Improving 3D US Fetal Brain Segmentation via Cross-Modality Label Transfer from MRI to US

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1 Introduction

Fetal brain imaging is crucial for prenatal diagnosis, with magnetic resonance imaging (MRI) providing high-resolution images and ultrasound (US) being widely accessible. However, accurate labeling of US images remains challenging due to low soft tissue contrast, speckle and shadowing artifacts. This study explores transferring MRI labels to US images to improve fetal US brain segmentation accuracy.

Previous studies, such as Hesse et al. [2], have explored using both manually annotated US volumes and weakly labeled US volumes obtained through annotated template images. Unlike these approaches, we investigate using MRI labels for better segmentation accuracy. MRI offers superior spatial resolution and tissue contrast, and is unaffected by maternal body habitus and fetal position.

We manually registered MRI labels to US images and trained a V-Net based segmentation network for fetal brain structures. This abstract focuses on the preliminary results of total brain volume (TBV) segmentation. The ultimate goal is to develop a robust tool for fetal brain segmentation, including substructures, which can then be applied to large US datasets, thereby improving prenatal diagnosis without relying on MRI data.

2 Methods

We used data from the YOUth Baby & Child US & MRI dataset, focusing on 15 subjects with MRI and US scans within 24 hours to minimize developmental discrepancies [5]. US imaging was performed during routine exams, and 3D US data was reconstructed from 2D planes [1]. After excluding poor-quality scans, we ended up with a total of 45 US scans (N = 12 subjects). MRI scans were combined into 3D volumes and pre-labeled with 19 anatomical structures using the BOUNTI tool [3, 6].

US and MRI data were manually registered using ITKsnap software, with the US as the moving image and the MRI as the fixed image [7]. The MRI labels were then transferred to the US data via inverse transformation.

We used a V-Net-based segmentation network with 3 downsampling and 3 upsampling stages for TBV segmentation [4]. Data was split into training, validation, and testing groups. A patch-based input approach was used, which divided images into smaller patches. Data augmentation included rotations, translations, zoom, Gaussian noise, and gamma correction.

The model was evaluated on a test set of 15 US scans (N = 4 subjects), with 10 augmentations per image to compute mean predicted masks. Performance was assessed using Dice Score, Hausdorff distance, and Center of Mass Distance.

3 Results and Discussion

The evaluation metrics showed promising results, with a mean Dice score of 0.894 (std ± 0.023) and center of mass deviations with a mean of 3.708 voxels (std ± 1.489). The segmentation result for TBV is illustrated in Fig. 1, showing strong agreement between the segmentation and the ground truth. Although the Hausdorff distance was relatively high (mean 24.237 voxels, std ± 12.244), this first model is primarily intended for localization and accurate cropping of the brain. Consequently, the center of mass metric is of greater significance, as the crop will be based on the center of mass.

Future work will focus on US alignment and training a network for brain substructure segmentation, targeting prominent structures like the cerebellum (CB), Cavum Septi Pellucidi (CSP), and brain stem (BS). By segmenting these structures, we can align the US data, which is often not in the same orientation. This alignment will provide a foundation for a subsequent model to focus on finer substructures using a more specialized network.

We also plan to apply our model to the complete YOUth dataset of around 50,000 scans (N=2777 subjects) at 20 and 30 weeks of gestation. Potential validation methods may involve comparing our results with MRI segmentation standards and volume growth curves from other studies.

Our goal is to develop a robust tool for fetal brain segmentation that uses the benefits of MRI quality while minimizing reliance on extensive MRI datasets. This approach could significantly advance fetal brain development research and improve fetal monitoring, aiding in early diagnosis and intervention.

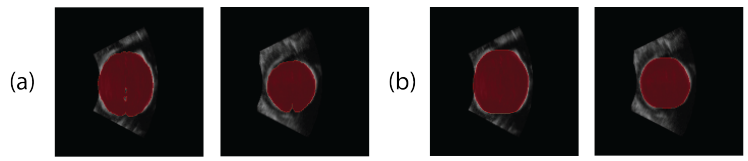

Fig. 1. Segmentation result for TBV: (a) Ground truth label overlay (b) Mean prediction result on US scan from test set

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