Second International Conference on Nexgen Technologies
Sengunthar Engineering College, Tiruchengode, Namakkal Dist. Tamilnadu (India)
8th - 9th March 2019 www.conferenceworld.in ISBN : 978-93-87793-75-0

Comparative analysis of Neural Network training in medical image segmentaton

Bijal Talati[1], Nimit Shah[2]

[1]*Computer Engineering Department, S.VI.T, Vasad,Gujarat (India)*

[2]*Electrical Engineering Department, C.U. Shah University, Wadhwan,Gujarat (India)*

ABSTRACT

The present medical scenario though it is very trustworthy and reliable because of the latest medical imaging modalities like MRI and CT and so forth, manual segmentation is prominently used for early malignancy detection, which is time-consuming. So there is a need for an automated method which will provide better insight to a medical expert. The present research based on the automated segmentation to detect malignancy from three dimensional medical images using artificial neural network (ANN). The advantage of ANN over traditional segmentation is reliability, robustness and deal with partial truth. The comparison of, unsupervised trained neural network and supervised training neural network has been shown. The result concludes the performance of supervised training neural network on medical images with having acquisition artifacts is above 0.80 without preprocessing

Keywords: Artifical neural network, dice coefficient, jaccard index

I. INTRODUCTION

With increasing use of medical imaging modalities like Computed tomography (CT), and Magnetic resonance images (MRI) for clinical studies, diagnosis and treatment planning, it has become compulsory to use computers to assist radiologist in clinical diagnosis and treatment plans. In medical imaging, to delineate the structure or tissue from medical images, segmentation is the primary step. Manual segmentation is usually accurate but is impractical for large dataset because it is tedious and time consuming. Due to the huge data available from medical modalities, fast, accurate and reliable automated process is requiring to accelerate clinical diagnosis.

Medical image generation is through the image acquisition process. During the acquisition process, environmental effect, illumination problem, sensor problems affect the quality of medical images. It has been found that medical images often suffer from low contrast, poor signal to noise ratio. This is technically known as artifacts found in medical images based on the medical imaging modalities like intensity inhomogeneity, partial volume effect or it can be motion or ring artifacts. In magnetic resonance imaging (MRI), in-homogeneity in the magnetic field usually gives rise to non-uniform intensity artifact. These artifacts slowly

varying the change in magnetic pixel values and could have adverse effect on the performance of intensity based automatic segmentation methods.

Image segmentation remains a difficult problem due to lack of a general mathematical model. Selection of one method over another exclusively depends on the type of the images. There is no universal method that can be successfully applied to all types of images. The selection of right segmentation method is a very difficult process. In general, the segmentation method can be placed into four classes like thresholding based approach, region growing, clustering and neural network approaches.

Segmentation techniques like thresholding, clustering and region based are the simplest and having limited applications. They are giving imprecision and inaccurate results in medical images due to the presence of medical acquisition artifacts. To overcome with the former issue, neural network based approach is suitable. Artificial neural networks (ANN) are well known for their good performance in classification, function approximation, image enhancement, segmentation, registration, feature extraction, and recognition.

In this paper, we describe the neural network supervised and unsupervised training based approach in medical image segmentation. Section 2 describes the supervised and unsupervised neural network technique; section 3 brief about the feed forward neural network; section 4 describe the performance parameters which are used in comparison of segmentation methods of neural network. Section V shows the result and implementation of the neural network and section 6 concludes the work.

II. ARTIFICIAL NEURAL NETWORK

An artificial neural network is a simulation of a real nervous system. It consists in a number of neurons that communicate with each other. This artificial computational model of a real nervous system was proposed in 1943 by McCulloch and ANN for specific application is network structure and network generalization. The suitable architecture for specific application involves: 1. choosing a suitable network type for application, 2. No. of layers, 3. No. of nodes in hidden layers and 4. Activation functions between layers. Network Generalization means how much the neural network is able to work with different data. Designers of ANN are always faced by the extend of network generalization, i.e. despite a well designing and training of ANN that decreases the performance error to the least value; ANN fails when fed with a new input data and gives worst performance. This paper will not attempt to describe ANNs in detail. More details about Neural Networks are presented in [1],[2],[3] or in the referenced papers.

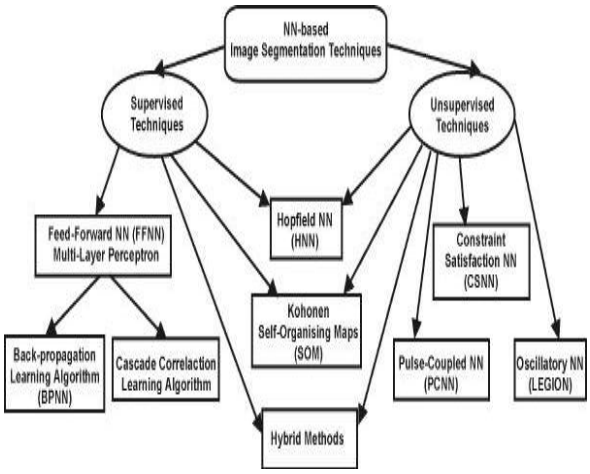

Figure 1: NN-based segmentation technique

The NN based image segmentation techniques reported in the literature can mainly be divided into two categories: supervised and unsupervised method as shown in fig. 1.

2.1 Supervised technique

In supervised technique, the expert or human uses their knowledge to select training data set and also does manual segmentation into k regions and assign label to it. The proposed architecture is trained using the selected images as training data. After the training, the similar images segment and labeled according to the knowledge stored in the neural network architecture.

2.2 Unsupervised technique

This method is automatically segmenting the image into k sub-regions and then automatically assigns labels to those regions.

III. MEDICAL IMAGE SEGMENTATION USING FEED-FORWARD NETWORK

3.1 Self Organizing Map (SOM)

This type of network is also known as Kohonen neural network. It is also known as Kohenen map. It is quite different from the above network types. SOMs can be used for dimensionality reduction. It consist of a two dimensional array of nodes and each node is associated with a weight and position within the map. This network is used unsupervised learning technique. During the iterative learning process, it finds the weight vector of each node. During iterative process, the most similar node also called as best matching unit (BMU) is found by a Euclidian distance similarity measure. A training process considers the neighboring nodes of best matching unit and update their corresponding weight vector as shown in (1).

$$w_i(t+1) = w_i(t) + \propto(t) h_{ci}(t)(x(t) - w_i(t)) \qquad (1)$$

Where $h_{ci}(t)$ the neighborhood function is typically considered as a Gaussian function, $\propto(t)$ is a monotonically decreasing learning coefficient. This process repeats for the large iterations. It preserves the most important topological and metric relationship of the primary datasets.

SOMs can be used for dimensionality reduction, it maintain the topology of the input data and making them useful for visualization problems. This type of network is also very useful in medical imaging applications such as edge detection and segmentation.

3.2 Multi Layer Perceptron Neural Network

A Multilayer Perceptron (MLP) artificial neural network is a special type of feed-forward network used in medical imaging applications. It is appropriate for medical imaging due to the following reasons: 1) it employs three or more layers, with nonlinear transfer functions in the hidden layer neurons. 2) They are able to associate training patterns with outputs for nonlinearly separable data. Feed-forward networks are particularly suitable for applications including feature extraction, optimization, compression and classification.

In case of MLP-ANN, the generalization of the network is possible by dividing the available data into training, testing and validation. The error rate is controlled for the validation data. The proper configuration of the network should be established by choosing proper numbers of hidden layers and neurons.

MLP-ANN is used in various applications such as feature extraction, classification, optimization, function approximation and compression. It is also used in medical imaging applications.

3.3 Hybrid Neural Network approach

In this approach, the combination of thresholding and clustering approach with neural network has been explored. In this paper, from thresholding the popular thresholding technique OTSU is combined with neural network. The segmentation result of Kmean clustering technique also combined with neural network and compare the performance with measures like dice coefficient and Jaccard index after insertion of image acquisition artifacts like Gaussian noise and speckle noise which generally present in real medical images. The basic working of Otsu thresholding and Kmean clustering is mentioned below:

3.3.1 Otsu

Otsu thresholding selects the threshold value to minimize the intra class variance of the black and white pixels. By plotting the grey level histogram, we can analyze the distribution of grey level values of an image by choosing the appropriate threshold value θ. We assume that the grey value histogram contains two peaks as foreground and background pixels/voxels. The objective is to select the minimum value between these two peaks known as threshold θ. Otsu defines this choice for θ as the value minimizing the weighted sum of within-class variances [Ots79]. This is equivalent to maximizing the between-class scatter. For an image taking on discrete voxel values k, the optimal threshold value θ is shown in (2):

$$\theta_{\text{Otsu}} = \text{argmax}_{\theta}\left\{\sum_{k<\theta} p(k)\,(\mu_0-\mu)^2 + \sum_{k\geq\theta} p(k)\,(\mu_1-\mu)^2\right\} \quad (2)$$

Where,

p is the normalized histogram

μ:= Mean {f(x)}

μ1:= Mean {f(x) | f(x) >= θ }

μ0:= Mean {f(x) | f(x) < θ }

3.3.2 K-mean clustering

K-Means clustering is a type of hard clustering algorithm. It belongs to an unsupervised cluster analysis algorithm and achieves a partitioned clustering method. It is a key technique in pixel-based methods. By using pixel-based K-means clustering, the approach is simple and also the computational complexity is relatively low compared with other segmentation methods like region-based or edge-based Algorithm with the mathematical equation is described as follows[5]:

1. Initialization of no. of clusters with value as k.
2. Select k cluster center randomly
3. Compute mean M or center of the cluster by eq(3)

$$M = \frac{\sum_{i.c(i)=k} x_i}{N_k} k = 1,2,\ldots\ldots, k \qquad (3)$$

4. Calculate the distance between each pixel to each cluster center

$$D(i) = \operatorname{argmin} \|x_i - M_k\|^2, i=1,2,..k\ 1,2..N \qquad (4)$$

5. If the distance is close to the center, then move to that cluster else move to another cluster.
6. Calculate or Re-estimate the center.
7. Repeat the steps until the center doesn't move.

IV. PERFORMANCE PARAMETER

In the analysis of medical images, it is often essential that objects/organs/structure can be segmented or distinguished from the background for proper diagnosis and treatment planning. No universally applicable segmentation technique will work for all type of medical images and all organs, and not all segmentation techniques are perfect. To see the effectiveness of the segmentation techniques, evaluation parameter like dice co-efficient and Jaccard co-efficient generally used [5].

4.1 Dice Co-efficient

To evaluate the performance of medical image segmentation algorithm, the most popular similarity measure is Dice co-efficient. The segmented result is compare with predefined ground truth information. It is calculated using the (5),

$$DC = \frac{2|M \cap N|}{|M| + |N|} \qquad (5)$$

Here, 'M' is the non-zero pixel element in ground truth image and 'N' is non-zero pixel element is the segmented image.

4.2 Jaccard Co-efficient

To calculate the similarity between the two set of image, Jaccard Co-efficient is used. It also measures the variation or this similarity between two images. It is calculated using the (6),

$$JC = \frac{|M \cap N|}{|M \cup N|} \qquad (6)$$

Where 'M' is the non-zero pixel element in ground truth image and 'N' is the non-zero pixel element is a segmented image.

V. IMPLEMENTATION AND RESULT

In medical imaging modalities such as CT, MRI and PET, no. of images vary as per the required thickness. This is further suplemented by the Expert's advice. In this research, the Sheep Logan Phantom dataset with three-dimensional data of size 128 X 128 is considered for the experiment. Artifacts in medical slices are added using Gaussian noise and Speckle noise to present a realistic medical image that consists of multiple noises due to sensors' noise and the intensity inhomogeneity. Moreover, to generate a real medical dataset, tumor (malignant tissue) in the phantom dataset is inserted randomly[6].

After successfully generation of medical images, neural network train with Gaussian noise having different mean and variance value. In this experiment, the researcher train with M=0.1, V=0.01, M=0.1,V=0.07 and speckle noise with parameter = 10. The performance of ANN in supervised and unsupervised training is compare with Dice co-efficient (DC) and Jaccard Co-efficient (JC).

The implementation of ANN is done in Matlab R2015b. The hardware configuration is i3-core processor (2.40 GHz), 4GB RAM, 64 bit Operating system. By using neural network toolbox, the following network parameter has been set: Training function: trainscg(scaled conjugate gradient), no. of epoch = 500 and performance is mean square error.

In neural network, Self Organizing Map (SOM) is unsupervised training network while Multiperceptron is supervised training network, so researcher trained neural network with various types of noise to insert the medical artifacts like Gaussian noise, speckle noise and salt and pepper noise with various types of noise parameter. The result of training with noise and its parameter is shown in Table 1,2,3,4,5,6 with red color and other results are testing on various types of noise parameter.

Table 1.Gaussian noise VS Dice-coefficient (DC)

Noise parameter		SOM	FF	ANN+ OTSU	ANN+ Kmean
M	V	DC	DC	DC	DC
0	0.01	0.83	0.95	0.91	0.92
	0.02	0.21	0.93	0.92	0.92
	0.03	0.31	0.94	0.88	0.90
	0.04	0.20	0.94	0.88	0.91
0.1	0.01	0.14	0.88	0.78	0.84
	0.02	0.14	0.84	0.75	0.91
	0.03	0.13	0.82	0.76	0.88
	0.04	0.18	0.83	0.82	0.90
0.2	0.01	0.12	0.87	0.55	0.89
	0.02	0.19	0.83	0.68	0.86
	0.03	0.16	0.86	0.63	0.85
	0.04	0.12	0.80	0.50	0.80

 ISBN : 978-93-87793-75-0

Table 2. Gaussian noise VS. Jaccard co-efficient

Noise parameter		SOM	FF	ANN+	ANN+
M	V	JC	JC	JC	JC
0	0.01	0.72	0.91	0.84	0.85
	0.02	0.12	0.88	0.86	0.86
	0.03	0.18	0.89	0.78	0.86
	0.04	0.11	0.86	0.78	0.85
0.1	0.01	0.07	0.82	0.64	0.74
	0.02	0.07	0.80	0.60	0.85
	0.03	0.07	0.81	0.62	0.82
	0.04	0.09	0.82	0.71	0.80
0.2	0.01	0.07	0.90	0.55	0.89
	0.02	0.11	0.81	0.68	0.86
	0.03	0.09	0.80	0.63	0.85
	0.04	0.07	0.82	0.50	0.80

Table 3. Salt and pepper noise Vs Dice-coefficient

Noise parameter	SOM	FF	ANN+	ANN+
	DC	DC	DC	DC
0.1	1	0.96	0.95	0.88
0.2	1	0.98	0.91	0.60
0.5	1	0.97	0.89	0.41
1	1	0.90	0.90	0.77

Table 4. Salt and pepper noise Vs Jaccard co-efficient

Noise parameter	SOM	FF	ANN+	ANN+
	JC	JC	JC	JC
0.1	1	0.94	0.91	0.80
0.2	1	0.95	0.91	0.43
0.5	1	0.94	0.78	0.28
1	1	0.90	0.83	0.53

Table 5. Speckle noise Vs Dice co-efficient

Noise parameter	SOM	FF	ANN+	ANN+
	DC	DC	DC	DC
5	1	0.96	0.94	0.68
10	1	0.96	0.76	0.34
15	1	0.93	0.94	0.68
25	1	0.96	0.93	0.62
35	1	0.96	0.82	0.76
40	1	0.95	0.82	0.75
50	1	0.95	0.83	0.76

Table 6. Speckle noise Vs Jaccard co-efficient

Noise parameter	SOM	FF	ANN+	ANN+
	DC	DC	DC	DC
5	0.99	0.92	0.90	0.52
10	1	0.92	0.91	0.21
15	1	0.93	0.90	0.52
25	1	0.91	0.87	0.45
35	1	0.92	0.90	0.76
40	1	0.92	0.88	0.68
50	1	0.93	0.89	0.70

VI. CONCLUSION

The implemented result depicts that the unsupervised training neural network (self organizing map) has no effect of salt and pepper noise and speckle noise but the performance degrades in Gaussian noise. In case of hybrid neural network where the researcher combined the individual techniques like Otsu thresholding as well as Kmean clustering technique with neural network, performance varies with different types of noise. In medical images, algorithm must be robust in all types of noise. The result of Multiperceptron concludes that in Gaussian noise, salt and pepper noise and speckle noise, dice coefficient and jaccard –coefficient is almost above 0.80.

In multiperceptron , the result totally depends on the training of dataset and its bias value. We can improve the result by using genetic algorithm or particle swarm optimization too.

REFERENCES

[1] Hebb, Donald Olding. "The organization of behavior; a neuropsycholocigal theory." A Wiley Book in Clinical Psychology. (1949): 62-78.

[2] Marvin Minsky and Seymour Papert, 1972 (2nd edition with corrections, first edition 1969) Perceptrons: An Introduction to Computational Geometry, The MIT Press, Cambridge MA, ISBN 0-262-63022-2

[3] Hopfield, John J. "Neural networks and physical systems with emergent collective computational abilities." Proceedings of the national academy of sciences 79.8 (1982): 2554-2558.

[4] Rumelhart, David E., Geoffrey E. Hinton, and Ronald J. Williams. Learning internal representations by error propagation. No. ICS-8506. California Univ San Diego La Jolla Inst for Cognitive Science, 1985.

[5] Zou, Yanni, and Bo Liu. "Survey on clustering-based image segmentation techniques." Computer Supported Cooperative Work in Design (CSCWD), 2016 IEEE 20th International Conference on. IEEE, 2016.

[6] Gach, H. Michael, Costin Tanase, and Fernando Boada. "2D & 3D Sheep- Logan phantom standards for MRI." Systems Engineering, 2008. ICSENG'08. 19th International Conference on. IEEE, 2008.

[7] S. Haykin and N. Network, "A comprehensive foundation," Neural Networks, vol. 2, no. 2004, 2004