Improving Fetal Head Contour Detection by Object Localisation with Deep Learning

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Abstract. Ultrasound-based fetal head biometrics measurement is a key indicator in monitoring the conditions of fetuses. Since manual measurement of relevant anatomical structures of fetal head is time-consuming and subject to inter-observer variability, there has been strong interest in finding automated, robust, accurate and reliable method. In this paper, we propose a deep learning-based method to segment fetal head from ultrasound images. The proposed method formulates the detection of fetal head boundary as a combined object localisation and segmentation problem based on deep learning model. Incorporating an object localisation in a framework developed for segmentation purpose aims to improve the segmentation accuracy achieved by fully convolutional network. Finally, ellipse is fitted on the contour of the segmented fetal head using least-squares ellipse fitting method. The proposed model is trained on 999 2-dimensional ultrasound images and tested on 335 images achieving Dice coefficient of 97.73 ± 1.32. The experimental results demonstrate that the proposed deep learning method is promising in automatic fetal head detection and segmentation.

Keywords: Fetal ultrasound · Object detection and segmentation · Deep learning · CNN · FCN.

1 Introduction

Ultrasound imaging (US) is the primary modality used in daily clinical practice for assessing the fetus condition such as detecting of possible abnormalities and estimating of weight and gestational age (GA) [1]. Fetal biometrics from ultrasound used in routine practice include occipital–frontal diameter (OFD), femur length (FL), biparietal diameter (BPD), crown-rump length, abdominal circumference, and head circumference (HC) [2, 3]. Fetal head-related measurements including BPD and HC are usually used for estimating the gestational age and fetal weight between 13 and 25 weeks of gestation [4–6]. The 2-dimensional fetal US scan is characterised by its non-invasive nature, real time capturing, wide availability and low cost. However, the US manual examination is highly dependent on the training, experience and skills of sonographer due to the image artefacts and poor signal to noise ratio [7].

Manual investigation of US images is also a time-consuming process and therefore developing automatic US image analysis methods is a significant task. Automated fetal head boundary detection is often performed as a prerequisite step for accurate biometric measurements. The automated fetal head contour detection from US images can be basically fulfilled by developing effective segmentation algorithms which is able to extract the segmented head structure. A number of fetal head segmentation methods have been developed over the past few years with varying degrees of success, including parametric deformable models [8], Hough transform-based methods [9], active contour models [10], and machine learning [11–13]. However, the presence of noise and shadow, intensity inhomogeneity, and lack of contrast in US images make the traditional segmentation methods are not sufficient or have a limited success on fetal head detection. It is a strong need to develop more accurate segmentation algorithm which is able to tackle the presented fetal head detection problems in US images.

Recently, deep convolutional neural networks (CNNs) has revolutionised the field of computer vision achieving great success in many medical image analysis tasks including image segmentation, detection and classification. In terms of segmentation accuracy, fully convolutional network (FCN) [14] has dominated the field of segmentation. FCN has demonstrated improved results in automatic fetal head detection and segmentation in [15–17]. However, FCN has some challenges which need to be tackled. The challenges are represented by being expensive to acquire pixel level labels for network training and having difficulties with imbalanced data samples which lead to a biased representation learned by the network.

In this paper, we propose deep learning based method to segment fetal head in ultrasound. The proposed method aims to improve the segmentation accuracy by incorporating object localisation mechanism in segmentation framework achieved by merging Faster R-CNN [18] with FCN [14]. This incorporation allows to leverage object detection labels to help with the learning of network, alleviating the need for large scale pixel level labels. The rest of this paper is organised as follows. In Section 2, the materials and proposed method are described. Results of the proposed method are presented and discussed in Section 3. Finally, the work is concluded in Section 4.

2 Materials and Methods

2.1 Materials

A publicly available dataset has been used in the training and evaluation of the proposed method [19]. The ultrasound images were captured from 551 pregnant women who received screening exam after (12- 20) weeks of gestation. The dataset includes 1334 2D ultrasound images of the standard plane and the corresponding manual annotation of the head circumference, which was made by an experienced sonographer. The data is randomly spilt into a training set of 999 images and a test set of 335 images. The size of each ultrasound image is 800×540 pixels with a pixel size ranging from 0.052 to 0.326 mm.

2.2 Methods

The framework of our proposed method can be divided into two stages: i) fetal head segmentation by adapting Mask R-CNN (Regional Convolutional Neural Network) [20], and ii) fetal head ellipse fitting using least-squares ellipse fitting method. Mask R-CNN [20] which was originally developed for object instance segmentation combined both localisation and segmentation in one architecture has been adapted to detect fetal head boundary. The proposed fetal head segmentation method comprises four major parts:

1. The feature extraction module is the first step of our method. The feature extraction module is a standard convolutional neural network consisting of convolutional and pooling layers. This module serves as a backbone feature extractor for the segmentation task. Ultrasound images and their masks are resized into $512 \times 512 \times 3$ and passed through the backbone network. We use Resnet101 architecture [21] as a backbone network. Instead of training the model from scratch, transfer learning is exploited by initialising the first 50 layers of the model with pre-trained Resnet50 weights from ImageNet competition. The resulted feature map becomes the input for Faster R-CNN.

2. The object localisation represented by fetal head is achieved using Faster R-CNN which is well-known deep learning based object detection model [18]. It is adopted to generate and predict a number of bounding boxes producing multiple ROIs. The object localisation in Faster R-CNN is achieved by Region Proposal Network (RPN). The RPN scans over the backbone feature maps resulted from ResNet101 producing candidate region proposals/ anchors. The candidate region proposals/anchors are examined by a classifier and regressor to check the occurrence of foreground regions. Two outputs are generated by RPN for each anchor which are anchor class (foreground or background) and bounding box adjustment to refine the anchor box location. Then, the top anchors/candidate bounding boxes which are likely to contain objects are picked. The location and size of the candidate bounding boxes (ROIs) are further refined to encapsulate the object. After that, the final selected proposals (regions of interest) are passed to the next stage.

3. The dimensions of candidate bounding boxes (ROIs) generated by the RPN are adjusted by applying ROIAlign to have same dimensions as they have different sizes. ROIAlign technique samples the feature map at different points and then apply a bilinear interpolation to produce a fixed size feature maps. These feature maps are fed into a classifier to make decision whether the ROI is positive or negative region.

4. The positive regions (fetal head region) selected by the ROI classifier is passed into the mask branch in Mask R-CNN which is known as mask network. The mask network is fully convolutional neural network (FCN) that generates masks on the localised ROI. The output of this stage is the segmented region of fetal head .

   The model is trained and weights are tuned using Adam optimiser for 75 epochs with adaptive learning rates (10^{-4} - 10^{-6}) and momentums of 0.9. Due to small training data set, heavily image augmentation is applied during training by randomly cropping of images to $256 \times 256 \times 3$, randomly rotate the images in the range of (-15, 15) degrees, random rotation 90 or -90 degrees, and random scaling of image in the range (0.5, 2.0). The network is trained under multi-task cross-entropy loss function combining the loss of classification, localisation and segmentation mask: $L = L_{cls} + L_{bbox} + L_{mask}$, where L_{cls} and L_{bbox} are class and bounding box loss of Faster R-CNN, respectively, and L_{mask} is mask loss of FCN.

   Finally, an ellipse is fitted to the predicted segmentation contours of fetal head using least-squares fitting method to mimic the measurement procedure used by the trained sonographers.

3 Results and Discussion

All of the experiments were run on an HP Z440 with NVIDIA GTX TITAN X 12GB GPU card, an Intel Xeon E5 3.50 GHz and 16GB RAM. Keras built on the top of Tensorflow has been used to implement the proposed system. The performance of the proposed method for segmenting the fetal head when compared with the ground truth was evaluated using many evaluation metrics such as Dice coefficient, mean absolute difference, mean difference, and mean Hausdorff distance which measures the largest minimal distance between two boundaries. The measurements can be defined as follows:

$$Dice(A, B) = \frac{2|A.B|}{|A| + |B|} \tag{1}$$

$$MeanAbsoluteDifference(A, B) = \frac{\sum |A - B|}{N \times M} \tag{2}$$

$$MeanDifference(A, B) = \frac{\sum A - B}{N \times M} \tag{3}$$

$$HausdorffDistance(A, B) = max(h(A, B), h(B, A)) \tag{4}$$

where

$$h(A, B) = max_{a \in A} min_{b \in B} \parallel a - b \parallel$$

A, B are the ground truth mask and resulted segmentation map from the proposed method, respectively. a,b are two sets of points from A and B, respectively, which represent the points on fetal head contour. N, M represent the dimensions of ground truth or predicted mask.

Figures 1 and 2 show some example of segmentation results. Figure 1 presents image examples as resulted from trained model used for validation without ellipse fitting. Figure 2 shows the image examples where ellipse is fitted and overlaid the test images.

The proposed system was evaluated on 355 US images achieving Dice coefficient of 97.73 ± 1.32, mean absolute difference (mm) of 2.33 ± 2.21, mean difference (mm) of 1.49 ± 2.85, and mean Hausdorff distance (mm) of 1.39 ± 0.82. The obtained results are comparable and often outperform the existing automated fetal head segmentation methods. Our model achieves higher performance than most recent work carried out by Heuvel et al. [19] who tested their method on the same 355 test images reporting Dice coefficient of 97.10 ± 2.73, mean absolute difference (mm) of 2.83 ± 3.16, mean difference (mm) of 0.56 ± 4.21, and mean Hausdorff distance (mm) of 1.83 ± 1.60.

Although Wu et al. [15] reported slightly better Dice coefficient of 98.4, yet, they reported boundary distance of 2.05 which is higher error than the boundary distance reported by our method. Furthermore, they tested their method on only 236 fetal head images and their results are affected by a refinement stage which is combing FCN with auto-context scheme. Sinclair et al. [16] reported comparable Dice coefficient of 98, however, they trained their model on large training set of 1948 images (double of our training data) and tested only on 100 images. Moreover, we obtain higher Dice coefficient than Li et al. [13] who achieved 96.66 ± 3.15 on 145 test images.

4 Conclusions

In this paper, an automated method to segment fetal head in ultrasound images has been presented. The developed method, which is based on merging Faster R-CNN and FCN, has proved to be efficient in fetal head boundary detection. Incorporating object localisation with segmentation has been proved to be comparable or superior to current approaches in extracting the fetal head measurements from the US data. The proposed system has been evaluated on a fairly large and independent dataset which included US images of all trimesters. The obtained results demonstrated that the proposed deep learning method is promising in segmenting anatomical structure of fetal head efficiently and accurately. The proposed object localisation-segmentation framework is generic and will be easily extended and developed to other ultrasound image segmentation tasks.

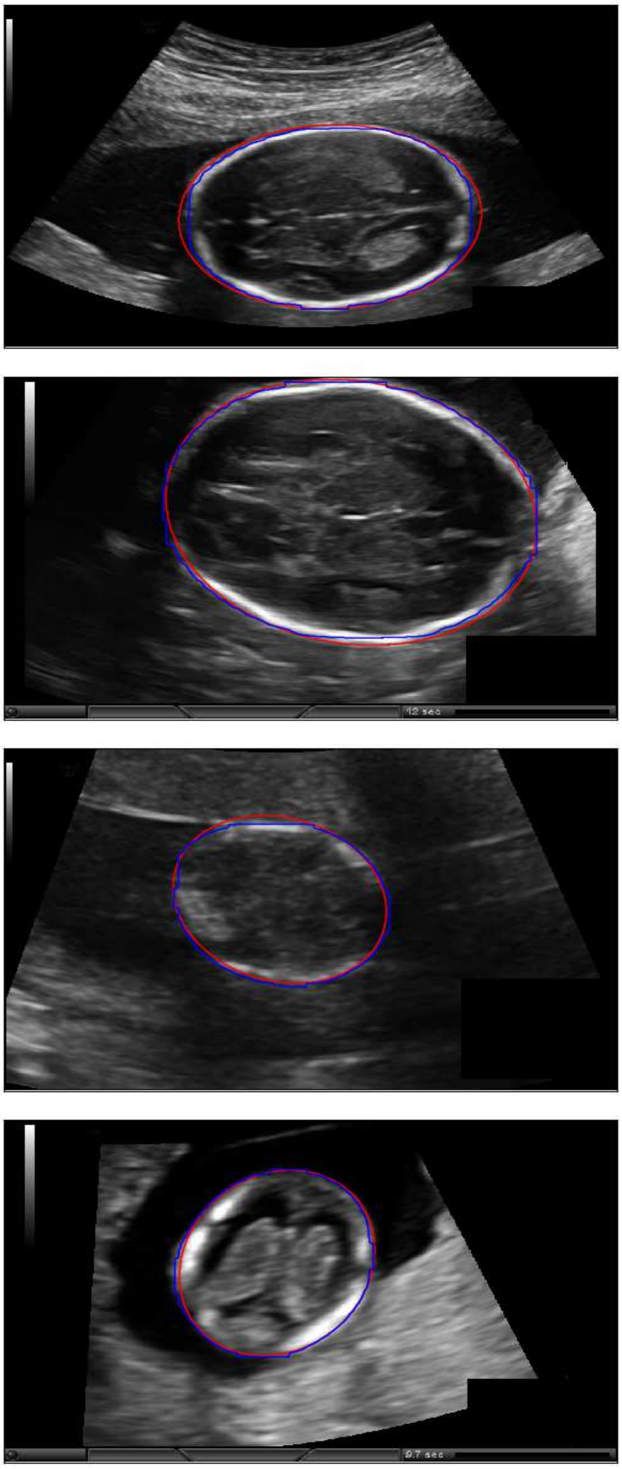

Fig. 1. Results of our model on four randomly images. Blue colour: without ellipse fitting; comparing with the expert annotating (red colour).

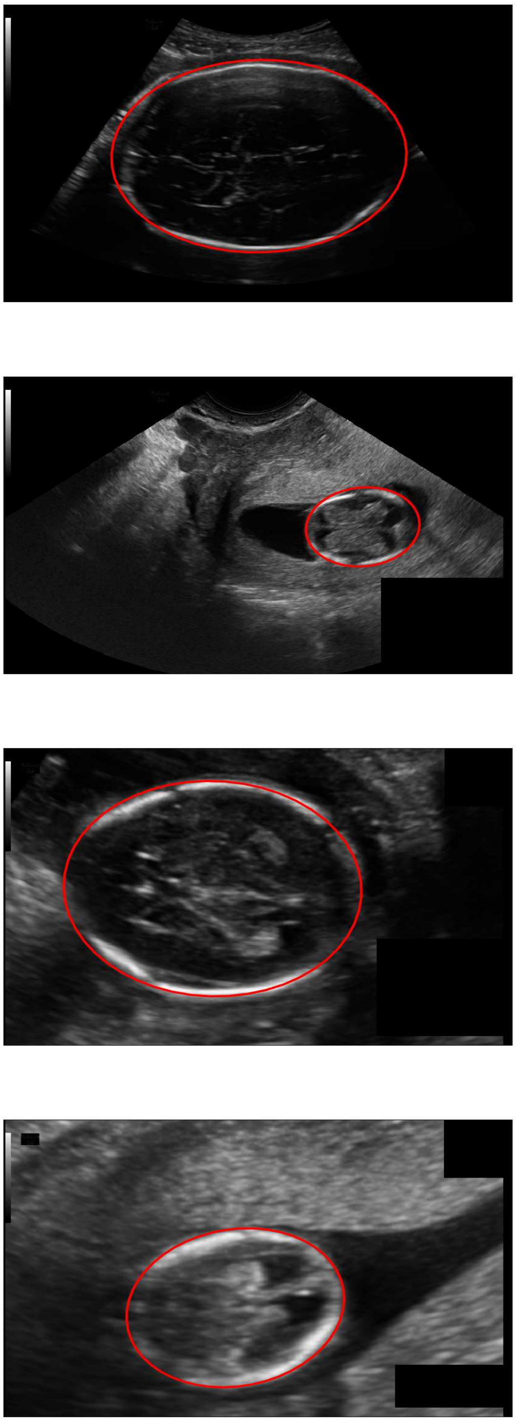

Fig. 2. Image examples show the ellipse fitted on unseen test data demonstrating the effectivity of our model.

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