Elasticity Detection of IMT of Common Carotid Artery

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Abstract - *This paper presents the prediction of the amount of elasticity of a given artery for different aged person to obtain absolute accuracy in detection and determination of the boundary of ultrasonic carotid artery and Intima-Media thickness. To satisfy the requirements the most popular training algorithm, the back-propagation based generalized delta rule(GDR) is developed. This procedure may simplify the job of the practitioner for analyzing accuracy and variability of segmentation results. Possible plaque regions are also highlighted. A thorough evaluation of the method in the clinical environment shows that inter observer variability is evidently decreased and so is the overall analysis time. The results demonstrate that it has the potential to perform qualitatively better than applying existing methods in intima and adventitial layer detection on B-mode images.*

Keywords - *Artery, boundary detection, intima media thickness, Ultrasonic, parallel programming.*

1. INTRODUCTION

A new fuzzy level set algorithm has been proposed for automated medical image segmentation. It utilizes fuzzy clustering as the initial level set function. The enhanced FCM algorithms with spatial information can approximate the boundaries of interest well[1]. Multilayer Back Propagation Network(MBPN) system has been developed for categorizing the carotid artery subjects. The obtained results show that MBPN system provides higher classification efficiency with minimum training and testing time[2]. Segmentation of images obtained from magnetic resonance imaging(MRI) is an important step in visualization of soft tissues in human body. The new emerging application Hopfield neural network promises to provide unique solution for the pattern classification of medical images[3]. ANFCIS(Adaptive neuro-fuzzy color image segmentation) consists of multilayer perception(MLP) like network which performs color image segmentation using multilevel thresholding. Threshold values for detecting clusters and their labels are found automatically using fuzzy C-means(FCM) clustering technique [4] [6]. After getting the idea about

segmentation and ultrasound images, the proposed system discussed different techniques and papers on the basis of particular clinical application as well as on the basis of methods used to segment out the

ultrasound images[5] Main image segmentation algorithms are classified and reviewed, then evaluation and comparison of image segmentation algorithms are discussed in depth based on the reason that evaluation of image segmentation is essential in the aspect of comparing the segmentation algorithms and providing advice for improvement[7][8][10].Four different snakes segmentation methods were tested on 80 longitudinal ultrasound images of carotid artery using receiver operating characteristics(ROC) analysis and the manual delineations of an expert concluded, the Lai and chin snakes segmentation method gave slightly better results[11]. B-mode ultrasonography is a diagnostic method allows measurement of IMT at the level of the Carotid artery and Femoral artery. As pointed out by the collected data to date, measurement of IMT but ultrasonography has become a morphological criterion for the detection of atherosclerosis[12][13]. Different filtering techniques based on statistical methods for the removal of speckle noise proposed by[14][16]. The quality of enhanced images is measured by the statistical quantity measures[15][18]. examined four algorithm for automated ultrasonic boundary detection in the quantification of Intima-media thickness in the human carotid artery. He concluded that the Dynamic programming algorithm provides superior performance in terms of accuracy and robustness. Seeded region growing is tested in isolating regions of interest[17][19]. A Novel segmentation techniques presents an extract cavity contours from ultrasound images[20]. The optimization problem is set up as a discrete multistage decision process and is solved by time-delayed discrete dynamic programming algorithm[21][23]. Two algorithms proposed for risk management in dynamic optimization based on multi-stage back-propagation scheme and function approximation[22][27]. Two different motion estimation methods, based on the block-matching and maximum gradient algorithms were examined to extract the radial displacement of carotid artery wall[24][25][28] A modified star algorithm is used to track the center of the carotid artery[26][29].

In this paper, a new technique is implemented to help identify carotid regions automatically by segmenting ultrasound images. This technique would dramatically decrease the time needed to analyze the ultrasonic images. In order to accomplish this segmentation solution, back-

propagation based generalized delta rule is applied to manipulate the image data.

II. METHODOLOGY

If the measure of atherosclerosis (such as IMT,plaque presence or plaque area) is used as surrogate endpoint, we can define this as the dependent variable in the statistical analysis and study which risk factors that independently predict development and progression of atherosclerosis. In this study the approaches applied are (i)estimated the distribution and risk factors for IMT by threshold.(ii).Optimum solution by dynamic programming (iii) characterized risk factors for atherosclerosis plaques and carotid stenosis.(iv)finally the elasticity of carotid artery evaluated.

Edge Detection

Canny's edge detector helps to detects meaningful discontinuities in intensity values. This method uses two thresholds to detect strong and weak edges.

$$[g, t] = edge (f, 'canny' , T, sigma)$$

where T is a vector, T = [t1, t2], sigma is a standard deviation of the smoothing filter.

Dynamic Programming

Dynamic programming is a technique for solving optimization problems where not all variables in the evaluation function are interrelated simultaneously. It has successfully been applied to ultrasonic boundary detection.

Back Propagation Algorithm
FeedForward Structures

The feedforward network is composed of a hierarchy of processing units, organized in a series of two or more mutually exclusive sets of neurons or layers. The first or input layer serves as a holding site for the inputs applied to the network. The last or output layer is the point at which the overall mapping of the network input is available. Between these two extremes lie zero or more layers of hidden units; it is in these internal layers that additional remapping or computing takes place.

Links or weights, connect each unit in one layer only to those in the next higher layer. There is an implied directionally in these connections, in that the output of a unit, scaled by the value of a connecting weight, is fed forward to provide a portion of the activation for the units in the next higher layer.

The delta rule and the Generalized delta rule

The GDR is a product learning rule for a feed forward, multilayer structured neural network that uses gradient descent to achieve training or learning by error correction. Network weights are adjusted to minimize an error based on a measure of the difference between desired and actual feed forward network output. Desired input/output behaviour is given in the training set.

The process consist of the following steps

1. Initialize all unit weights in the network
2. Apply an input(stimulus) vector to the network
3. Feed Forward or propagate the input vector to determine all unit outputs.
4. Compare units responses in the output layers with the desired or target response.
5. Compute and propagate an error sensitivity measure backward(starting at the output layer) through the network, using this as the basis for weight correction.
6. Minimize the overall error at each stage through weight adjustments.

The following notation is used:
    i: input pattern(vector)
    o: corresponding output pattern or response(vector)
    w: network weights(vector)
    t: desired (or target) system output(vector)

The training set

The training set for this type of network consists of ordered pairs of vectors and is denoted

$$H = \{(i^k, t^k)\} \quad K = 1, 2, \ldots \ldots n$$

eq[1]

Weight adjustment strategy

Initially postulate a form for individual weight correction, or update, based on the difference between t^p and o^p, for a respecified i^p as the product form.

Error sensitivity

Several forms of the chain rule are used to formally develop the DR and GDR training algorithms.

$$\frac{\partial \varepsilon}{\partial w_{ji}} = \sum_p \frac{\partial \varepsilon_p}{\partial w_{ji}} \qquad eq.[2]$$

Activation Function

A semi linear activation function f_j, for the jth neuron

$$o_j^p = f_{j\,(net_j^p)} \qquad eq.[3]$$

Learning rate

The learning rate determines what amount of the calculated error sensitivity to weight change will be used for the weight correction. The "best" value of learning rate depends on the characteristics of the error surface.

To move in a direction opposite the gradient, the weight correction is therefore

$$\Delta^p W_{ji} \in \delta_j^p \delta_i^p \qquad eq.[4]$$

Output units

For an output unit, using the error definition

$$\Delta^p W_{ji} \in (t_j^p - O_i^p) \qquad eq.[5]$$

Sample based weight correction for output units becomes

$$\Delta^p W_{ji} \in (t_j^p - O_i^p) \, f_i'(net_j^p) \, O_i^p \quad eq.[6]$$

Hidden units

The recursive formulation for update of the hidden-layer weights:

$$\delta_k^{\overline{n}} = f_k'(net_k^{\overline{n}})\sum_n \delta_n^{\overline{n}} w_{nk} \qquad eq.[7]$$
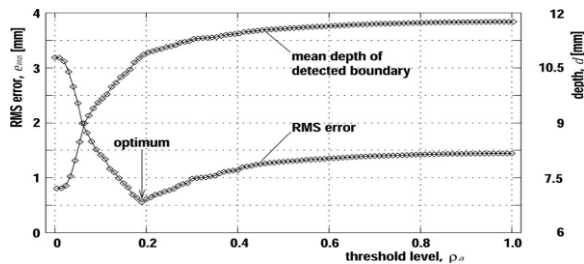
III. RESULTS AND DISCUSSION
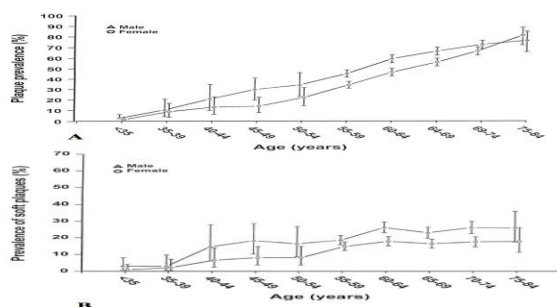

Fig. 1
Optimum solution

Fig. 2
Elasticity of plaque for male and female of different age group

TABLE-I
Classification of plaques based on % of Diameter

Percentage of Diameter	Classification of Carotid Plaques	Frequency	Percent
0% to 20%	Normal to Mild	49	40.8
20% to 60%	Moderate	39	32.5
60% to 80%	Severe	26	21.7
80% to 99%	Critical	6	5.0
100%	Occluded	0	0.0
Total		120	100.0

IV. DISCUSSION

We have proposed an intelligent technique for detecting intima and adventitia in B-mode ultrasonic images. Our method inherits the property of guaranteeing the global minimal result from TDP. Simultaneously it increases the robustness against the speckle noise effect in the ultrasonic images. Our experimental results show that this method can effectively alleviate the problems caused by the TDP when applied in CCA(far-wall) IMT measurement. In general, prediction of elasticity of carotid artery can be determined based on results analysed.

Our future aim is to test this system on images made by some other sonography instrumentation. The system should be able to select features fully automatically according to different instrumentations, The final goal is to make this system portable within the current B-mode ultrasonic instrumentation.

As a final remark, we want to point out that in addition to the intima and adventitia detection, several other medical applications are based on detecting near-parallel contours. The technique proposed in this paper is potentially applicable in these situations as well.

V. CONCLUSION

In conclusion, the proposed method is based on segmentation procedure to automatically measure ultrasonic artery images. The human knowledge of the artery image is incorporated in the system, which makes the system capable in processing images of different quality. Human factors in the determination of the boundaries are reduced. Evaluation of the system shows reduced inter observer variability as well as overall analysis time. The automated artery boundary detection and segmentation, system can replace the old manual system in clinical application environment.

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