Ultrasonic Marker Pattern Recognition and Measurement Using Artificial Neural Network

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Abstract: - Ultrasound screening is performed during early pregnancy for assessment of fetal well being and prenatal diagnosis of fetal chromosomal anomalies including measurement of nuchal translucency (NT) thickness. The drawback of current NT measurement technique is restricted with inter and intro-observer variability and inconsistency of results. Hence, we present an automated detection and measurement method for NT in this study. Artificial neural network was trained to locate the region of interest (ROI) that contains NT. The accuracy of the trained network was achieved at least 93.33 percent which promise an efficient method to recognize NT automatically. Border of NT layer was detected through automatic computerized algorithm to find the optimum thickness of the windowed region. Local measurements of intensity, edge strength and continuity were extracted and became the weighted terms for thickness calculation. Finding showed that this method is able to provide consistent and more objective results.

Key-Words: - nuchal translucency, ultrasound, fetal, pattern recognition, artificial neural network

1 Introduction

Latest studies show that fetal abnormalities can be detected through assessment of particular ultrasound markers such as nuchal translucency (NT), nasal bone, long bone biometry and Doppler assessment of ductus venous [4]. So far, measurement of NT thickness in the first trimester of pregnancy has been proposed as the most powerful marker in the early screening for fetal abnormalities such as Trisomy 21, 18 and 13 [1]. An increased NT thickness that more than 2.5mm in between 10 and 13 weeks plus six days has also been associated with an increased risk of congenital heart and genetic syndrome [7] [8] [9]. Based on previous literatures, nuchal translucency is the subcutaneous fluid filled space between the back of the neck of a fetus and the overlying skin [4]. Normally it can be viewed in the ultrasound images for all fetuses during the first trimester of pregnancy [7]. The NT thickness is measured as the maximum thickness of the translucent space in the sagittal view of fetus through the ultrasonic prenatal screening. However, measurement of NT by locating the sonogram calipers manually requires highly trained and experienced operators [10], and is therefore prone to errors, and intra-observer and inter observer repeatability can be questioned [11]. Efforts have been made by numerous investigators worldwide to try to find an approach for boundary detection in ultrasonic NT images which is less reliant on human operators. As it is reducing the amount of human intervention, it will also reduces inter-observer variability and moreover to prevent the problem of drift in measurements over time in a longitudinal studies.

Artificial neural networks have been widely applied in ultrasonic image processing chain for the tasks ranging from pattern recognition to identification, features extraction and recognition [12]. It present a potentially appealing alternative for all image processing steps, from the low level pixel processing, up to the level of image understanding. Furthermore, from a practical perspective, the massive parallelism and fast adaptability of neural networks holds the promise of efficient implementation of algorithms mimicking tasks performed by the visual and central nervous systems of living organisms [12]. The five main image processing chain mentioned above are (a) Image pre-processing; construction of image from filtering data (b) Reduction; windowing to extract relevant parts of the image or to transform the image (c) Image segmentation; decomposition of the image in accordance to certain criteria (d) Object recognition; identifying, describing and classifying objects in the image (e) Scene understanding; eliciting of high level information from the image. Early research has shown that there is a highly significant performance of neural network to process segmentation and recognition on ultrasound images. Zumray D. and Tamer O. [13] using hybrid neural network called intersecting spheres neural nets to increase the classification performance on medical ultrasonic images and to decrease the overall
computational time. V. R. Newey and D. K. Nassiri [14] proposed automated technique to measure artery diameter in flow-mediated dilation (FMD) ultrasound images, by using artificial neural networks to identify and track the artery walls. Two networks were trained to identify artery anterior and posterior walls using over 3200 examples from carotid artery ultrasound images and results shows that the trained nets are correctly classified approximately 97 percent of the randomly selected test samples. Diagnosis of ultrasound breast tumors by using means of artificial neural network to classify texture features was also proposed by Goldberg V. et al. [15]. They show promise for potentially decreasing the number of unnecessary biopsies by a significant amount in patients with sonographically identifiable lesions.

Apart from pattern recognition techniques in ultrasound images mentioned above, there also has been a little research focus on computerized automation of ultrasonic measurement. Bernardino et al. [2] developed a semi-automated computerized measurement system, which uses the Sobel operator to detect the border of the NT layer in fetal ultrasound images. The location of the edge is entirely determined by local evaluation of single image feature such as the intensity or the intensity gradient. But a single image feature is not sufficient for detecting the borders in fetal ultrasound images since ultrasound image usually contains a lot of speckle noises and other imaging artifacts. It is therefore impossible to detect the border of NT layer correctly in single image feature. Also, a method for automated NT measurements based on dynamic programming was proposed by Y.B. Lee and M.H. Kim [3]. Ultrasonic measurement of NT thickness is performed by manual tracing the two echogenic lines. They presented a computerized method of detecting the border of NT layer by minimizing a cost function using dynamic programming. Nevertheless, the limitation of the proposed method is that it can be only applied when NT position lies horizontally within the windowed images.

Keeping the facts above, we present an automated method to detect and recognize the fetal NT based on 2 dimensional ultrasound images by using artificial neural network techniques. Prior to assess the presence of NT, several image preproccessing techniques were implemented to locate the position of NT due to random shape and position of embryo in ultrasound images. The investigation was followed by iteration forward propagation method to measure the maximum thickness of NT within the windowed images. Fig. 1 illustrates the location of NT in ultrasound fetal image.

In section 2, we describe the procedure of image acquisition, material and methods used to identify and measure NT. Result is discussed in Section 3 and we draw some discussions and conclusions in Section 4 and Section 5.

2 Material and Methods

In this section, we describe the procedure of image acquisition, method of NT detection and measurement. The images of fetus with NT were obtained using KNOTRON (Sigma 330 Expert) ultrasound machine with a 3.5MHz convex transducer. Mid sagittal view of the fetal profile must be obtained by moving the transducer probe from side to side so that the inner edges of the two thin echogenic lines that border the NT layer is obtained [16]. The magnification of the image should be at least 75 percent zooming such that the head and thorax region occupy full screen of the image in the neutral position. The ultrasound images are obtained as the sequence of moving pictures. Still frame which is suitable for the proposed work is chosen.

In order to compute NT thickness, the region of interest (ROI) that encloses NT must be defined for reducing the undesired interference from the ultrasound image. The redundant information outside the defined region will be discarded to minimize the errors during the measurement of NT afterwards. However, conventional image segmentation techniques are not applicable to ultrasound image processing due to its speckle noise and image artifacts. A wide variety of segmentation techniques have been considered and we propose to use neural networks in our study. We used a multilayer feed forward neural network throughout this study.

2.1 Architecture of neural network learning and feature extraction

ANN is a parallel distributed mainframe [5] that has a natural tendency for storing experiential information. A key benefit of neural networks is that a model of the system can be built from the available data. Image classification using neural networks is done by texture
feature extraction and then applying the backward propagation algorithm. In this study, we used one of the common applied feed forward ANN architectures, which is multilayer perceptron (MLP) network. The main advantages of MLP compared to other neural model structures are that it is simple to implement and it can approximate any input/output map [6]. MLP consists of (a) an input layer with neurons representing input variables to the problem, (b) one or more hidden layers containing neuron(s) to help capture the nonlinearity in the system, and (c) an output layer with neuron(s) representing the dependent variable(s). We used the logistic function as an activation function for determining the output of neural network, as shown in equation 1 below.

$$f(x) = \frac{1}{1 + e^{-x}}$$  

(1)

In this works, catalogs containing a total of 150 ultrasound fetal images with NT and without NT are vectorized into 50 x 30 matrixes respectively as the neuron input for training purposes. The output neuron node of the target NT value and non NT value is set as 0.1 and 0.9 respectively. The mean squared error (MSE) of the forward propagation is calculated using equation 1 below.

$$E_p = \frac{1}{2} \sum_{j=1}^{N} (t_{pj} - O_{pj})^2$$  

(2)

where $E_p$: MSE, $t_{pj}$: target value for $j^{th}$ output neuron, $O_{pj}$: actual output of $j^{th}$ output neuron, $N$: total number of output neuron. Back-propagation is an essential to minimize the total network error by adjusting the weights. During this process, weight connecting neuron must be adjusted according to the general equation as defined below:

$$\Delta w_{ji} = \eta \delta_j O_i$$  

(3)

Where $\eta$ is learning rate, $\delta_j$ is error signal and $O_i$ is output neuron. The adjustment of weight will be stop when the MSE of the forward propagation is lower than the threshold value. During training, momentum value was fixed at 0.9, and learning rate was determined at level 1 on the hidden layer and 0.1 at the output layer. The training process was carried on for 1,000 epochs or until the cross-validation data’s mean-squared error (MSE), calculated by Equation 2, did not improve for 100 epochs to avoid over-fitting of the network. Now, the neural network is being well trained and can be tested using the actual data.

### 2.2 Neural network testing

For the network testing phase, neuron in the input layer will be the center of potential NT contained window $C_{ij}$, where it can be compute through the convolution between a template of NT image $NT_{ij}$, and sample ultrasound fetal images $f_{ij}$.

$$C_{ij} = f_{ij} \ast NT_{ij}$$  

(4)

Fig. 2 illustrates the outcomes of convolution between sample ultrasound fetal images and NT template. The potential NT contained windows are vectorized into M x N sized matrix $V_k$, where $k$ is the number of $C_{ij}$.

![Fig. 2 Location of centre potential Window](image)

The $V_k$ is practiced within the trained network in order to identify the probability of each window, which is the calculated neuron in output layer. Maximum value of the neuron in output layer, which nearest to 0.9 is chosen as the final ROI. Fig. 3 shows the experimental result of ROI extraction by choosing the window with highest probability. In order to justify the performance of trained neural network, two different groups of testing images $k_1$, $k_2$ were used. Each groups of testing catalogue consisting 30 numbers of ultrasound fetal images. The first group $k_1$ were new registered images with nuchal translucency screening from a consecutive group of patients by using the same ultrasound scanner as the one used in training, where the second group of images $k_2$ were randomly selected from Health Centre, Universiti Teknologi Malaysia which contains no nuchal translucency in the images, Table 1 lists the performance of neural network on different groups of ultrasound fetal images.

Simulations result shows that the trained network capable achieving as high as accuracy about 93.33 percent and able to provide reliable and consistent findings.

<table>
<thead>
<tr>
<th>Threshold</th>
<th>Group $k_1$</th>
<th>Group $k_2$</th>
<th>Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>output &gt; 0.85</td>
<td>27 (TP)</td>
<td>1 (FP)</td>
<td></td>
</tr>
<tr>
<td>output &lt; 0.85</td>
<td>3 (FN)</td>
<td>29 (TN)</td>
<td>93.33%</td>
</tr>
</tbody>
</table>
Accuracy = (TP + TN) / (TP + TN + FN + FP)

2.3 NT measurement

Conventional edge detection such as Sobel and Canny techniques is not suitable to evaluate the NT measurement, as more than two echogenic lines will be mapped within the output image. In order to solve that problem, we had applied our unique developed algorithm for NT edge detection, known as “Bidirectional Iterations Forward Propagations Method (BIFP)”. Let’s assume the acquired ROI is an M x N rectangle, and then all possible borders $T_N$ are considered as polylines with N nodes:

$$T_N = [p_1, p_2, ..., p_{N-1}, p_N]$$ (5)

where the pixels $p_{N-1}$ and $p_N$ are horizontal neighbors and N is the horizontal length of a contour line. The function of NT backbone $b(r)$ is build according to reference points $r$, which are defined as follows:

$$r_{1,2} = \min [f(p_{1,N})]$$ (6)

The term $f(p_{1,N})$ measures the intensity gradient and intensity of pixels along $p_1$ and $p_N$, as shown in Fig. 4. Applied equation (6), the $b(r)$ is formulated based on linear equation, as expressed follows:

$$y_j = \nabla b(r)x_i + r_1 \quad (i = 1, ..., N) \quad (j = r_1, ..., r_2)$$ (7)

$$\nabla b(r) = \frac{|r_1 - r_2|}{N}$$ (8)

where $x_i$ and $y_j$ are the coordinate along this linear equation. The bidirectional forward propagation tracking process is used to scan through the NT edges of upper and lower boundaries within the M x N ROI referring to $b(r)$, and stored in the array of $T_{N1}$, $T_{N2}$, as shown below:

$$T_{N1} = \max [\nabla \text{ROI} (x_i, y_j - d_1)]$$ (9)

$$T_{N2} = \max [\nabla \text{ROI} (x_i, y_j + d_2)]$$ (10)

The NT thickness is taken along every five pixels of polylines $T_{N1}$ and $T_{N2}$. The maximum thickness of the subcutaneous translucency between skin and the soft tissue overlying the cervical spine should be measured. Therefore, the largest thickness is recorded as the NT measurement and calibrated with scale of ultrasound image to get the exact thickness in millimeter, as shown in Fig. 5.

3 Result and Analysis

We run the algorithm on a set of ultrasound images, with 640 x 480 sized fetus NT obtained by transabdominal ultrasonography. Using the Sobel and Canny edge detectors’ results in discrete borders is not correctly matched to the borders, whereas our method extracts continuous borders accurately in Fig. 6.
In order to access the performance and usefulness of the trained and validated system in a real application, a thorough evaluation of the method was carried out at the Medical Electronics Research Laboratory, Universiti Teknologi Malaysia, Malaysia. New Images were registered from a consecutive group of patients and control subjects \((n=30)\) using the same ultrasound scanner as the one used in training. Fig. 7 shows part of our experimental results using sample patients’ data where the obtained findings demonstrated that the state of the art of BIFP computerized method is able to produce accurate border in most of the samples. In cases of extremely poor in contrast and resolution of ultrasound images as shown in the last two samples in Fig. 7, miss calculation and discontinuity border detection are not able to be avoided since BIFP heavily dependent on the weighted terms including intensity gradient and edge strength.

![Fig. 7 Experimental results of NT edge detection using the state of the art BIFP method. Left are original sample images, right are the findings of BIFP algorithm.](image)

We calculated their means and standard deviations \((SD)\) between automatic and manual measurements for the maximum NT thickness. The covariance \((COV)\) of respective methods was then calculated according to formula below:

\[
\text{cov}(X,Y) = \frac{\sum_{i=1}^{N} (x_i - \bar{x})(y_i - \bar{y})}{N}
\]

where \(X\): manual method, \(Y\): automated method, \(N\): total number of sample, \(\bar{x}\) and \(\bar{y}\) are mean of each method.

\[
corr = \frac{\text{cov}(X,Y)}{\sqrt{\text{var}(X)\times\text{var}(Y)}}
\]

The correlation for two analyzing methods was least 0.98 for all of the measurements using Equation 11. Table 2 presents a comparison of the measures from the manual and automated system respectively.

<table>
<thead>
<tr>
<th>Manual System(mm)</th>
<th>Automated System(mm)</th>
<th>Correlation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean ± SD</td>
<td>Mean ± SD</td>
<td></td>
</tr>
<tr>
<td>NT(_{\text{max}})</td>
<td>2.66 ± 0.23</td>
<td>2.71 ± 0.28</td>
</tr>
<tr>
<td>SD: Standard deviation</td>
<td>p &lt; 0.001 for differences between analyzing systems</td>
<td></td>
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### 4 Discussion

The key to reduce inter and intro-observer variability is a reduction in the amount of human being intervention. Our method contributes this reduction through two approaches. First, the NT position is automatically detected in the two dimensional ultrasound fetal images; hence, the manual initial tracing is avoided. Second, by applying BIFP in the scale image, two smooth boundaries of NT instead of separated boundary segments are derived. It enables automatic measurement of maximum NT thickness without distortion of echogenic lines.

In our study, we have compared our automated detection and measurement system with manual tracing and caliper on screen measurement, and were found to be almost equally accurate. However, the limitation of present method is to acquire the correct scanning plane of two dimensional ultrasound fetal images. If the tested images are not in the true sagittal view or coincide in the suitable plane, ultrasound markers might not appears in appropriate position and cause errors in NT measurement. To encounter the limitation mentioned above, we will investigate real time techniques to select the optimum plane of two dimensional ultrasound images in an automatic way during the scanning procedure.

### 5 Conclusion

We have proposed a method for automated fetal NT detection and measurement based on artificial neural
network. Border of NT layer was detected through bidirectional iterations forward propagations method (BIFP) to find the optimum thickness of the windowed region. Local measurements of intensity, edge strength and continuity were extracted and became the weighted terms for thickness calculation. Findings showed that the system is able to provide consistent and reproducible results.

ACKNOWLEDGMENTS
The authors are so indebted and would like to express our thankfulness to Health Centre, Universiti Teknologi Malaysia and Ministry of Science, Technology and Innovation (MOSTI), Malaysia for supporting and funding this study under Vote 79327. Our appreciation also goes to the Progressive Healthcare and Human Development Research Group members for their ideas and comments on this paper.

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