2013 IEEE 10th International Symposium on Biomedical Imaging:
From Nano to Macro
San Francisco, CA, USA, April 7-11, 2013

LEARNING BASED AUTOMATIC HEAD DETECTION AND MEASUREMENT FROM FETAL ULTRASOUND IMAGES VIA PRIOR KNOWLEDGE AND IMAGING PARAMETERS

Dong Ni[1], *Yong Yang*[1], *Shengli Li*[2], *Jing Qin*[3], *Shuyuan Ouyang*[2], *Tianfu Wang*[1], *Pheng Ann Heng*[3]

[1]National-Regional Key Technology Engineering Laboratory for Medical Ultrasound, School of Medicine, Shenzhen University, P R China
[2]Department of Ultrasound, Affiliated Shenzhen Maternal and Child Healthcare Hospital of Nanfang Medical University, P. R. China
[3]Department of Computer Science and Engineering, The Chinese University of Hong Kong, Hong Kong, P. R. China

ABSTRACT

A novel learning based automatic method is proposed to detect the fetal head for the measurement of head circumference from ultrasound images. We first exploit the AdaBoost learning method to train the classifier on Haar-like features and then, for the first time, we propose to use prior knowledge and online imaging parameters to guide the sliding window based head detection from ultrasound images. This approach can significantly improve both detection rate and speed. The boundary of the head in the localized region is further detected using a local phase based method, which is insensitive to speckle noises and intensity changes in ultrasound images. Finally iterative randomized Hough transform (IRHT) is employed to determine an ellipse on the head contour. Experiments performed on 675 images (500 for classifier training and 175 for measurement) showed that mean-signed-difference between automatic and manual measurements is 2.86 mm (1.6%). The statistical analysis further indicated that there was no significant difference between these two measurements. These results demonstrated the proposed fully automatic framework can be used as a consistent and accurate tool in clinical practice.

Index Terms— Fetal ultrasound, Biometry, Prior knowledge and imaging parameters, AdaBoost, Local phase information, Hough transform

1. INTRODUCTION

Head circumference (HC) is one of the important biometric measurements for evaluating fetal growth in obstetric sonography. During routine examinations, the sonographer manually plots minor and major ellipse axes on the ultrasound image and estimates HC by calculating the circumference of the ellipse. However, this procedure could be experience dependent, time consuming, and contribute to inter- and intra-observer error [1]. Moreover, ultrasound scan operators are often suffered from repetitive stress injury caused by multiple keystrokes [2].

Recently a number of automatic or semi-automatic methods for HC measurement have been developed. Active contour model [3] and deformable model [4] have been employed for fetal head segmentation from ultrasound images. However, these methods are semi-automatic and can often get stuck in local minima. Carneiro [5, 6] proposed a constrained probabilistic boosting tree classifier for automatic biometric measurements from fetal ultrasound images. However, as the author mentioned, 20% of automatic measurements showed a relatively large error and were treated as outliers. Among most recent literatures, Hough transform based methods play an important role for HC measurement in ultrasound images [7, 8, 9]. The common process of such methods includes two steps. First the head contour is roughly detected based on image processing techniques, such as thresholding methods [7], morphological operators [8], clustering [9], edge detector [10]. Second, Hough transform is used to detect the ellipse on the preprocessed image. Wei Lu and Jinglu Tan [9] claimed that iterative randomized Hough transform (IRHT) was fast and could detect incomplete ellipse in images with strong noise compared with randomized Hough transform (RHT) [11]. However, there are still some shortcomings in existing methods. First, ellipse detection on the entire ultrasound image leads to more computation, and strong noises in background regions would make the Hough transform fail. Another limitation is that errors will occur when the head skull is not detectable due to low image contrast or very large gaps.

Fig. 1. Illustration of large variations of HC appearance.

In this paper, we propose a fast and robust framework to automatically detect and measure HC from ultrasound images by addressing these shortcomings. Our framework includes three steps: region of interest (ROI) localization (i.e. head region detection), head contour detection, and ellipse fitting. For head region localization, one of the difficulties is the large variance of object size and appearance due to different gestational ages and ultrasonic scanning depths, as shown in Fig. 1. While some efforts have been dedicated to improving the classifier performance by making using of the state of the art learning methods [5, 6], little attention has been paid to integrate valuable prior clinical knowledge and medical imaging parameters in run-time to improve detection rate and speed. In this paper, we propose to guide the sliding detection window by using the gestational age and the ultrasound scanning depth. Experimental results demonstrated that the proposed method can significantly improve the head detection rate and speed. To our knowledge, this is the first time to incorporate prior knowledge and ultrasound imaging parameters into object detection tasks. After head region detection, the head contour in the localized region is detected using a phase based method [12], which is robust to speckle noises and intensity changes. Finally iterative randomized Hough transform (IRHT) is employed to determine an ellipse on the head contour.

2. METHOD

2.1. Prior Knowledge & Imaging Parameters Guided Head Region Localization

Learning based object detection often involves two steps: offline classifier training and online object detection. At the training stage, we exploit the AdaBoost learning algorithm [13] to select a set of Haar-like features from given training samples, and train the classifier. AdaBoost is an efficient algorithm for constructing a strong classifier as linear combination of weak classifier by iteratively selecting the best weak classifiers, which is widely used in object detection. Five types of Haar-like features were used in this study (Fig. 2(a)). The feature value is the difference between the sum of the pixels' intensity within white and black regions. The first four features selected by AdaBoost is shown in Fig. 2(b).

At the detection stage, we employ the sliding-window object detection algorithm to identify and localize the fetal head region in ultrasound images. This approach involves scanning the image with a rectangular window of variable location and size, and applying a classifier to the sub-image defined by the window. The sliding-window W can be defined as

$$W = [L_x, L_y, \Delta_x, \Delta_y, \Delta_s] \tag{1}$$

where L_x and L_y represent the initial window size in x and y direction, Δ_x and Δ_y represent the scanning grid interval in x and y direction, Δ_s is the scale interval of the window size. The choice of scanning grid and scale interval affects both the speed of the detector as well as accuracy [13]. In general, larger scanning and scale interval increases the scanning speed, but tends to decrease the detection rate.

One drawback of directly applying traditional sliding-window technique to our application is that contextual cues in fetal ultrasound images cannot be fully considered and

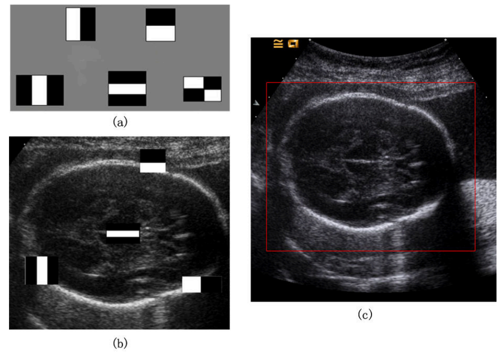

Fig. 2. Selected features from the AdaBoost algorithm. (a) Five Haar features used. (b) The first four features selected by AdaBoost. (c) Localized head region.

leveraged. To increase both detection rate and speed, we propose to incorporate prior knowledge and imaging parameters into the detection procedure. Statistics research in obstetrical biometry [14] has showed that biometric parameters have a relationship with the gestational age. Based on this fact, we propose a quadratic polynomial model to estimate HC using least-squares fitting methods. The polynomial model $\widetilde{HC}$ to estimate HC is defined as

$$\widetilde{HC} = p_1 z^2 + p_2 z + p_3 \tag{2}$$

where z represents the gestational age, and p_1, p_2, p_3 are the coefficients. Then the pixel size of the head region can be determined according to the ultrasound scanning depth, which can be automatically obtained from ultrasound scanner before the measurement. Since the fetal head is treated as an ellipse, HC can be calculated as

$$HC = \pi[3(a+b) - \sqrt{(3a+b)(a+3b)}] \tag{3}$$

where a and b are one-half of the ellipse's major and minor axes respectively. Suppose $b = \lambda a$ (λ is the ratio between the minor and major axes, which can be obtained from the clinical literature [14]), the major axes a can be calculated by

$$a = \widetilde{HC}/[3\pi(\lambda+1) - \pi\sqrt{(3+\lambda)(1+3\lambda)}] \tag{4}$$

Suppose the scanning depth is d mm and the pixel length of the scanning line is p, the physical length of each pixel should be d/p mm. Therefore, according to Eq. 4, the pixel length p_a of the major axes can be calculated by

$$p_a(z) = p * \widetilde{HC}/[3d\pi(\lambda+1) - d\pi\sqrt{(3+\lambda)(1+3\lambda)}] \tag{5}$$

Finally, we can obtain the sliding window function as:

$$W = [\gamma p_a, \lambda\gamma p_a, \Delta_x, \Delta_y, \Delta_s] \tag{6}$$

where γ is the constant obtained by experiments. One typical result of head localization is shown in Fig. 2(c). Experimental results reported in 3.2 demonstrate that our prior knowledge and imaging parameters guided detector is better than the traditional detector in terms of both detection rate and speed.

2.2. Head Contour Detection And Ellipse Fitting

An elliptical region-of-interest (ROI) automatically obtained from the localized head region by defining the outer ellipse and inner ellipse. Then, we employed phase-based edge detection methods[12] to detect the head contour in the ROI intensity gradient based detector, phase-based detector is theoretically intensity invariant and therefore performs better in ultrasound images with great intensity inhomogeneity caused by speckle, attenuation or signal dropout. Implementation details of the phase-based detector can be found in [12]. After that, the skeleton of the bright objects are extracted approximately treated as an ellipse in clinical practice, we propose an improved iterative randomized Hough transform (IRHT) to detect the ellipse from the skeleton image. This approach iteratively applies RHT to the skeleton image and adaptively adjusts the location of the estimated ellipse. The main difference between our method with [9] is that some geometry constrains are used to eliminate the false candidates in each iteration. These constrains are obtained from the detected region of interest, including that the center of the ellipse is near the center of the ROI and the length of the major and minor axes is less than the size of the ROI. One of the ellipse fitting results is shown in Fig. 3(c).

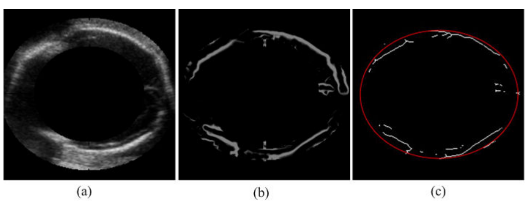

Fig. 3. Head contour detection and ellipse fitting. (a) Localized elliptical region of interest. (b) Head contour detected by phase-based method. (c) Ellipse fitted on the skeleton image.

3. EXPERIMENTAL RESULTS AND DISCUSSION

Dataset. We used 675 expert annotated ultrasound images with fetal head in our experiments. These images were acquired using a Siemens acuson Sequoia 512 ultrasound scanner from Shenzhen Maternal and Child Health Hospital. Fetal gestational age was from 17 to 38 weeks. Among them, 500 images were used for classifier training and the rest 175 images were used for the automatic measurement using the proposed approach. The algorithms were implemented on a personal computer with a 2.8-GHz Intel Dual Core CPU, 4 Gbytes of RAM. The average computational time of an image was around $1s$.

Performance of Head Region Localization. The training set consisted of 500 positive samples generated from the annotation and 1200 negative samples randomly extracted near the annotation position. Notice that the original image region was transformed into a square size of 80×80 pixels. We compared our proposed detector with the detector without the guidance of prior knowledge and imaging parameters in terms of both detection rate and speed, where 175 ultrasound images were tested. The result was validated by comparing the detected region with the expert annotation. The detection rate was 92.1% for our detector and 87.6% for the traditional detector. Our detector achieved obvious improvement. The detection speed was compared by adjusting the scale interval of the sliding windows. The result in Fig. 4 showed that our detector was faster than the traditional detector in all scale intervals. Especially, the computational time decreased significantly from 390ms to 78ms when scale interval was 0.1. The proposed detection method can be implemented in real time and potentially can improve the outcome during clinical diagnosis.

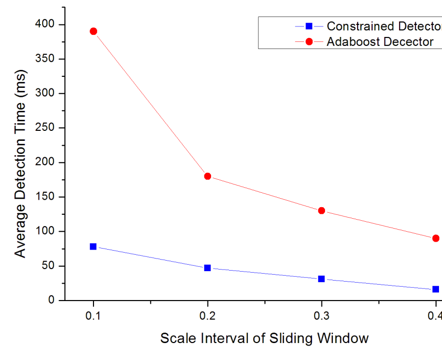

Fig. 4. Comparison of detection speed. The horizontal axes show the scale incremental interval of sliding-window.

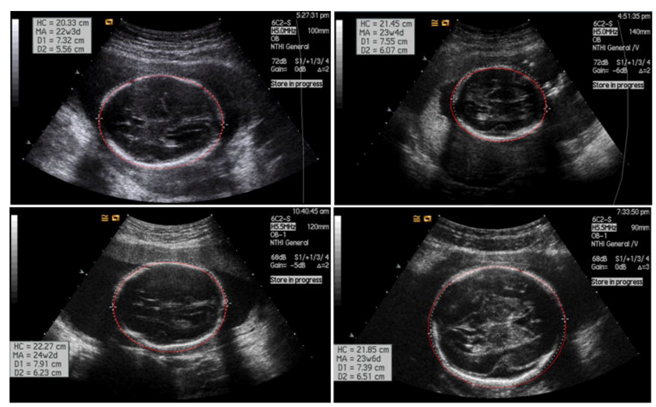

Fig. 5. Four typical automatic measurement results overlaid on the expert annotated images.

Comparison between Automatic and manual measurements. Next, we compared the automatic measurements with the manual results measured by the sonographer. Fig. 5 showed four typical results to visually compare the difference between automatic and manual measurements. The automatic measurements (red line) were overlayed on the manual measurements (white dot line). The high overlap between them demonstrated the accuracy of the proposed automatic methods. Table 1 showed the results of agreement analysis between automatic and manual measurements. The mean-signed-difference (MSD) between the average automatic measurements and manual measurements was 2.86

Table 1. Agreement between automatic and manual methods.

MSD (mm)	*p* value for *t*-test	MAD (mm)	95% limits of agreement(%)
2.84 (1.6%)	0.45	5.58 (1.73%)	-4.87, 4.35

mm (1.6%). The mean absolute difference (MAD) was 5.58 mm (1.76%). The p value indicated that the difference between automatic and manual measurements was not significant. The 95% limits of agreement were -4.87%, 4.35%. Fig. 6 showed scatter plots of the automatic measurements against the manual measurements. The narrow limits and the closeness of the data points to the line of equality indicated a high degree of agreement.

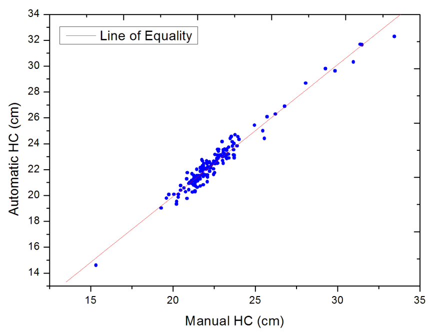

Fig. 6. Scatter plots of automatic vs. manual measurements.

4. CONCLUSION

We presented a learning based method for fully automatic fetal head detection and measurement from ultrasound images. Head region localization can benefit the following ellipse detection and fitting. Incorporation of prior knowledge and ultrasound imaging parameters can significantly improve the detection speed and rate. Experimental results demonstrated that proposed automatic measurements were in good agreement with manual measurements. In the future we will extend the proposed prior knowledge and imaging parameters guided framework to the detection of other anatomical structures, especially those in fetal ultrasound images.

5. ACKNOWLEDGEMENT

The work described in this paper was supported in part by National Science Foundation of China (Project No. 61101026, No. 81270707 and No. 61233012), in part by Shenzhen key Basic Research Project (Project No. 201101013).

6. REFERENCES

[1] N.J. Dudley, "A systematic review of the ultrasound estimation of fetal weight," *Ultrasound Obstet Gynecol*, vol. 25, no. 1, pp. 80–89, 2005.

[2] D. Janga and O. Akinfenwa, "Work-related repetitive strain injuries amongst practitioners of obstetric and gynaecological ultrasound worldwide," *Archives of Gynecology and Obstetrics*, vol. 286, pp. 353–356, 2012.

[3] Vikram Chalana, Thomas C. Winter III, Dale R. Cyr, David R. Haynor, and Yongmin Kim, "Automatic fetal head measurements from sonographic images," *Academic Radiology*, vol. 3, no. 8, pp. 628–635, 1996.

[4] Sandra M.G.V.B. Jardim and Mrio A.T. Figueiredo, "Segmentation of fetal ultrasound images," *Ultrasound Med Biol*, vol. 31, no. 2, pp. 243–250, 2005.

[5] G. Carneiro, B. Georgescu, S. Good, and D. Comaniciu, "Detection and measurement of fetal anatomies from ultrasound images using a constrained probabilistic boosting tree," *Medical Imaging, IEEE Transactions on*, vol. 27, no. 9, pp. 1342–1355, sept. 2008.

[6] Gustavo Carneiro, Bogdan Georgescu, Sara Good, and Dorin Comaniciu, "Automatic fetal measurements in ultrasound using constrained probabilistic boosting tree," in *MICCAI*, vol. 4792, pp. 571–579. 2007.

[7] V. Salari, I. Zador, L. Chik, and R. Sokol, "Automated measurements of fetal head from ultrasound images," *Medical imaging IV: Image processing*, vol. 1233, pp. 213–216, 1990.

[8] C.W. Hanna and A.B.M. Youssef, "Automated measurements in obstetric ultrasound images," in *Image Processing, 1997. Proceedings., International Conference on*, oct 1997, vol. 3, pp. 504 –507 vol.3.

[9] Wei Lu, Jinglu Tan, and Randall Floyd, "Automated fetal head detection and measurement in ultrasound images by iterative randomized hough transform," *Ultrasound Med Biol*, vol. 31, no. 7, pp. 929–936, 2005.

[10] Jinhua Yu, Yuanyuan Wang, Ping Chen, and Yuzhong Shen, "Fetal abdominal contour extraction and measurement in ultrasound images," *Ultrasound Med Biol*, vol. 34, no. 2, pp. 169–182, 2008.

[11] L. Xu, E. Oja, and P. Kultanen, "A new curve detection method: randomized hough transform (rht)," *Pattern Recogn. Lett.*, vol. 11, no. 5, pp. 331–338, May 1990.

[12] A. Belaid, D. Boukerroui, Y. Maingourd, and J.-F. Lerallut, "Phase-based level set segmentation of ultrasound images," *IEEE Transactions on Information Technology in Biomedicine*, vol. 15, no. 1, pp. 138–147, jan. 2011.

[13] Paul Viola and Michael J. Jones, "Robust real-time face detection," *International Journal of Computer Vision*, vol. 57, pp. 137–154, 2004.

[14] R. J. M. Snijders and K. H. Nicolaides, "Fetal biometry at 14-40 weeks' gestation," *Ultrasound Obstet Gynecol*, vol. 4, no. 1, pp. 34–48, 1994.