless number of inputs. Furthermore, these systems can learn from each incremental case and can be exposed, within minutes, to more cases than a clinician could see in many lifetimes. Artificial intelligence complements the vast number of digital images created in hospitals, the products of next-generation imaging scanners, especially hybrids that include MRI, CT, PET, and SPECT. In recent years, machine learning algorithms are rapidly being used in medical image analysis.[21][22] These machine learning techniques are used to extract compact information to improve the performance of medical image analysis. Recently, deep learning methods using deep convolutional neural networks have been applied to medical image analysis to provide promising results.[21][22] The neural network model is shown in Figure 2 below.

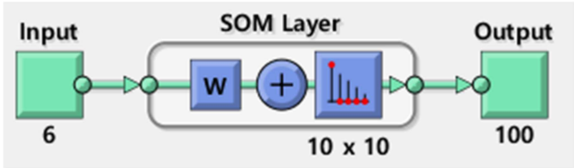


Figure 2. A neural network model

Applications cover the full spectrum of medical image analysis, including detection, segmentation, classification, and computer-assisted diagnostics.[23] As a result, if artificial intelligence and healthcare professionals interact to accommodate deep thinking platforms, such as automation, in diagnosing a patient's disease state, artificial intelligence will play an important role in the analysis of medical image data, which will only be feasible.[24][25]

I. Experiments and results

Digital image processing is the use of computer algorithms to perform image processing on digital images. As a subfield of digital signal processing, digital image processing has many advantages over analog image processing. It allows a much wider range of algorithms to be applied to the input data. The aim of digital image processing is to improve the image data by suppressing unwanted distortions and enhancement of some important image features so that our AI-Computer Vision models can benefit from this improved data to work on. For the experiment, we acquired brain tumor MRI from The Cancer Imaging Archive site. The image was preprocessed to 256 x 256 pixels for segmentation and stored in a bitmap format. The stored images were segmented with 127 ~ 200 as the threshold. Six parameters per image were extracted from the segmented image using DWT. We learned neural networks by inputting extracted parameters into the neural networks. Figure 5 is a flow chart showing the whole process of the experiment.

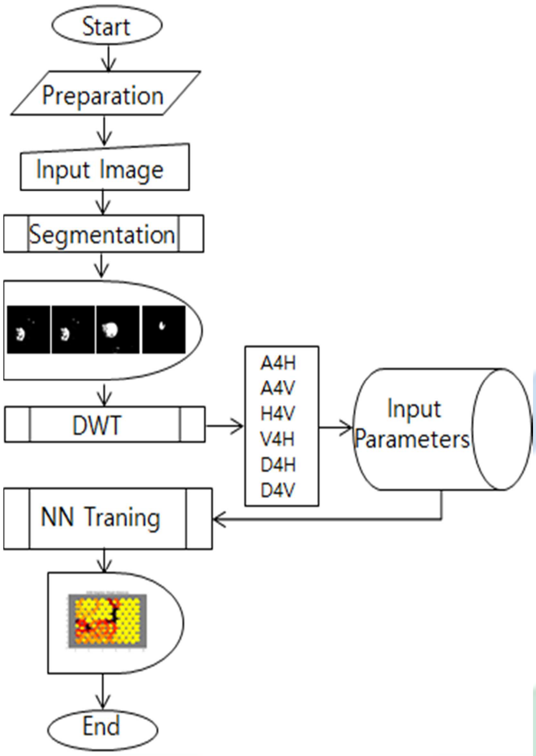
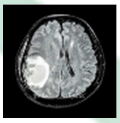
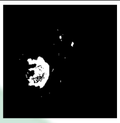
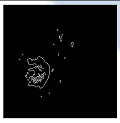
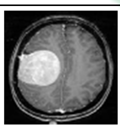
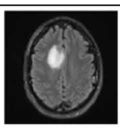
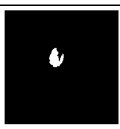
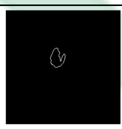
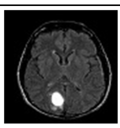
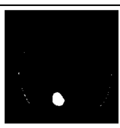
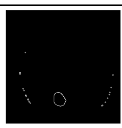


Figure 2. Experiment Flowchart

Table 1. Image segment and edge

	Original	Segment	Edge
Image1			
Image2			
Image3			
Image4			

1. Segmentation by MATLAB Program

In medical image segmentation, thresholding is a simple, yet effective, way of partitioning an image into a lesion and other regions. This image analysis technique is a type of image segmentation that isolates objects by converting grayscale images into binary images. In this study, we segmented four brain tumor MRI images (images 1 to 4). The segmented results are shown in Table 1.

2. Feature Extraction by DWT

We performed a program using MATLAB Tool Box to extract brain tumor MRI features. The six parameters for feature extraction are horizontal low frequency (A4H), vertical low frequency (A4V), horizontal high frequency (H4V), vertical high frequency (V4H), horizontal diagonal high frequency (D4H), and vertical diagonal high frequency (D4V). A total of 96 features were extracted by extracting 16 feature values for each parameter. Table 2 shows the meanings and abbreviations of the feature parameters of the coefficient matrix.

Table 2. Feature parameters of the coefficient matrix.

Abbreviation	Feature extraction parameter
A4H	Horizontal low frequency
A4V	Vertical low frequency
H4V	Horizontal high frequency
V4H	Vertical high frequency
D4H	Diagonal High frequency (horizontal)
D4V	Diagonal High frequency (vertical)

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Tables 3 to 10 show the segmented parameter display and the characteristic values of the original image and the segmented image as graphs. It was confirmed that the slope change of the graph was large in the feature value of the segmented image. The reason for this is that the part corresponding to the background part of the image is removed during the segmentation process and the part with the lesions has a high frequency.

Table 3. Feature extraction value of MRI_Brain_Tumor1_Seg.pgm image

A4H	-0.5	-0.5	-0.5	-0.5	-0.5	-0.5	-0.4	-0.26	-0.4	-0.3	-0.33	0.43	0.5	-0.49	-0.45	-0.09
A4V	-0.5	-0.5	-0.5	-0.5	-0.5	-0.5	-0.5	-0.5	-0.48	-0.5	-0.5	-0.47	-0.39	-0.5	-0.46	0.5
H4V	-0.5	-0.5	-0.5	-0.5	-0.5	-0.5	-0.5	-0.48	-0.39	-0.5	-0.48	-0.45	-0.31	-0.5	-0.42	0.5
V4H	-0.5	-0.5	-0.5	-0.5	-0.5	-0.5	-0.47	-0.46	-0.39	-0.3	-0.39	0.12	0.5	-0.49	-0.49	-0.4
D4H	-0.5	-0.5	-0.5	-0.5	-0.5	-0.4	-0.24	-0.37	0.5	-0.3	-0.04	-0.03	0.37	-0.49	-0.35	-0.18
D4V	-0.5	-0.5	-0.5	-0.5	-0.5	-0.5	-0.5	-0.47	-0.49	-0.5	-0.5	-0.43	-0.48	-0.5	-0.37	0.5

Table 4. Feature Extraction in brain MRI tumor1 image.

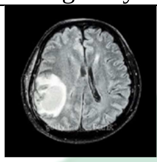
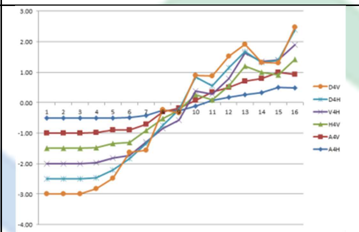
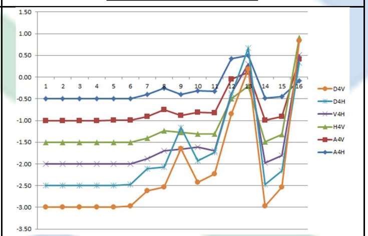
	Originally	Segmentation
Exam. Image		
Feature Extract.		

Table 5. Feature extraction value of MRI_Brain_Tumor2_Seg.pgm image

A4H	-0.5	-0.5	-0.5	-0.5	-0.50	-0.4	-0.2	-0.05	-0.02	0.27	0.43	0.48	0.50	0.50	0.48	0.3
A4V	-0.5	-0.5	-0.5	-0.5	-0.50	-0.5	-0.5	-0.50	-0.50	-0.50	-0.50	-0.50	-0.47	0.08	0.48	0.5
H4V	-0.5	-0.5	-0.5	-0.5	-0.50	-0.5	-0.5	-0.50	-0.50	-0.50	-0.50	-0.49	-0.42	-0.09	-0.09	0.5
V4H	-0.5	-0.5	-0.5	-0.5	-0.49	-0.4	0.01	0.11	-0.01	0.50	-0.16	-0.26	-0.16	-0.15	-0.39	0.3
D4H	-0.5	-0.5	-0.5	-0.5	-0.44	0.3	0.5	0.23	0.16	0.20	-0.39	-0.40	-0.49	-0.44	0.14	0.3
D4V	-0.5	-0.5	-0.5	-0.5	-0.50	-0.5	-0.5	-0.50	-0.50	-0.50	-0.50	-0.48	-0.06	0.50	-0.36	-0.3

Table 6. Feature Extraction in brain MRI tumor2 image.

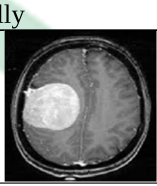
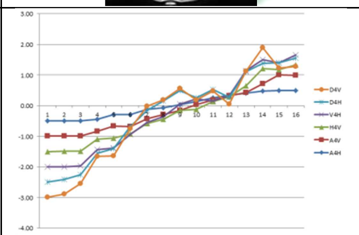
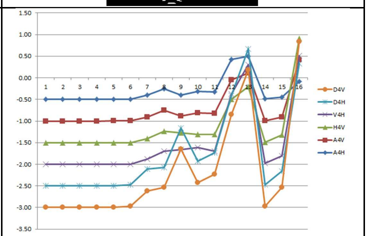
	Originally	Segmentation
Exam. Image		
Feature Extract.		

Table 7. Feature extraction value of MRI_Brain_Tumor3_Seg.pgm image

A4H	-0.5	-0.5	-0.5	-0.5	-0.5	-0.5	-0.5	-0.5	-0.5	-0.5	-0.5	-0.5	-0.5	-0.45	-0.04	0.5
A4V	-0.5	-0.5	-0.5	-0.5	-0.5	-0.5	-0.5	-0.5	-0.5	-0.5	-0.5	-0.46	-0.12	0.21	0.5	0.5
H4V	-0.5	-0.5	-0.5	-0.5	-0.5	-0.5	-0.5	-0.5	-0.5	-0.5	-0.49	-0.47	-0.09	0.5	0.3	-0.05
V4H	-0.5	-0.5	-0.5	-0.5	-0.5	-0.5	-0.5	-0.5	-0.5	-0.5	-0.5	-0.5	-0.48	-0.36	0.27	0.5
D4H	-0.5	-0.5	-0.5	-0.5	-0.5	-0.5	-0.5	-0.5	-0.5	-0.5	-0.5	-0.5	-0.42	0.5	0.15	0.01
D4V	-0.5	-0.5	-0.5	-0.5	-0.5	-0.5	-0.5	-0.5	-0.5	-0.5	-0.43	-0.05	0.47	0.33	0.5	0.11

Table 8. Feature Extraction in brain MRI tumor3 image.

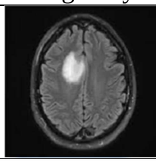
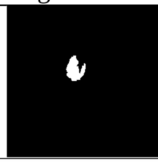
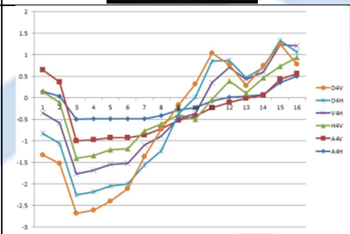
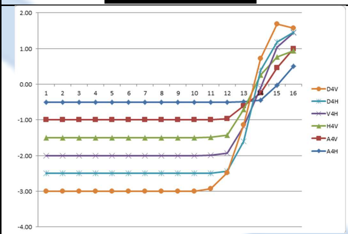
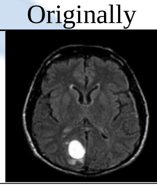
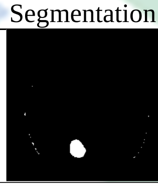
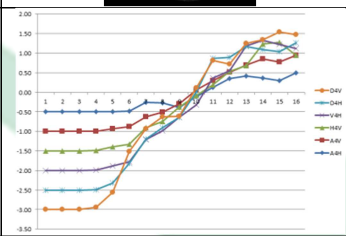
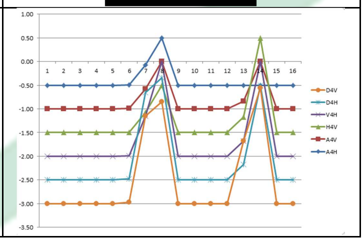
	Originally	Segmentation
Exam. Image		
Feature Extract.		

Table 9. Feature extraction value of MRI_Brain_Tumor4_Seg.pgm image

A4H	-0.5	-0.5	-0.5	-0.5	-0.5	-0.49	-0.08	0.5	-0.5	-0.5	-0.5	-0.5	-0.5	-0.5	-0.5	-0.5
A4V	-0.5	-0.5	-0.5	-0.5	-0.5	-0.5	-0.5	-0.5	-0.5	-0.5	-0.5	-0.5	-0.34	0.5	-0.5	-0.5
H4V	-0.5	-0.5	-0.5	-0.5	-0.5	-0.5	-0.5	-0.5	-0.5	-0.5	-0.5	-0.5	-0.34	0.5	-0.5	-0.5
V4H	-0.5	-0.5	-0.5	-0.5	-0.5	-0.49	-0.08	0.5	-0.5	-0.5	-0.5	-0.5	-0.5	-0.5	-0.5	-0.5
D4H	-0.5	-0.5	-0.5	-0.5	-0.5	-0.49	0.5	-0.35	-0.5	-0.5	-0.5	-0.5	-0.5	-0.5	-0.5	-0.5
D4V	-0.5	-0.5	-0.5	-0.5	-0.5	-0.5	-0.5	-0.5	-0.5	-0.5	-0.5	-0.5	0.5	-0.06	-0.5	-0.5

Table 10. Feature Extraction in brain MRI tumor4 image.

	Originally	Segmentation
Exam. Image		
Feature Extract.		

3. Self-organizing map using NN

A self-organizing map (SOM) consists of a competitive layer that can classify a dataset of vectors with any number of dimensions into as many classes as the layer has neurons. The neurons are arranged in a 2D topology, which allows the layer to form a representation of the distribution and a two-dimensional approximation of the topology of the dataset. Self-organizing maps learn to cluster data based on similarity, topology, with a preference of assigning the same number of instances to each class. Self-organizing maps are used both to cluster data and to reduce the dimensionality of data. Tables 11 to 14 show original and segmented images of self-organizing maps of four brain tumor MRIs, respectively. The self-organizing maps in each table represent Neighbor Weight Distances, Neural Networks Training self-organizing map Input Planes, and Neural Networks Training self-organizing map Sample Hits.

Table 11. Self-organizing map of brain MRI tumor1 image

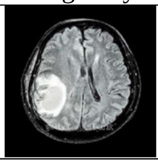
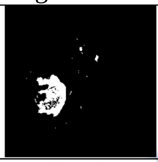
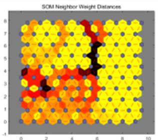
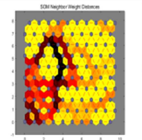
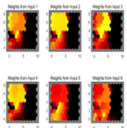
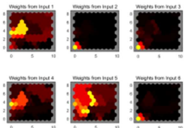
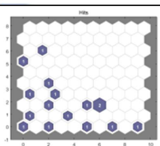
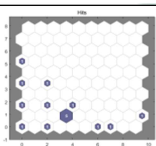
	Originally	Segmentation
Exam. Image		
SOM Neighbor Weight Distances		
NN Training SOM Input Planes		
NN Training SOM Sample Hits		

Table 12. Self-organizing map of brain MRI tumor2 image

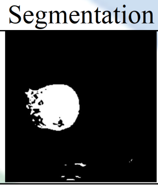
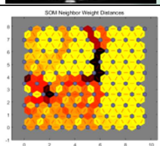
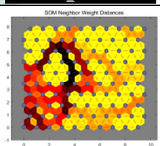
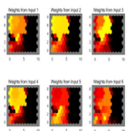
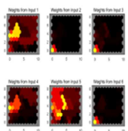
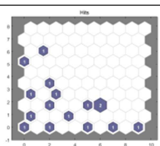
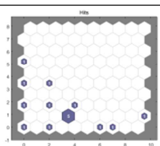
	Originally	Segmentation
Exam. Image		
SOM Neighbor Weight Distances		
NN Training SOM Input Planes		
NN Training SOM Sample Hits		

Table 13. Self-organizing map of brain MRI tumor3 image

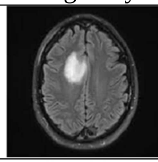
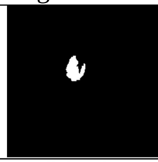
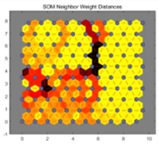
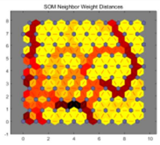
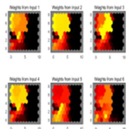
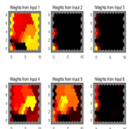
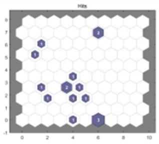
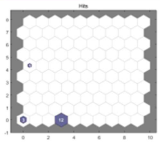
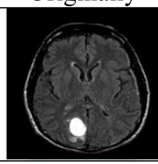
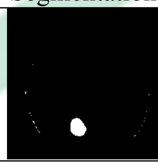
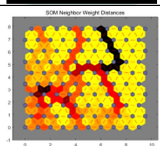
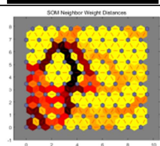
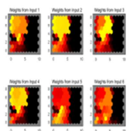
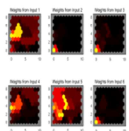
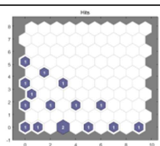
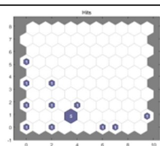
	Originally	Segmentation
Exam. Image		
SOM Neighbor Weight Distances		
NN Training SOM Input Planes		
NN Training SOM Sample Hits		

Table 14. Self-organizing map of brain MRI tumor4 image

	Originally	Segmentation
Exam. Image		
SOM Neighbor Weight Distances		
NN Training SOM Input Planes		
NN Training SOM Sample Hits		

IV. Conclusion

In this study, we proposed a method of segmenting tumor lesions and extracting optimal feature parameters from brain tumor MRI. To this end, brain tumor images were segmented and edge was detected at the segment. The detected edge becomes the exact region of interest of the brain tumor lesion. The segmentation image was decomposed by DWT and 96 features were extracted with 6 variables. To evaluate the extracted feature values, we compared the extracted feature values with the values of the original image. As a result of the comparison, the patterns of change were similar, and the extracted feature values were found to be largely changed at a specific portion. Also, the neural network identified the self-organizing map(SOM) Neighbor Weight Distances, Neural Networks Training self-organizing map(SOM) Input Planes, and Neural Networks Training self-organizing map(SOM) Sample Hits. As a result, the deviation of the pixel neighbor values in the segmented image was large. Perhaps, the reason is that it contains feature values. If the feature extraction method proposed in this study is used, it will be able to be used for disease recognition by AI and automatic diagnosis of medical images.

Conflict of Interest

The author(s) declare(s) that there is no conflict of interest regarding the publication of this article.

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