## Nuchal Translucency Marker Detection Based on Artificial Neural Network and Measurement via Bidirectional Iteration Forward Propagation

LAI KHIN WEE, TOO YUEN MIN, ADEELA AROOJ, EKO SUPRIYANTO Department of Clinical Science and Engineering Faculty of Health Science and Biomedical Engineering Universiti Teknologi Malaysia UTM Skudai, 81310 Johor MALAYSIA laikw2@gmail.com eko@utm.my http://www.biomedical.utm.my

*Abstract:* - Ultrasound screening is performed during early pregnancy for assessment of fetal viability 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 intra-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

Recent studies show that fetal abnormalities can be detected through assessment of particular ultrasound markers such as nuchal translucency (NT), nasal bone, long bone biometry, maxillary length, cardiac echogenic focus and Doppler assessment of ductus venous [4] [23] [24]. 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 11 and 13 weeks plus 6 days has also been associated with an increased risk of congenital heart diseases and genetic syndrome [7] [8] [9] [25].

The term nuchal translucency was coined by Niclaides and colleagues to describe the collection of fluid that is normally present behind the neck of the first trimester fetus. Nicolaides wrote the term translucency encompasses both septated(cystic hygroma) and nonseptated lesions [21]. 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]. By 1995, first large studies of NT confirmed that NT thickness can be reliably measured at 11-14 weeks, when combined with maternal age, can provide an effective means of screening Down syndrome. The importance of measuring NT as a screening tool can be evaluated from

the fact that all over Europe, America and UK, NT measurement is included in their prenatal screening programmes. According to National institute of Health And Clinical Excellence (NICE) guideline the combined test, (NT, beta human chorionic gonadotrophins and pregnancy associated plasma protein-A) should be offered to screen Down Syndrome between 11 weeks and 13 weeks + 6 days to all pregnant women [22]. The NT thickness is measured as the maximum thickness of the translucent space in the sagittal view of fetus through the ultrasonic prenatal screening. The ability to achieve a reliable measurement of NT depends on proper training and adherence to a standard technique to achieve uniformity of results from different operators. However, measurement of NT by locating the sonogram callipers manually requires highly trained and experienced operators [10], and is therefore prone to errors, 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 reduce inter-observer and intra-observer variability. Moreover, it is expected to prevent the problem of drift in measurements over time in 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 presents 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 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. Ashok A. Ghatol [15] described their studies on assessment of the feasibility to identify breast cancer malignancy identification using selforganizing map of artificial neural network. The outcome obtained for the automatic lesions recognition appear promising where it concluded that shape parameters play a key role when separating carcinomas from fibroadenomas. Diagnosis of ultrasound breast tumors by using means of artificial neural network to classify texture features was also proposed by Goldberg V. et al. [16]. 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 artefacts. 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, however, for clinical purposes; some interactive tools may still be needed in order to correct residual detection errors in extremely poor images. Gustavsson et at. [17] [18] [19] have suggested a global optimization approach based on dynamic programming to automatic extract the boundaries of carotid artery which takes multiple image features into account. Their method has obtained acceptable results for automated ultrasonic measurement. 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, techniques image pre-processing several 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 methods, we describe the procedure of image acquisition, material and methods used to identify and measure NT. Finding is discussed in section results and we draw some analysis and conclusions in section discussion and section conclusion.



Fig. 1 Location of Nuchal Translucency

#### 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 with freeze-frame capability. The Fig. 2 shows the block diagram of image acquisition from ultrasound machine to our developed hardware. 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 [20]. 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 gain setting remained unchanged throughout the entire study. The ultrasound images were obtained as the sequence of moving pictures. Still frame which is suitable for the proposed work was chosen.



Fig. 2 Block diagram of image acquisition from ultrasound machine

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 was 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 proposed 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 containing one or more hidden layers. The function of neurons in the hidden layer is to arbitrate between the input and the output of the neural network. The input feature vector is fed into the source nodes in the input layer of the neural network. The neurons of the input layer constitute the input signals applied to the neuron in the hidden layers. The output of the hidden layer can be used as input for next hidden layer or output layer. The output layer produces the output result and terminates the neural computing process when it meets its target eventually. 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 f(x) for determining the output of neural network, as shown in equation 1 below.

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

In this works, catalogue containing a total of 150 ultrasound fetal images with NT and without NT are vectorized into M x N matrix respectively and fed as the input of neuron nodes in input layer for training purposes. The dimensional matrix M x N can be fixed for an image of any size. In this study, the dimensional matrix is 50 x 30 which produced 1500 elements of image feature vector. Therefore, we used multilayer perceptron network with 1500 input nodes, 100 hidden nodes and one output node, as illustrated in Fig. 3.

The value produced by the output neural node was used to calculate the probability of given image whether it contains a NT or not, and its value range between 0.9 and 0.1. When the output value of an ultrasound fetal images was exceeded, the set threshold was nearest to 0.9, the system classified the given image contains NT. Conversely, when the value is close to 0.1 or below the set threshold, the system classified the given image contains no NT.



Input layer

Fig. 3 Structural graph depicts the multilayer neural network used in this study. Numbers indicate the number of nodes.

During the training phases, we iteratively executed the back propagation learning algorithm for the training set and then produced the synaptic weight vectors that were applied to the neural network. The mean squared error (MSE) of the backward propagation is calculated using equation 2. Our developed NT detection model classified the location of NT by applying the final synaptic weight vectors to the multilayer neural network.

$$E_{p} = \frac{1}{2} \sum_{j=1}^{N_{o}} (t_{pj} - O_{pj})^{2}$$
<sup>(2)</sup>

Where  $E_p$ : MSE,  $t_{pj}$ : target value for  $j_{th}$  output neuron,  $O_{pj}$ : actual output of  $j_{th}$  output neuron.  $N_o$ : 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 3 and 4 as defined below:

$$\Delta w_{ji}^{\ m} = \eta \delta_j O_i + \alpha \Delta w_{ji}^{\ (m-1)} \tag{3}$$

$$w_{ij}^{(m+1)} = w_{ij}^{(m)} + w_{ij}^{(m)}$$
(4)

Where  $\eta$  is learning rate,  $\delta_{pj}$  is error signal and  $O_{pi}$  is output neuron. The adjustment of weight will be stopped 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 10,000 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. A plot of MSE versus the number of epoch is shown in Fig. 4. The training halted once the threshold is achieved at 2863 epochs. Descending graph shows that the weight is adjusted near to the target output. 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 nodes in the input layer will be the centre of potential NT contained window  $C_{i,j}$ , where it can be computed through the convolution between a template of NT image  $NT_{i,j}$ , and sample ultrasound fetal images  $f_{i,j}$ .

$$C_{i,j} = f_{i,j} * NT_{i,j} \tag{5}$$

Fig. 5 illustrates the outcomes of convolution between sample ultrasound fetal images and NT template. The potential NT contained windows were vectorized into 50 x 30 sized matrix  $V_k$ , where k is the number of  $C_{i,j}$ . 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 nodes in output layer, which was nearest to positive 0.9 was chosen as the final ROI. Fig. 6 shows the experimental result of ROI extraction by choosing the window with highest probability.



Fig. 4 MSE versus the number of epoch for network training.

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 consisted of 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  $k_1$  and  $k_2$  groups of 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.

Fig. 5 Location of centre potential NT window

Fig. 6 Experimental result of ROI extraction. (a) The window with highest probability. (b) ROI on sample ultrasound image. (c) Resultant windowed NT region

 Table 1 – PERFORMANCE OF THE NEURAL NETWORK FOR NT RECOGNITION AND DETECTION

Threshold	Group $k_1$	Group $k_2$	Accuracy		
neural network output > 0.85	27 true-positive (TP)	1 false-positive (FP)	93.33%		
neural network output < 0.85	3 false-negative (FN)	29 true-negative (TN)			
Total	30	30			
$\overline{Accuracy} = (TP + TN) / (TP + TN + FN + FP)$					

#### 2.3 NT measurement

Conventional edge detection such as Sobel and Canny techniques has a drawback in 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  $M \times N$  rectangle, and then all possible borders  $T_N$  are considered as polylines with N nodes:

$$T_N = [\boldsymbol{p}_1, \boldsymbol{p}_2, \dots, \boldsymbol{p}_{N-1}, \boldsymbol{p}_N]$$
(6)

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  $b(\mathbf{r})$  is build according to reference points r, which are defined as follows:

$$r_{1,2} = \min[f(p_{1,N})]$$
 (7)

The term  $f(\mathbf{p}_{1,N})$  measures the intensity gradient and intensity of pixels along  $p_1$  and  $p_N$ , as shown in Fig. 7. Applied equation (7), the  $b(\mathbf{r})$  is formulated based on linear equation, as expressed follows:

$$y_j = \nabla b(\mathbf{r}) x_i + r_1$$
 (*i* = 1,...,*N*) (*j* = r\_1,..., r\_2) (8)

$$\nabla b(r) = \frac{|r1 - r2|}{N} \tag{9}$$

Where  $x_i$  and  $y_j$  are the coordinate along this linear equation. Fig. 8 illustrates the linear equation coincide with both reference points  $r_1$  and  $r_2$ . 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  $b(\mathbf{r})$ , and stored in the array of  $T_{NI}$ ,  $T_{N2}$ , as shown below:

$$T_{NI} = \max\left[\nabla \operatorname{ROI}\left(x_{i}, y_{i} - d_{1i}\right)\right]$$
(10)

$$T_{N2} = \max\left[\nabla \operatorname{ROI}\left(x_{i}, y_{j} + d_{2i}\right)\right]$$
(11)

Where  $d_{1i}$  and  $d_{2i}$  are y-coordinates for maximum intensity gradient of both upper and lower border. The NT thickness was 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. 9.



Fig. 7 Intensity gradients and intensity of pixels along  $p_1$  and  $p_N$ .



Fig. 8 Formation of NT backbone  $b(\mathbf{r})$  using both reference points  $r_1$  and  $r_2$ .



Fig. 9 Experimental result of maximum thickness NT measurement (a) Sample original image (b) Edge tracking and NT measurement.

### **3** Result and Analysis

The result of this study is divided into two parts. The first parts of finding are the result of ultrasonic NT region of interest recognition and detection using trained network. The second part is the automated measurement of NT using the state of the art BIFP computerized method.

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. We ran the algorithm on a set of ultrasound images, with 640 x 480 sized ultrasound fetus images obtained by transabdominal ultrasonography. 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.

Table 1 lists the performance of trained neural network on two different groups of testing samples. The accuracy of the neural network for detecting NT was 93.33 percent (56 of 60). Based on equations 12, 13, 14 and 15 the calculated sensitivity was 90 percent (27 of 30), the specificity was 96.67 percent (29 of 30), the positive predictive value was 96.43 (27 of 28) and the negative predictive value was 90.63 (29 of 32). These results indicate the developed diagnostic model making well recognition and detection of NT.

$$Sensitivity = TP / (TP + FN)$$
(12)  
Specificity = TN / (TN + FP) (13)

$$Positive Predictive Value = TP / (TP + FP)$$

$$Negative Predictive Value = TN / (TN + FN)$$

$$(13)$$

$$(14)$$

$$(14)$$

$$(15)$$

Fig. 11 shows part of our experimental results using sample patients' data and 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. 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. 10. In cases of extremely poor in contrast and resolution of ultrasound images as shown in the last two samples (j) and (k) in Fig. 11, miss calculation and discontinuity border detection are hardly to be avoided since BIFP heavily dependent on the weighted terms including intensity gradient and edge strength.

For quantitative analysis, 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:

$$\operatorname{cov}(X,Y) = \sum_{i=1}^{N} \frac{(xi-\overline{x})(yi-\overline{y})}{N}$$
 (16)

Where X: manual method, Y: automated method, N: total number of sample,  $\overline{x}$  and  $\overline{y}$  are mean of each method.

$$corr = \frac{\operatorname{cov}(X, Y)}{\sqrt{\operatorname{var}(X) \times \operatorname{var}(Y)}}$$
(17)

The correlation for two analyzing methods was least 0.98 for all of the measurements using Equation 17. Table 2 presents a comparison of the measures from the manual and automated system respectively.

<b>Comparison Between Manua</b>	L AND AUTOMATED	ANALYZING SYSTEMS
---------------------------------	-----------------	-------------------

	Manual System(mm)	Automated System(mm)	Correlation
	Mean $\pm$ SD	$Mean \pm SD$	
$NT_{max}$	$2.66\pm0.23$	$2.71\pm0.25$	0.98

SD: Standard deviation

p < 0.001 for differences between analyzing systems



Fig. 10 Comparison of various edge detectors (a) Original image (b) Sobel detector (c) Canny detector (d) BIFP edge detector





Fig. 11 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.

#### 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. Since the neural network is re-trainable, it could be optimized if a larger set of NT ultrasound images is applied. 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.

#### References:

- [1] R. J. Snijders, P. Noble, N. Sebire, A. Souka, K.H. Nicolaides, "UK multicentre project on assessment of risk of trisomy 21 by maternal age and fetal nuchal translucency thickness at 10-14 weeks of gestation", *The Lancet*, Vol. 352, 1998, pages 343 -346
- [2] F. Bernadino, R. Cardoso, N. Montenegro, J. Bernardes, J. Marques de Sa, "Semiautomated ultrasonographic measurement of fetal nuchal translucency using a computer software tool", *Ultrasound in Med. & Biol.*, Vol. 24, No. 1, 1998, pages 51-54
- [3] Yong B. Lee and Myoung H. Kim, "Automated Ultrasonic Measurement of Fetal Nuchal Translucency Using Dynamic Programming", *CIARP*, 2006, pages 157-167
- [4] Nicolaides, K., Sebire, N., Snijders, R., "The 11-14 weeks scan: the diagnosis of fetal abnormalities", *Parthenon Publishing*, NY, 1999.
- [5]S. Haykin, "Neural Network a Comprehensive Foundation; a Computational Approach to Learning and Machine Intelligence", *Macmillan*, NY, 1994.

- [6] Menhaj, M. B., Hesabi., "Fundamentals of neural networks", *Tehran*, 1998.
- [7] N. Zosmer, VL. Souter, CS. Chan, IC. Huggon, KH. Nicolaides "Early diagnosis of major cardiac defects in chromosomally normal fetuses with increased nuchal translucency", *Br J Obstet Gynaecol*, Vol. 106(8), 1999, pages 829-833
- [8] J.Hyett, G.Moscosco, KH. Nicolaides "Cardiac defects in1st trimester fetus with trisomy 18", *Fetal Diag Ther*, Vol. 10(6), 1995, pages 381-386
- [9] AP. Souka, E. Krampl, S. Bakalis, V. Heath, KH. Nicolaides, "Outcome of pregnancy in chromosomally normal fetuses with increased nuchal translucency in the first trimester", *Ultrasound Obstet Gynecol*, Vol. 18(1), 2001, pages 9-17
- [10]Abuhamad, A., "Technical aspects of nuchal translucency measurement", *Seminars in perinatology* 29, 2006, pages 376-379
- [11]Pandya, P. Altman, D. Brizot, M. Pettersen, KH. Nicolaides, "Repeatability of measurement of fetal nuchal translucency thickness", *Ultrasound on Obstetrics and Gynecology* 5, 1995, pages 335-337
- [12]Paul, Cristea, "Application of Neural Networks in Image Processing and Visualization", Springer Netherlands, pages 59-71
- [13]Zumray D., Tamer O., "Segmentation of Ultrasound Images using hybrid Neural Network", *Elsevier Science Pattern Recognition Letters* 23 1825–1836, 2002.
- [14]V. R. Newey, D. K. Nassiri, "Online artery diameter measurement in ultrasound images using artificial neural networks", *Ultrasound in Medicine & Biology*, Volume 28, Issue 2, 2002, pages 209-216
- [15]Sudhir D. Sawarkar, Ashok A. Ghatol, "Breast Cancer Malignancy Identification using Self-Organizing Map", WSEAS International Conference on Circuits, System, Electronics, Control & Signal Processing, USA, 2006, pages 20-25
- [16]Goldberg V., Manduca A., Ewert DL., Gisvold JJ., Greenleaf JF., "Improvement in Specificity of Ultrasonography for Diagnosis of Breast Tumors by Means of Artificial Intelligent", *Med Phys.*, Vol. 19(6), 1992, pages 1475-1481

- [17]Q. Liang, I. Wendelhag, J. Wilkstrand, T. Gustavsson, "A multiscale dynamic programming procedure for boundary detection in ultrasonic artery images", *IEEE Trans. Med. Imag.*, Vol. 19, No. 2, 2000, pages 127-142
- [18]I. Wendelhag, Q. Liang, T. Gustavson, J. Wilkstrand, "A new automated computerized analyzing system simplifies readings and reduces the variability in ultrasound measurement of intimamedia thickness", *Stroke*, Vol. 28, 1997, pages 2195-2200
- [19]T. Gustavsson, Q. Liang, I. Wendelhag, J. Wilkstrand, "A dynamic programming procedure for automated ultrasonic measurement of the carotid artery," *Proc. IEEE Computers Cardiology*, 1994, pages 297-300
- [20]S. Nirmala, V. Palanisamy, "Measurement of Nuchal Translucency Thickness for Detection of Chromosomal Abnormalities Using First Trimester Ultrasound Fetal Images", (IJCSIS) International Journal of Computer Science and Information Security, Vol. 6, No. 3, 2009
- [21]Nicolaides, K: "Nuchal translucency and other first trimester sonographic markers of chromosomal

abnormalities", Am J Obstet Gynecol, Vol 191, 2004, pages 45-47

- [22]NICE Clinical Guideline 62, "Antenatal Care", *Routine care for healthy pregnant women*, March 2008
- [23]Lai Khin Wee, Eko Supriyanto, "Automatic Detection of Fetal Nasal Bone in 2 Dimensional Ultrasound Image Using Map Matching", WSEAS International Conference on Automatic Control, Modeling & Simulation, Italy, 2010, pages 305-309
- [24]Eko Supriyanto, Lai Khin Wee, Too Yuen Min, "Ultrasonic Marker Pattern Recognition and Measurement Using Artificial Neural Network", *WSEAS International Conference on Signal Processing*, Italy, 2010, pages 35-40
- [25]Lai Khin Wee, Lim Miin, Eko Supriyanto, "Automated Risk Calculation for Trisomy 21 Based on Maternal Serum Markers Using Trivariate Lognormal Distribution", WSEAS International Conference on Automatic Control, Modeling & Simulation, Italy, 2010, pages 327-332