SEGMENTATION OF THE PLACENTA IN EARLY STAGE PREGNANCY 3D ULTRASOUND USING DEEP LEARNING

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ABSTRACT

First trimester placental volume measured with 3D ultrasound has been shown to be correlated to adverse pregnancy outcomes This could potentially be used as a screening test to predict the "at risk" pregnancy. However, manual segmentation whilst accurate is very time consuming. Semi-automated methods provide close agreement to manual segmentation but remain significantly operator dependant. To generate a screening tool fully automated placental segmentation is required. In this paper a previously published deep convolutional neural network, Deep Medic, was trained using the output of the semi-automated Random Walker method as the ground truth. A set of 300 ultrasound volumes was used to train, validate and test the neural network. Dice similarity coefficients from the neural network had a median value of 0.73. This work shows the feasibility for applying convolutional neural networks to automating segmentation of 3D ultrasound placental volume.

Index Terms— Ultrasound, Deep learning, Placenta

1. INTRODUCTION

A healthy placenta is vital for fetal growth and development. A small placenta early in pregnancy has been demonstrated in pregnancies that will later develop significant pathologies such as pre-eclampsia and fetal growth restriction. [1, 2, 3, 4, 5, 6]. A technique to estimate the placental volume from 3D ultrasound images could be employed as a universal screening tool at population level. This would potentially identify those pregnancies at risk of developing problems enabling clinicians to treat them before either the mother or baby are harmed. Manual segmentation of the placenta in 3D ultrasound volumes is time consuming and operator dependant. Semi-automated techniques have been developed using Virtual Organ Computer-Aided Analysis (VOCAL ™, General Electric Healthcare, Milwaukee, WI, USA) and Random Walker (RW) algorithms [7]. These techniques provide a much faster solution than manual segmentation of the placenta but user input is still required to draw contours or create seeding, limiting clinical application.

Supervised learning using manually segmented or semi-automated segmented placental volumes as the ground truth could fully automate the segmentation of the placenta. Previous studies have applied deep learning to segment lesions in brain MRI [8] and to segment the placenta from fetal MRI [9]. In this work a previously published open source convolutional neural network, DeepMedic [8], was used to segment the placenta from 3D ultrasound volumes. The ground truth for our training is derived from the semi-automated RW method [7].

2. METHODS

The previously published neural network, DeepMedic[8], was configured as shown in Figure 1. The feature maps for the convolutional layers were chosen based on our hardware. The neural network was trained using an Nvidia GTX 750 Ti with CUDA 7.5 and cuDNN 5.1. The memory of the GTX 750 TI was 2 GB and restricted the resolution of the input volumes and the number of feature maps that were used in the neural network.
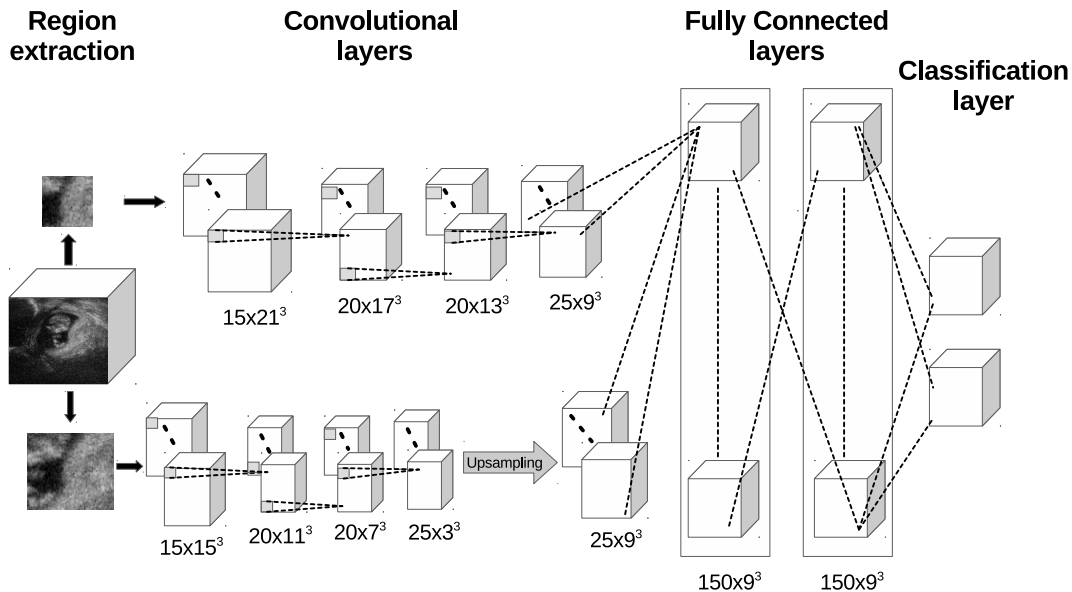
Fig. 1. Architecture of the neural network used in this paper. Two convolutional pathways are used each with four convolutional layers. The top pathway is at normal resolution and the bottom pathway is down-sampled by a factor of three in each dimension.

The semi-automated RW algorithm [10] was used to segment the placenta from the 3064 cases of 3D volumetric ultrasound data collected from a previous study investigating prediction of birth weight by measuring placental volume[3]. These volumes were obtained using a GE Voluson 730 Expert (GE Medical Systems, Milwaukee, Wisconsin, USA) using a 3D RAB 48L (4-8mHz) transducer. The volumes and placenta segmentations were quality assured by clinicians and reduced to a final set of 2893 by excluding cases where the full placental volume had not been imaged and those which had been saved in a lossy compressed format and so were not compatible with the original RW technique. Out of the 2893 cases 240, 40 and 20 cases were randomly selected for training, validation and testing respectively. The mean gestational age (standard deviation) of the cases used in the training, validation and testing were 86.7 days (4.1 days), 87.4 days (3.8 days) and 87.5 days (3.5 days) respectively. The original volumetric data and the placenta segmentations were resampled to have isotropic pixel spacing of 0.7 mm. The volumes were normalised to have zero mean and unary variance. Masks of the ultrasound region were input to the neural network to speed up training and restrict the network to only consider the field of view.

The neural network was trained for 35 epochs with 20 sub-epochs and took 26 hours to run. Validation of the image segments was performed throughout training and a full validation of the whole image carried out every five epochs. The initial learning rate was set at 0.001 and decreased by a half at epochs $12, 16, 19, 22, 25, 28$ and 31.
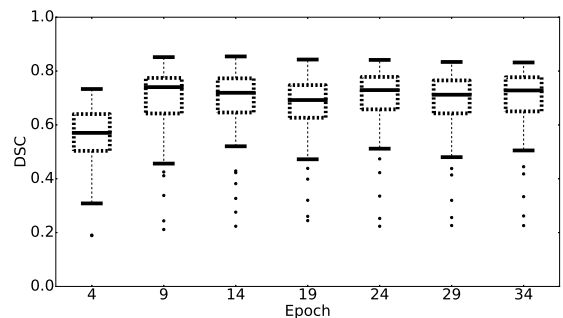
3. RESULTS

Fig. 2. A box plot of the DSC from the full validation of the neural network during the training. The box represents the first quantile and the horizontal lines are the second quantile.

The median (first quartile,third quartile) value of the final Dice Similarity Coefficient (DSC) of the predicted segmentations of the validation cases in the final epoch was 0.73 (0.65,0.78). The performance of the full validation measured
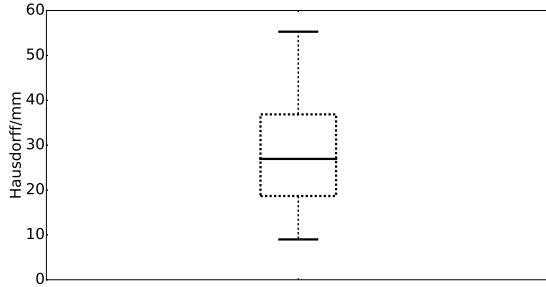
Fig. 3. A box plot of the Hausdorff distance from the predicted segmentation of the validation cases of the neural network. The box represents the first quantile and the horizontal lines are the second quantile.

Fig. 4. A box plot of the DSC from the predicted segmentation of the validation cases of the neural network. The box represents the first quantile and the horizontal lines are the second quantile.
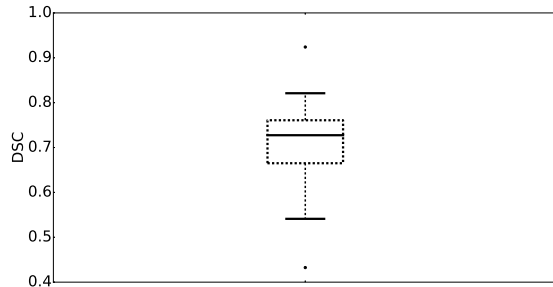
every five epochs is shown in Figure 2. The Hausdorff distance was computed for the validation cases and is shown in Figure 3. The median (first quartile,third quartile) Hausdorff distance was 27 mm (9 mm, 55 mm).

The DSC for the test cases is shown in Figure 4. The median (first quartile,third quartile) value of the final Dice Similarity Coefficient (DSC) of the predicted segmentations of the test cases was 0.73 (0.66,0.76).
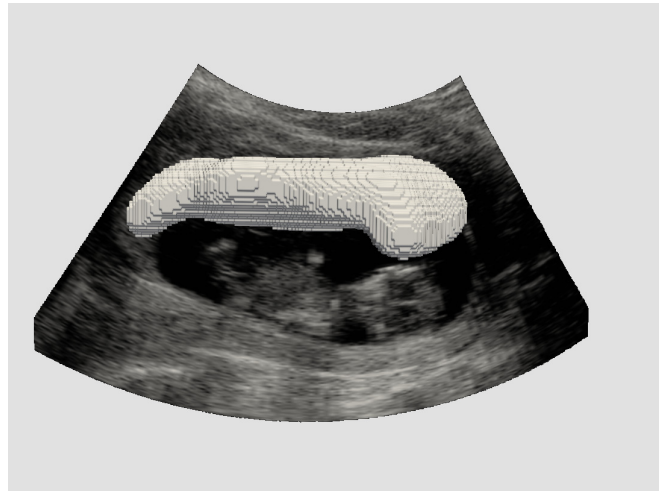
A comparison of the segmentation predicted by the neural network on one of the validation cases is shown in Figure 5. The largest connected component was selected from the output from DeepMedic and was Gaussian smoothed using a kernel of three voxels.

4. CONCLUSION

The initial results of using DeepMedic to segment the placenta in 3D ultrasound demonstrate similar performance in terms of DSC and Hausdorff distance to those obtained to segment lesions in brain MRI and fetal MRI presented in [8] and

(a) Segmentation of the placenta using the RW technique.

(b) Predicted segmentation with post processing.

Fig. 5. Comparison of the segmentation produced using the random walker method to that obtained using the neural network.

[9].

A number of compromises were made to adjust to our currently available hardware. In comparison to the work in [8] the number of features computed was reduced due to the a lack of available memory. From the data set of 2893 cases, 300 cases were used to train, validate and test the neural network due to the lengthy runtime. Due to the limitations of our hardware the input 3D volumes to the neural network were down-sampled to have an isotropic and homogeneous spacing of 0.7 mm. The original volumetric data from the modality is sampled in non-Cartesian coordinates with a generally lower inhomogeneous spacing between sample points.

The results presented here suggest that the application of deep learning to segment the placenta in 3D ultrasound is

promising. Compared to previous organs that have been segmented using cuDNN, the placenta is highly variable as its position is dependent upon the implantation site in the uterus. This results in both effecting the visual appearance and geometric position in space of the target organ. The results we report seem to be concordant with previously reported work which would indicate that this heterogeneous organ position seems to be a minor challenge that is overcome using this segmentation technique. More powerful hardware and higher GPU memory will allow an increase in the feature set, the number of cases used and the resolution of the volumetric data. These improvements may lead to better performance of the segmentation and a reliable automated segmentation tool for the placenta in 3D ultrasound.

5. ACKNOWLEDGEMENTS

6. REFERENCES

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