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Enhancing prenatal care through deep learning

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Discussion

The work presented in this thesis has contributed to enhancing prenatal care for fetal ultrasound and fetoscopic surgery by employing deep learning-based methods. In this chapter, we discuss the major contributions of this work, limitations, and possible future directions to prenatal care research, encompassing fetal ultrasound and fetoscopic surgery.

7.1 Contributions to prenatal care research

Although many deep learning-based methods have been developed to support fetal ultrasound imaging [13; 18; 19; 28; 29; 31; 42; 93; 98; 115; 117; 152; 153; 159; 184; 223; 233] and fetoscopic surgery [15; 16; 35; 36; 166], in this thesis, we present the following contributions that may have significant clinical and technical impacts on the fields of fetal ultrasound and fetoscopic surgery.

7.1.1 Automatic fetal biometry

Fetal biometry requires following strict procedures which standardize the ultrasound examination [167]. The most important first step is the identification of *standard plane* during the ultrasound examination, which is a prerequisite for performing measurements. Standard planes are characterized by providing an optimal, standardized view of the examined structures based on the presence of desired anatomical structures and their appropriate exposure [132]. Obtaining proper biometric measurements is subject to intra- and inter-observer variabilities, and depends on both the correctness of standard plane acquisition and utilization of proper measuring technique [167]. Furthermore, the fetus' position, the quality of the equipment, the operator's skill, and maternal factors such as obesity and diabetes can impact the accuracy of measurements and complicate the interpretation of biometric data.

Recent efforts have been significantly invested in achieving the challenging task of automatic fetal biometry during routine fetal ultrasound examinations. However, many limitations exist in previous approaches, such as errors prone to non-well-generalizable algorithms or focusing solely on one fetal body part (i.e., head, abdomen, or femur). Furthermore, these approaches do not benefit from temporal context, as they use only static video frames.

Motivated by these limitations, we developed a multi-task deep learning-based method designed to analyze $2D + t$ spatio-temporal fetal ultrasound videos (Chapter 2). This method automatically detects the standard planes of the entire fetal body during routine fetal ultrasound examinations. Notably, this method enables direct measurements of fetal biometry, encompassing parameters such as head circumference (HC), biparietal diameter (BPD), abdominal circumference (AC), and femur length (FL), extracted directly from fetal video recordings. Our proposed approach demonstrates the effectiveness of adding the temporal context of video in contrast to static video frames, providing a more robust feature learning representation.

We validated the performance of our method, by comparing measurements made by our deep learning-based method with manual measurements by experienced clinicians. The results show that our proposed method has the potential to become an auxiliary tool for fetal biometric measurement in routine fetal ultrasound examinations in clinical settings, especially for less experienced clinicians. To the best of our knowledge, this is the first work that compares the performance of human experts and deep learning-based methods in performing fetal biometric measurements on the entire fetal body, including the fetal head, abdomen, and femur, from ultrasound videos.

7.1.2 Fetal birth weight prediction

In the case of fetal birth weight (FBW), despite the common use of ultrasound to estimate fetal birth weight before the delivery, standard prediction models have been shown to cause errors of up to 15% [172]. Measurement techniques and observer variability contribute significantly to systematic and random error. Therefore, medical examination standardization and substantial training are required for accurate FBW estimation. Averaging multiple measurements, improving image quality, refining measuring techniques, and developing fetal weight estimation formulae [59] are the existing mechanisms that can improve the accuracy of standard measurement techniques. In current clinical practice, the gold standard method for FBW estimation is heuristic formulae [79], including fetal biometric measurements of body organs – HC, BPD, AC, and FL, extracted from fetal ultrasound. With this approach, there is, however, a tendency to overestimate weights in smaller pregnancies while underestimating those of bigger fetuses [137].

Recently, automated methods based on regression algorithms [128; 129] and deep neural network-based models [65] have been investigated for more accurate and personalized FBW prediction. In Chapter 3, we introduced an end-to-end method for predicting birth weight directly from fetal ultrasound video scans. This marks the first attempt to automate fetal birth weight prediction using fetal ultrasound image features and deep learning. Here, we combined Transformers and Convolutional Neural Networks (CNNs) to leverage their advantages in local and global feature representation learning, as well as spatio-temporal context embedded within the video. However, we were unable to match clinical experts solely using ultrasound video features.

To address this limitation, we incorporated clinical (tabular) data and explored multimodal feature learning. In Chapter 4, we presented a method that enhances the accuracy of birth weight estimation by incorporating tabular clinical data through the use of a Dynamic Affine Feature Map Transform module. We assessed the robustness of our approach by conducting a human observer study to demonstrate how manual and deep learning-based measurements complement each other. The experiments show that our method not only relies on tabular (clinical) data of fetal biometry measurements but also on image feature representation, making it a valuable support tool for less experienced clinicians. To the best of our knowledge, both research works represent the first attempts to predict fetal birth weight by employing deep learning-based methods, incorporating both ultrasound image features and multimodal data.

7.1.3 Fetal weight prediction

Throughout pregnancy, estimated fetal weight (EFW) plays a crucial role in assessing intrauterine fetal growth and development. Recent studies indicate a high correlation between abdominal circumference (AC), measured on the abdomen standard plane, and EFW [32]. AC emerges as a reliable marker for identifying small or large-for-gestational-age fetuses and determining the appropriate delivery method (Cesarean or vaginal) [26; 46; 96; 99].

Initial research in Chapter 3 and Chapter 4 emphasizes the significance of the fetal abdomen plane in reducing estimated errors of fetal birth weight. Building on this, we tested the hypothesis that ultrasound frames of the fetal abdomen alone are sufficient for reliable fetal weight estimation, potentially rendering head and femur scans unnecessary.

Chapter 5 introduces a novel method for directly estimating fetal weight at various gestational ages (GAs) using ultrasound video scans of the fetal abdomen and GA. Our approach, utilizing abdominal ultrasound video scans, minimizes the inefficiencies and risks associated with manual biometry methods requiring multiple measurements. This advantage is further underscored by the ease and speed of capturing the fetal abdominal plane compared to other biometric measurements, such as the head or femur.

Comparison between manual biometry [79] and a deep learning-based approach in our study reveals comparable results with no significant differences. The deep learning approach, relying solely on ultrasound video scans of the fetal abdomen, not only saves time but also reduces the risk of critical measurement errors associated with manual biometry. Our findings suggest that a deep learning-based method using ultrasound video scans of the fetal abdomen alone could serve as a viable alternative to manual biometry.

7.1.4 Fetoscopic surgery

Routine fetal ultrasound examinations can detect various abnormalities that may require prompt and efficient surgical intervention during pregnancy. Advances in fetal surgeries, such as repairing Congenital Diaphragmatic Hernia [52], Spina Bifida [48], or performing fetoscopic laser photocoagulation for TTTS [140], have transformed the field of maternal-fetal medicine [173]. Particularly for TTTS, the outcomes for affected fetuses were historically poor before the availability of these advanced surgical techniques [76]. However, with the early identification of TTTS through prenatal care and timely fetal surgery intervention, the prospects for a healthy outcome for both twins have significantly improved [9].

Precise detection and identification of placental vessels play a crucial role in the success of fetoscopic laser photocoagulation for TTTS, contributing to the reduction of potential complications such as Twin Anemia Polycythemia Sequence (TAPS) or preterm birth [17; 39]. One crucial aspect is collecting multi-center data, which allows for capturing the variability arising from different clinical settings and imaging equipment at various clinical sites. However, the clarity of placental vessels can be compromised within a limited field of view, poor visibility due to the turbid environment of the amniotic sac, and high inter-subject variability, posing a challenge for surgeons to accurately target abnormal blood vessels. Therefore, enhancing the capability to detect and identify placental vessels with precision under diverse conditions, including varying lighting, angles, and levels of turbidity, holds the potential to significantly improve the success rates of the treatment.

There is a significant limitation to the application of current state-of-the-art methods in clinical settings. Recently proposed methods, as highlighted in studies [12; 16], are computationally demanding, rendering them impractical for real-time applications. Furthermore, these methods often face challenges in segmentation performance, specifically in accurately identifying and separating small placental vessels—a critical aspect for achieving optimal surgical treatment outcomes.

In Chapter 6, we introduced a novel method for accurate and fast real-time placental vessel segmentation during fetoscopic laser photocoagulation for TTTS. Our objective was to propose a lightweight segmentation neural network prototype applicable in a clinical environment. The network integrates multi-scale feature fusion and a novel attention mechanism to effectively capture both fine and coarse-grained details of the vessels while maintaining computational efficiency. A channel-attention mechanism enables the network to focus on the most crucial regions of the image, thereby enhancing segmentation accuracy. Additionally, we introduced novel custom data augmentation approaches to address visibility challenges arising from hardware-based artifacts and poor visibility within the amniotic sac. Our method underwent evaluation using a comprehensive test set from six fetal medicine centers across Europe, constituting, to the best of our knowledge, the largest dataset of intra-operative video frames during TTTS fetoscopic laser treatment. Furthermore, we enhanced the quality of annotations in the publicly available dataset [12]. Our study revealed that our proposed method generalizes effectively to data acquired from external medical centers.

7.2 Limitations and future directions

The methods presented in this thesis have the potential to greatly enhance clinical workflow and can serve as a valuable computer-assisted tool for clinicians during routine examinations and interventions. The application of these methods could result in significant improvements to patient care by increasing efficiency and accuracy in clinical applications which is a general direction of the future work.

7.2.1 Fetal ultrasound

The research presented in this thesis, which focuses on fetal ultrasound, has the potential to be applied in clinical settings, particularly for less experienced clinicians. These applications aim to assist clinicians in the decision-making process during fetal ultrasound examinations, encompassing fetal biometry, the estimation of fetal weight throughout pregnancy, and the estimation of fetal birth weight before delivery. This helps assess the optimal delivery method – whether vaginal or Cesarean.

Despite their potential benefits, it is important to note that the methods described in this thesis have certain limitations that must be taken into consideration. One such limitation is that the ultrasound data used in this research were obtained from a single device manufacturer (General Electric Healthcare). This means that the results obtained may not be generalizable to different domains [113; 235], such as other ultrasound devices and manufacturers. Another limitation is that the data used only represent a local demographic, which may not be representative of other populations. Specifically, the dataset used in this research consisted only of singleton, healthy pregnancies. Therefore, it remains unclear whether the methods described would be equally effective in detecting abnormalities in pregnancies with different characteristics, such as multiple gestations or high-risk pregnancies. Additionally, the regression algorithms presented for the estimation of fetal birth weight and fetal weight lack explainability. Currently, visual attention maps, which are crucial for decision-making in the case of weight estimation, have not been provided.

Further research is needed to explore the generalizability of the proposed methods by incorporating a large amount of data from various medical centers, ultrasound devices, and populations. Moreover, our future directions involve expanding upon this work to include fetal disease classification, amniotic fluid measurements, and the comprehensive analysis of entire ultrasound examinations, leveraging long-range free-hand ultrasound videos. Long-range ultrasound videos can aid in providing more reliable decisions based on the global context. Furthermore, explainable artificial intelligence (XAI) [206] should be more actively involved in fetal ultrasound analysis, especially in the case of regression algorithms, to provide more valuable feedback for both clinicians and patients.

7.2.2 Fetoscopic surgery

The research presented in this thesis focuses on fetoscopic surgeries for TTTS and holds practical relevance in clinical settings. The application aims to assist fetal surgeons in real-time visualization of placental vessels during fetoscopic laser photocoagulation for TTTS, with the potential to shorten surgery duration and enhance success rates.

However, it is important to note several limitations in our approach. Firstly, the method is specifically designed for segmenting placental vessels and does not differentiate between arteries and veins, which would be clinically valuable [50]. Additionally, segmentation of other structures such as fetuses or surgical tools is excluded, as they are not relevant to our clinical application. Lastly, our method is not trained on video recordings and lacks $2D+t$ spatio-temporal features, which could improve segmentation results by incorporating temporal information from neighboring frames [36; 199; 209; 211].

In future work, we aim to extend our solution by incorporating temporal-consistent segmentation [215] to reduce prediction errors and fluctuations during real-time segmentation [156; 237]. From a clinical perspective, we plan to enhance the solution by incorporating more detailed classes, such as dividing vessels into arteries and veins. This refinement is valuable for treatment outcomes, especially for the automatic classification of abnormal blood vessel connections in the placenta, known as arteriovenous anastomoses [125], which connect the blood circulations of both twins. Our initial work on placental vessel segmentation can provide valuable features for image registration during the video mosaicking process [3; 14; 16; 69; 149; 197] of the entire placenta. Both the classification of abnormal blood vessel connections and video mosaicking can significantly reduce the time of the fetoscopic procedure. Finally, we aim to implement our solution in clinical trials at the hospital and assess the benefits of using deep learning-based computer-assisted surgery in terms of improving the success rate of fetoscopic laser surgeries, especially for less experienced fetoscopic surgeons.

7.3 Conclusions

This thesis has presented several deep learning-based methods that contribute to and could significantly enhance the field of prenatal care. Specifically, we investigated novel methods, including automatic fetal biometry, estimation of fetal weight and birth weight, and placental vessel segmentation during Twin-to-Twin Transfusion Syndrome fetoscopic laser surgery. The algorithms we demonstrated, based on deep learning, represent cutting-edge methods in their respective domains. Additionally, the methods we introduced have the potential to be applied within a clinical environment to assist clinicians in the decision-making process, especially for less experienced practitioners. Our goal and future direction are to implement these methods in clinical environments to drive tangible enhancements in prenatal care.