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Assessment of Obstetric Ultrasound Images using Machine Learning

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Abstract

Ultrasound-based fetal biometry is used to derive important clinical information for identifying IUGR (intra-uterine growth restriction) and managing risk in pregnancy. Accurate and reproducible biometric measurement relies heavily on a good standard image plane. However, qualitative visual assessment, which includes the visual identification of certain anatomical landmarks in the image is prone to inter- and intra-reviewer variability and is also time-consuming to perform. Automated anatomical structure detection is the first step towards the development of a fast and reproducible quality assessment of fetal biometry images. This thesis deals specifically with abdominal scans in the development and evaluation of methods to automatically detect the stomach and the umbilical vein within them.

First, an original method for detecting the stomach and the umbilical vein in fetal abdominal scans was developed using a machine learning framework. A classifier solution was designed with AdaBoost learning algorithm with Haar features extracted from the intensity image. The performance of the new method was compared on different clinically relevant gestational age groups.

Speckle and the low contrast nature of ultrasound images motivated the idea of introducing features extracted from local phase images. Local phase is contrast invariant and has proven to be useful in other ultrasound image analysis application compared with intensity. Nevertheless, it has never been implemented in a machine learning environment before. In our second experiment, local phase features were proven to have higher discriminative power than intensity features which enabled them to be selected as the first weak classifiers with large classifier weight.



Third, a novel approach to improving the speed of the detection was developed using a global feature symmetry map based on local phase to select the candidate locations for the stomach and the umbilical vein. It was coupled with a local intensity-based classifier to form a “hybrid” detector. A nine-fold increase in the average computational speed was recorded along with higher accuracy in the detection of both the anatomical structures.

Quantitative and qualitative evaluations of all the algorithms were presented using 2384 fetal abdominal images retrieved from the image database study of the Oxford Ultrasound Quality Control Unit of the INTERGROWTH-21st project.

Finally, the “hybrid” detection method was evaluated in two potential application scenarios. The first application was clinical scoring in which both the computer algorithm and four experts were asked to record presence or absence of the stomach and the umbilical vein in 400 ultrasound images. The computer-experts agreement was found to be comparable with the inter-expert agreement. The second application concerned selecting the standard image plane from 3D abdominal ultrasound volume. The algorithm was successful in selecting 93.36% of the images plane defined by the expert in 30 ultrasound volumes.





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Chapter 1 Introduction

1.1 Motivation

Small for gestational age (SGA) refers to the situation when a fetus is smaller than expected for the number of weeks of pregnancy. Newborn babies with SGA are often associated with having intrauterine growth restriction (IUGR), which is a more specific condition where the fetus fails to reach its growth potential. 18 million babies are born every year with low birth weight because of IUGR and/or prematurity, resulting in significant short- and long term morbidity and mortality (Lawn et al., 2005). Growth restricted fetuses have poorer neonatal outcomes and it is recognised that developmental delay associated with IUGR leads to significant health care and developmental problems during childhood and most likely in adult life (Barker, 2006). Recognition of the serious risks associated with IUGR has elevated its diagnostic importance among perinatologists. Thus, obtaining accurate assessment of fetal growth and gestational age from fetal biometry for identifying risks to the fetus/neonate is very important.

Historically, X-ray was used to measure fetal dimensions (e.g. fetal head, pelvic dimension) (Shenton, 1922) before the development of ultrasound. The development of two-dimensional (2D) ultrasound made it possible to measure the dimensions of bones and soft tissue structures of the fetus faster and more reliably than with x-rays. 2D ultrasound is currently considered to be the first choice for a safe, non-invasive, accurate and cost-effective investigation in the fetus. It has progressively become an indispensable obstetric tool and plays an important role in pregnancy management. Comprehensive ultrasound examination during pregnancy includes standard fetal biometric measurements, which are primarily used to estimate the gestational age of the fetus, to track fetal growth patterns, to estimate fetal

weight and to detect abnormalities. A detailed description of ultrasound-based fetal biometry used for age estimation and growth assessments is given in Section 2.2.

Fetal biometry is determined from standardized ultrasound planes taken from the fetal head, abdomen and thigh. The acquisition of optimal image planes from which these measurements are taken is crucial to allow for accurate and reproducible biometric measurements, and also to minimize inter- and intra-observer variability. Criteria and description of standard fetal biometric planes are presented in Section 2.5.

The importance of quality control for the scanning procedures and measurements has been emphasized (Dudley, 2006, Ville, 2008) and a quality control policy based on image scoring has been proposed (Salomon et al., 2006). To highlight challenges in scanning and acquiring the standard image plane, scans made by several different sonographers for finding the abdominal measurements after they had been briefed on the scanning protocol for a growth study known as INTERGROWTH-21st are shown in Figure 1.1. Even though all the scans shown in the figure are magnified satisfactorily, the appearance of the stomach and the umbilical vein are inadequate in some of the scans. According to Salomon's grading, scans in the first column are acceptable with the stomach and the umbilical vein clearly identified and in the correct position. However, elongated umbilical vein appearance in the second column's images indicates that the plane is too angled.

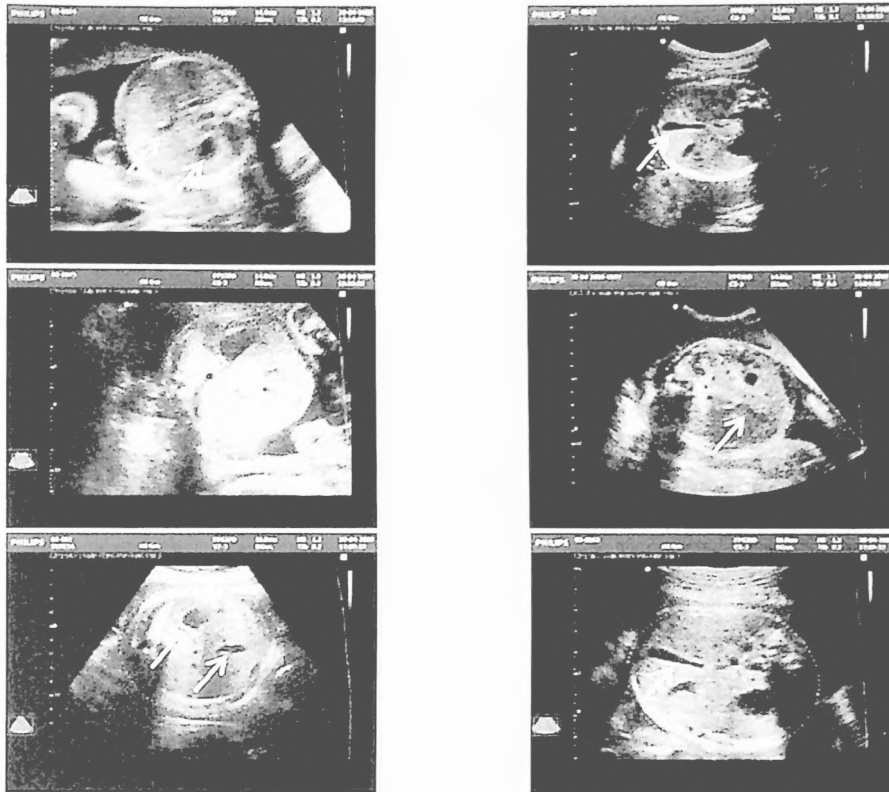


Figure 1.1: Scans acquired by different sonographers for finding abdominal measurement during image quality training session. The stomach and the umbilical vein (white arrows) are clearly visible in the images in the first column. However, elongated umbilical vein in images in the second column indicates that the plane is too angled.

There are several limitations of visual image quality assessment. The process of image review, which includes the visual identification of certain anatomical landmarks in the image, requires significant human resources. Extensive qualitative analysis is also time-consuming and costly. Furthermore, there is an issue of inter- and intra-reviewer variability and also bias imposed by a human reviewer. An automated image scoring system, which 1) can perform the evaluation quickly, 2) is robust to appearance variations of the visual object of interest, and 3) efficient and economical for any scale of implementation would be a valuable support to the quality control process.

This thesis deals specifically with the development of automated methods for the detection of two important landmarks (the stomach and the umbilical vein) in fetal abdominal ultrasound scans using machine learning. The plane containing these two landmarks is described in the early proposal for using the abdominal circumference measurement for fetal weight estimation (Campbell and Wilkin, 1975). The plane containing these two landmarks was adopted in constructing the widely used chart for abdominal circumference size (Chitty et al., 1994) and also proposed in the image quality scoring system (Salomon and Ville, 2005).

1.2 Contributions

The main contributions of this thesis are summarized below:

1. The development of an original method to detect the stomach and the umbilical vein in fetal abdominal scan using a machine learning technique (Chapter 3). Parts of this chapter have been published at peer-reviewed conferences:
 - i. Quality Control of Fetal Ultrasound Images: Detection of Abdomen Anatomical Landmarks using Adaboost. *IEEE International Symposium on Biomedical Imaging (ISBI)*, 2011.
 - ii. Image Analysis Using Machine Learning: Anatomical Landmarks Detection in Fetal Ultrasound Image. *IEEE Signature Conference on Computers, Software, and Applications (COMPSAC)*, 2012.
2. The investigation of introducing features extracted from the local phase¹ image into the machine learning framework for the detection of the two anatomical landmarks

¹ Local phase concept used in this thesis is different than the term 'phase' used in the radio frequency signal used at acquisition time for ultrasound images. Detailed explanation can be found in Chapter 4.



(stomach and umbilical vein) (Chapter 4). Part of this chapter has been published at a peer-reviewed conference:

- i. Multi-Scale Local Phase Features for Anatomical Object Detection in Fetal Ultrasound Images. *Medical Image Understanding and Analysis Conference (MIUA)*, 2012.

3. The development of a faster and more accurate detector using a hybrid approach for the detections of the stomach and the umbilical vein (Chapter 5). Part of this chapter has been published at a peer-reviewed conference:

- i. Integration of Local and Global Features for Anatomical Object Detection in Ultrasound. *International Conference on Medical Image Computing and Computer Assisted Intervention (MICCAI)*, 2012.

4. The evaluation of the proposed detection method in two clinical application scenarios (Chapter 6). Parts of this chapter has been published at a peer-reviewed conference:

- i. Automated Selection of Standardized Planes from Ultrasound Volume. *MICCAI Workshop on Machine Learning in Medical Imaging (MLMI)*, 2011.

and as abstracts in the following clinical meetings:

- ii. A Pilot Study of Automated Image Scoring for Quality Control Purposes in the Context of Multicentre Studies: Abdominal Circumference. *World Congress on Ultrasound in Obstetrics and Gynecology*, 2011.
- iii. Automated Fetal Biometry Image Landmark Detection for Confirming Correct Image Planes: Abdominal Circumference. *World Congress on Ultrasound in Obstetrics and Gynecology*, 2012.



- iv. Automated Standard Plane Selection from Fetal Abdominal Ultrasound Volumes using a Machine Learning Algorithm. *World Congress on Ultrasound in Obstetrics and Gynecology*, 2012.

1.3 Thesis Outline

Chapter 2 describes the background knowledge on fetal growth restriction and the current clinical practice which uses ultrasound for its assessment along with its challenges and the quality control process. The chapter also provides the review of related image analysis work in fetal ultrasound domain and the application of machine learning for detection purposes in medical imaging.

Chapter 3 describes the initial method used for the detection of important anatomical landmarks in fetal abdominal ultrasound images using machine learning framework.

Chapter 4 deals with utilizing features from multi-scale local phase images in the same detection framework. The efficiency of the new feature sets are compared to the performance intensity-based features used in Chapter 3.

Chapter 5 introduces a new hybrid approach for the enhancement of the performance and the speed of the detection. A multi-scale feature symmetry measure derived using local phase is combined with the local intensity-based detector (developed in Chapter 3) is utilized for fast object detection and its detection performance is analysed.

Chapter 6 evaluates the application of the proposed algorithm in two potentials scenarios: comparison with experts' agreements in recording the presence and absence of the anatomical structures in fetal abdominal scan and utilizing the algorithm for the selection of standard plane from 3D volumes.

Chapter 7 concludes the thesis and discusses directions for future work.