A NOVEL METHOD WITH A DEEP NETWORK AND DIRECTIONAL EDGES FOR AUTOMATIC DETECTION OF A FETAL HEAD

*Siqing Nie[1], Jinhua Yu[*1,2], Ping Chen[3], Jianqiu Zhang[1], Yuanyuan Wang[1]*

[1]Department of Electronic Engineering, Fudan University, Shanghai, China
[2]Key laboratory of Medical Imaging Computing and Computer Assisted Intervention of Shanghai
[3]Ultrasound Department, Shanghai First Maternity and Infant Hospital, Tongji University, Shanghai, China

ABSTRACT

In this paper, we propose a novel method for the automatic detection of fetal head in 2D ultrasound images. Fetal head detection has been a challenging task, as the ultrasound images usually have poor quality, the structures contained in the images are complex, and the gray scale distribution is highly variable. Our approach is based on a deep belief network and a modified circle detection method. The whole process can be divided into two steps: first, a deep learning architecture is applied to search the whole image and determine the result patch that contains the entire fetal head; second, a modified circle detection method is used along with Hough transform to detect the position and size of the fetal head. In order to validate our method, experiments are performed on both synthetic data and clinic ultrasound data. A good performance of the proposed method is shown in the paper.

***Index Terms*—**Fetal head, deep learning, circle detection

1. INTRODUCTION

Ultrasound technology is widely used in prenatal clinic examination thanks to its safety, low cost and non-invasiveness. In the first trimester of pregnancy, fetuses are usually small in size, and the ultrasound images acquired usually have low quality. However, there are many medical indexes that need to be measured in the first trimester for abnormality diagnosis, such as nuchal translucency (NT) and crown-rump length (CRL). NT and CRL are both related to the fetal head, hence fetal head detection is important.

Several fetal head detection methods have already been proposed, such as those proposed by Wei Lu et al. using iterative randomized Hough transform [1], by Namburete et al. using shape properties of pixel clusters [2], and by Yinhui Deng et al. based on a hierarchical structural model [3]. These methods are usually focused on certain types of images, for example, images of fetuses with bright head skull or in the same pose. On the other hand, Carneiro et al. described a method for detecting fetal anatomies using a constrained probabilistic boosting tree [4], where five parameters need to be searched.

In order to deal with more complex ultrasound images containing fetuses in different poses, we introduce a deep learning architecture into the fetal head detection process. Compared with shallow networks, deep multilayer networks can fulfil complex functions more efficiently and achieve better generalization performance on difficult recognition tasks [5-6]. Yet, the training of a deep architecture network used to be difficult because of the non-convex optimization involved [6]. However, the situation have been changed since 2006 when Hinton introduced a successful approach to the training of deep neural network [7, 8]. Deep architecture show good performances in image classification [8-13]. Carneiro et al. used deep architecture in left ventricle segmentation based on ultrasound data [14-15].

In this paper, we introduce a novel fetal head detection method based on ultrasound images from fetuses at first trimester. The method can be divided into two steps. First, we build a deep belief network, the input of which is an image patch, and the output is the probability that the patch contains the whole fetal head. Then, search the ultrasound image exhaustively, with the top hypothesis chosen as the result patch. Second, a modified circle detection method is applied to the result patch to detect the position and size of the fetal head. As images vary in gray-scale distribution, a patch is first preprocessed by using histogram equalization and SRAD filter. Then, the patch is divided into eight regions according to the directions, and a Kirsch edge operator is applied to each of the regions to enhance the edge in the corresponding direction. The directional edge detection method enhances the edges whose gradient points out along the radii from the center of the patch, which is approximately the center of the head circle, and at the same time, it weakens the edges in other directions. Finally, Hough transform is used for the circle detection.

In this paper, Section 2 introduces the method we propose, Section 3 presents the experiments and results, and Section 4 comes with the conclusions and future work.

Thanks to agency National Basic Research Program of China (2015CB755500), National Natural Science Foundation of China (61471125), and Doctoral Fund of Ministry of Education (20110071120019) for funding.

2. METHOD

In this paper, a novel method for automatic fetal head detection is proposed. First, a deep belief network is used to search the whole image to determine the result patch that contains the whole fetal head. Then, a modified method is used to detect the position and size of the fetal head in the result patch.

2.1. Deep belief network

A deep belief network (DBN) was first proposed by Hinton in 2006 [8]. DBNs are first pre-trained layer-by-layer, using the RBM and then refined by using a gradient-descent based supervised method. Restricted Boltzmann Machines (RBMs) [16-17] are the building blocks of DBNs.

RBM is a two-layer network, which is fully connected between the two layers. The joint distribution $p(\mathbf{v}, \mathbf{h})$ over the visible units $\mathbf{v}$ and hidden units $\mathbf{h}$ has an energy[16] given by

$$E(\mathbf{v},\mathbf{h}) = -\sum_{i\in visible} b_i v_i - \sum_{j \in hidden} b_j h_j - \sum_{i,j} v_i h_j w_{ij} \quad (1)$$

where v_i, h_j are the binary states of visible unit i and hidden unit j, b_i and b_j are the biases, and w_{ij} is the weight. The probability that the network assigns to a visible vector $\mathbf{v}$ is given by

$$\mathrm{p}(\mathbf{v}) = \frac{\sum_h e^{-E(\boldsymbol{v},\boldsymbol{h})}}{\sum_{v,h} e^{-E(\boldsymbol{v},\boldsymbol{h})}} \quad (2)$$

The weight w_{ij} is updated using the difference between two correlations

$$\Delta w_{ij} = \varepsilon\left(\langle v_i h_j\rangle_{data} - \langle v_i h_j\rangle_{recon}\right) \quad (3)$$

where ε is the learning rate, and the angle brackets are used to denote expectations of data and reconstructed confabulation. In the pre-training step, a greedy layer-wise unsupervised learning method is used: first train the lower layer, then use the lower layer's output as the upper layer's input. The pre-training step is unsupervised. After pre-training layer by layer, the weights of the network are fine-tuned by a supervised gradient-descent based learning method.

The structure of the DBN used in the paper is as shown in Figure 1. For training, the whole network can be treated as a binary-classifier, which can determine whether a given patch contains the whole fetal head or not. The input are two classes of patches, the positive patches containing the whole fetal head, and the negative patches containing part of the fetal head or with no head in them. For testing, an exhaustive patch searching is done in a test image, with each patch being input into the DBN to get the probability of that patch belonging to the positive class. As shown in equation (4), consider the top hypothesis as the result patch.

$$I(x, \mathrm{y}) = \underset{I(x,y)}{\operatorname{argmax}}\, P_{head}(I(x,y)|W) \quad (4)$$

where $I(x, y)$ is the patch centered at (x, y), $P_{head}(\bullet)$ denotes the probability of the patch belonging to the positive class,

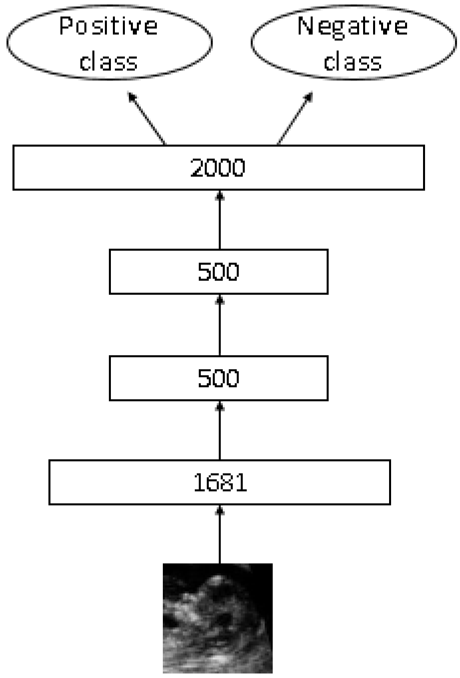


Fig. 1. The structure of the DBN used in the proposed method. The numbers indicate the number of neurons in each layer.

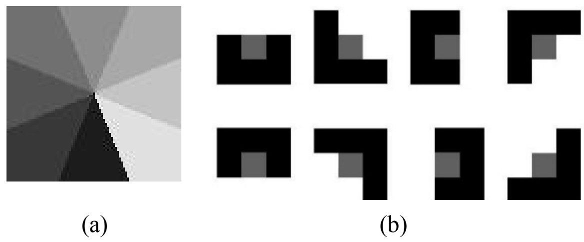


Fig. 2. (a) Eight types of regions for a patch indicated in different colors. (b) Eight Kirsch edge operators in different directions.

and W contains all the weight of the DBN. For the purpose of reducing the computation, the DBN step is trained and tested on the images down-sampling to half size

2.2. Modified circle detection method

After the result patch containing the entire fetal head is identified, we use a modified circle detection method to determine the position and size of the fetal head. The image patch is first preprocessed using histogram equalization and SRAD filter.

Different from traditional edge detection method, gradient direction is taken into account in the proposed method, making good use of the characteristic of image patches in our situation. To detect the circle of the fetal head, the edges on the head skull should be enhanced and the edges inside or outside the head should be weaken. The gradients on the skull usually point out along the radii from the center of the fetal head. Considering the size of image patch which fully contains the fetal head is the same as or slightly bigger than that of fetal head, the center of the fetal head can be approximately replaced by that of the image patch. A directional edge method based on Kirsch edge operator is used to enhance the edges on the fetal head. Each image patch is divided into eight regions, that is, the top, bottom, left, right, upper left(UL), upper right(UR), lower left(LL) and lower right(LR) regions, according to the directions (see Figure 2(a)). For each region, a Kirsch edge operator in the corresponding direction is applied, so a total of eight Kirsch edge operators are applied (see Figure 2(b)). The pixels whose gradient points out along the radii from the center toward the circumference have strong responses, while edges in other directions are weakened. A combination of the filtered images of the eight regions results in the final filtered image, in which a lot of artifacts are prevented. Then, a threshold is chosen to binary the filtered image, followed by the application of Hough transform to the binary edge image to detect a circle.

3. EXPERIMENTS AND RESULTS

To validate our method, experiments are performed on both synthetic data and clinic ultrasound data.

3.1. Experiments on synthetic data

In synthetic data, a large ellipsoid is used to simulate the uterus, a circle is used to simulate the fetal head, and a smaller ellipsoid is used to simulate the fetal body. We create a DBN with 5 hidden layers: 1681-500-500-2000-2. 59000 image patches, including 1600 positive patches and 57400 negative ones, are chosen from 200 synthetic images and used for training. Another 200 synthetic images are used for testing. In testing, all the images are detected correctly, that is, the result image patches contain the entire fetal head. The detection accuracy is 100%. The distance between the center of the result patch and the real head is 0.8280 (±1.0442) pixel.

Then the modified circle detection method is applied to the result patches determined in the DBN step. We use the true positive rate (TP), false negative rate (FN), similarity index (SI), Hausdorff distance (HDF) and the average distance to evaluate the method. TP, FN, SI is defined by

$$\mathrm{TP} = \frac{|S_A \cap S_T|}{S_T} \tag{5}$$

$$\mathrm{FN} = \frac{|S_A \cap S_T - S_T|}{S_T} \tag{6}$$

$$\mathrm{SI} = \frac{|S_A \cap S_T|}{|S_A \cup S_T|} \tag{7}$$

where S_T is the area of the real circle and S_A is the area of the detected circle. Assume $A = \{a_1, \ldots, a_m\}$ is the gold standard circle curve, and $B = \{b_1, \ldots, b_m\}$ is the detected circle curve, where $a_i, b_i \in R^2$. The HDF is defined by

$$HDF(A,B) = \max\left(\max_i\{d(a_i,B)\}, \max_j\{d(b_j,A)\}\right) \tag{8}$$

where $d(a_i, B) = \min_j \|b_i - a_i\|$. The average distance is defined by

$$e(A,B) = \frac{1}{2}\left(\frac{1}{m}\sum_{i=1}^{m} d(a_i,B) + \frac{1}{m}\sum_{i=1}^{m} d(b_j,A)\right) \tag{9}$$

Parameters	Proposed method	SRAD edge based method	KAD edge based method
TP	0.9831 (±0.0151)	0.9990 (±0.0069)	0.9629 (±0.0523)
FN	0.0169 (±0.0151)	0.0010 (±0.0069)	0.0371 (±0.0523)
SI	0.8974 (±0.0246)	0.6917 (±0.1519)	0.8689 (±0.0832)
HDF	2.9791 (±1.6121)	10.4557 (±5.2825)	4.1549 (±1.0116)
Average distance	0.8143 (±1.5315)	7.1782 (±3.8003)	2.1822 (±0.4982)

Table 1. Results of circle detection using the modified circle detection method in synthetic data, compared with SRAD edge based method and KAD edge based method.

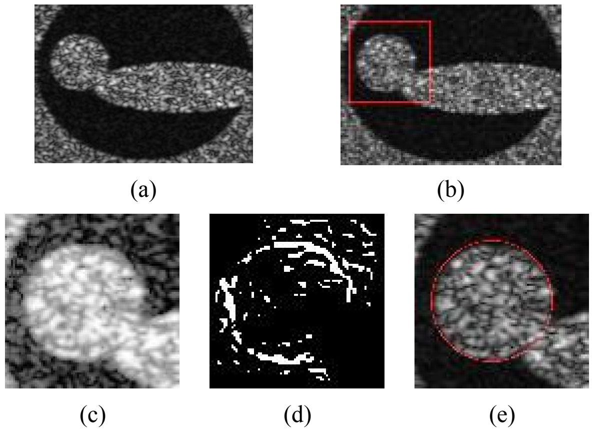
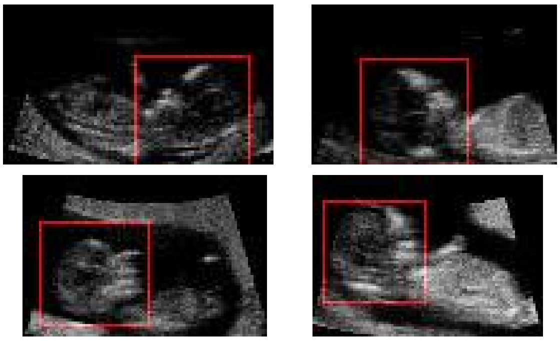


Fig. 3. The results of the proposed method in synthetic data. (a) Original image. (b) The result patch in the original image. (c) The patch image after histogram equalization and SRAD filtering. (d) Directional edge image. (e) The result detection of the fetal head

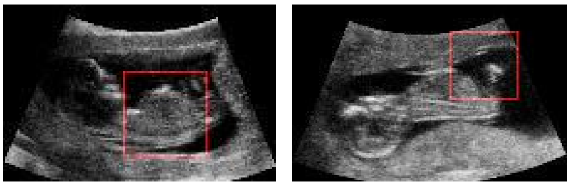
SRAD edge based method and the KAD edge based method, which replace the edge image used in the Hough transformation into edge image computed by SRAD filter [18] and KAD filter [19], are used for comparison. The result of the proposed method comparing with these two method is in Table 1. It can be seen that the performance of the proposed method is better than the other two methods. The TP and FN of SRAD seem better than the proposed method, but that's because the result circle of the SRAD edge based method are usually larger and overlap the real circle. When $S_A \cap S_T \rightarrow S_T$, TP → 1, FN → 0. However, the much better SI、HDF and average distance can show the better performance of the proposed method. The difference between the proposed method and KAD edge based method is more obvious in the clinic data. The results of the proposed method in different stages is shown in Figure 3.

3.2. Experiments on clinic ultrasound data

The experiments are performed on a dataset composed of 346 clinic ultrasound images of fetuses at 11-14 weeks. These data are middle slices of the 3D data collected from 204 patients using Philips iU22 Ultrasound System with a V6-2 probe. To validate the effectiveness of the circle



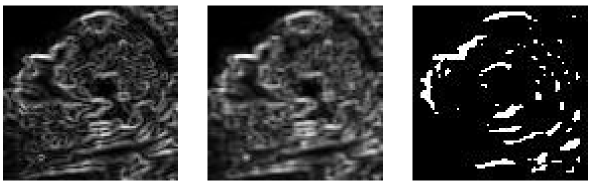
(a)



(b)

Fig. 4. Some of the correctly detected and incorrectly detected results after the deep belief network. (a)Correctly detected cases. (b) Incorrectly detected cases.

(a) (b) (c)



(d) (e) (f)

Fig. 5. (a) Original patch image. (b) After histogram equalization and SRAD filtering. (c) Directional edge image. (d) SRAD edge image. (e) KAD edge image. (f) Binary the direction edge image with threshold 0.2.

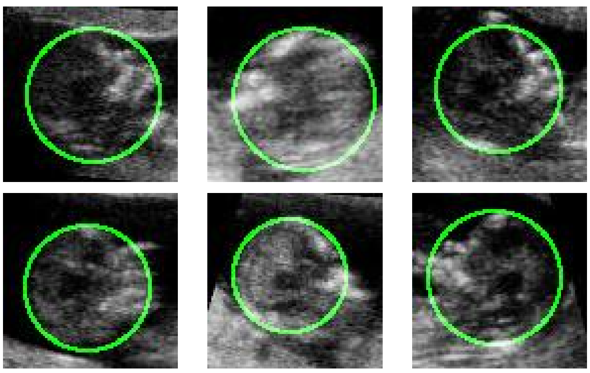


Fig. 6. Some of final head detection results.

Parameters	**Proposed method**	**SRAD edge based method**	**KAD edge based method**
TP	0.9404 (±0.0726)	0.9489 (±0.0694)	0.9235 (±0.0755)
FN	0.0596 (±0.0726)	0.0511 (±0.0694)	0.0765 (±0.0755)
SI	0.8472 (±0.0969)	0.7483 (±0.1052)	0.7577 (±0.1145)
HDF	5.2033 (±3.6478)	9.4000 (±5.0600)	8.9981 (±4.7198)
Average distance	2.7830 (±1.8830)	4.6454 (±2.4522)	4.7979 (±2.4532)

Table 2. Results of circle detection using the modified circle detection method in clinic ultrasound data, compared with those from SRAD edge based method and KAD edge based method.

detection, a best circle of the fetal head is manually drawn as the golden ground for each data.

A DBN with the same structure as in the synthetic experiments are used. 54000 image patches, including 1384 positive patches and 52616 negative ones, are chosen from 173 images and used for training. Another 173 images are used for testing. Of those tested, 164 images are detected correctly. The detection accuracy is 94.8%. The distance between the center of the result patch and the real head is 3.5753 (±2.7581) pixel. Figure 4 gives some examples of the correctly and incorrectly detected cases.

The modified circle detection method is applied to the 164 images whose patches are correctly determined. The image after histogram equalization and SRAD is shown in Figure 5(b). After the histogram equalization step and SRAD step, the image's contrast is improved, and weak edges are enhanced. Also the speckle noise is reduced and the image is smoother. The directional edge filtered image is shown in Figure 5(c). Compared with the SRAD edge detection result and KAD edge detection result, the proposed method enhances the edges on the head circle, and removes lots of artifacts inside and outside the fetal head. Some of final head detection results are shown in Figure 6. The final result circle shows the position and size of the fetal head. The head detection result achieved with the proposed method is compared with the SRAD edge based method and KAD edge based method in Table 2. The TP and SI of the proposed method are 0.9404 (± 0.0726) and 0.8472 (±0.0969), higher than that of the KAD edge based method. The FN, HDF and average distance of the proposed method are 0.0596 (±0.0726), 5.2033 (±3.6478) pixel and 2.7830 (±1.8830) pixel, lower than those of the KAD edge based method. As for the SRAD edge based method, it can be seen that the TP and FN of the SRAD edge based method is 0.9489 (±0.0694) and 0.0511 (±0.0694), slightly better than the proposed method. The reason is the same as explained in synthetic data experiments. The lower SI (0.7483 (±0.1052)) and larger HDF (9.4000 (±5.0600)) and average distance (4.6454 (±2.4522)) of the SRAD edge based method shows the better performance of the proposed method.

4. CONCLUSIONS AND FUTURE WORKS

In the paper, a new method is proposed for automatically detecting a fetal head in ultrasound images of first trimester fetuses. A deep belief network is trained to estimate an image patch containing the whole fetal head, followed by the use of a modified circle detection method to detect the position and size of the fetal head. The method shows good performance in both synthetic data and clinic ultrasound data. It can be applied to images having different gray scale distributions and with various fetal poses. In future, the accuracy of patch estimation needs to be improved and 3D fetal head localization could be done based on the results.

REFERENCES

[1] W. Lu, J. Tan, and R. Floyd, "Automated Fetal Head Detection And Measurement In Ultrasound Images By Iterative Randomized Hough Transform," *Ultrasound in medicine & biology*, vol. 31, no. 7, pp. 929-936, 2005.

[2] A.I.L. Namburete, J.A. Noble, "Fetal Cranial Segmentation In 2D Ultrasound Images Using Shape Properties Of Pixel Clusters," *In Biomedical Imaging (ISBI), 2013 IEEE 10th International Symposium on,* San Francisco, CA, USA, 2013, pp. 720-723.

[3] Y. Deng, Y. Wang, and P. Chen, "Automated Detection Of Fetal Nuchal Translucency Based On Hierarchical Structural Model," *Computer-Based Medical Systems (CBMS), 2010 IEEE 23rd International Symposium on*, Perth, Australia, 2010, pp.78-84.

[4] G. Carneiro, B. Georgescu, S. Good, 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, 2008.

[5] G.E. Hinton, "Connectionist Learning Procedures," *Artificial Intelligence*, vol. 40, pp. 185–234, 1989.

[6] P.E. Utgoff, D.J. Stracuzzi, "Many-Layered Learning," *Neu-ral Computation*, vol. 14, pp. 2497–2539, 2002.

[7] Y. Bengio, "Learning deep architectures for AI." *Foundations and trends® in Machine Learning*, vol. 2, no. 1, pp. 1-127, 2009.

[8] G.E. Hinton, R. Salakhutdinov, "Reducing the Dimensionality of Data with Neural Networks," *Science*, vol. 313, pp. 504-507, July, 2006.

[9] G. E. Hinton, S. Osindero, and T.W. Teh, "A Fast Learning Algorithm for Deep Belief Nets," *Neural Computation*, vol. 18, pp. 1527-1554, 2006.

[10] S. Zhou, Q. Chen, and X. Wang, "Discriminative Deep Belief networks for image classification," *Image Processing (ICIP), 2010 17th IEEE International Conference on*, Hong Kong, China, 2010, pp. 1561-1564.

[11] S. Zhong, Y. Liu, and Y. Liu. "Bilinear deep learning for image classification," *Proceedings of the 19th ACM international conference on Multimedia*, Gothenburg, Sweden, 2011, pp. 343-352.

[12] P. Vincent, H. Larochelle, Y. Bengio, and P.A. Manzagol, "Extracting and composing robust features with denoising autoencoders," *In Proceedings of the 25th international conference on Machine learning*, Helsinki, Finland, 2008, pp. 1096-1103.

[13] K. Yu, W. Xu, and Y. Gong, "Deep learning with kernel regularization for visual recognition," *In Advances in Neural Information Processing Systems*, Vancouver, B.C., Canada, 2009, pp. 1889-1896.

[14] J.C. Nascimento, G. Carneiro, "Non-rigid Segmentation using Sparse Low Dimensional Manifolds and Deep Belief Networks," *Computer Vision and Pattern Recognition (CVPR), 2014 IEEE Conference on*. Columbus, OH, United States, 2014, pp.288-295.

[15] G. Carneiro, J.C. Nascimento, and A. Freitas, (2012). "The segmentation of the left ventricle of the heart from ultrasound data using deep learning architectures and derivative-based search methods," *Image Processing, IEEE Transactions on,* vol. 21, no. 3, pp. 968-982, 2012

[16] G.E. Hinton, T.J. Sejnowski, "Learning and relearning in Boltzmann machines," *MIT Press, Cambridge, Mass*, vol. 1, pp. 282-317, 1986.

[17] G.E. Hinton, "Training products of experts by minimizing contrastive divergence," *Neural computation*, vol. 14, no. 8, pp. 1771-1800, 2002.

[18] Y. Yu, S.T. Acton, "Speckle reducing anisotropic diffusion," *Image Processing, IEEE Transactions on*, vol. 11, no. 11, pp. 1260-1270, 2002.

[19] J. Yu, Y. Wang, Y. Shen, "Noise reduction and edge detection via kernel anisotropic diffusion," *Pattern Recognition Letters*, vol. 29, no. 10, pp. 1496-1503, 2008.