# Fetal Head Detection on Images from a Low-Cost Portable USB Ultrasound Device

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**Abstract**

Ultrasound (US) has been shown to be a safe and effective imaging modality in detecting pregnancy complications such as breech presentation. The non-invasiveness of this technique, alongside its cost efficacy and availability have promoted its uptake in the developed world for routine pregnancy scans and examinations. However the use of US is far less common in low income countries, particularly in rural areas, as there is a lack of training for effective use of this technology and accurate interpretation of the images as well as a relatively high cost associated with the current US devices. Recent technological advancements in the field have led to lower-cost and portable US devices, facilitating its use in the developing world. In light of the factors that can affect the quality of image interpretation, we have investigated whether a combined machine learning and data acquisition approach to fetal head detection using a low-cost USB probe is equivalent to the same analysis on a high end probe solution. The results presented show that the algorithm works successfully on images obtained from both devices and that statistically no significant difference between the performance of the algorithm on the two is seen.

## 1 Introduction

### 1.1 Diagnostic Ultrasound

Ultrasound ($US$) as a form of medical technology, is often employed for diagnostic purposes in the field of obstetrics. The non-invasive nature of US has favoured its use over other imaging and radiological modalities, particularly as there have been no reports of any adverse effects as a result of using this technology. Furthermore, US has proved to be very effective in identifying some of the most prevalent maternal and neonatal mortality and morbidity factors [8], as well as providing useful information about the growth of the fetus and its relative position in the womb. Emerging advances in this field have paved way for smaller machines with higher accuracy, and subsequently to the development of portable US devices and recently USB devices to plug into laptops and smart phones.

Whilst it is important to note the benefits that the use of portable US machines entails, one also needs to bear in mind that user training still remains a critical and challenging factor to be addressed for effective implementation of this technology. Ultrasound image analysis and interpretation is highly influenced by image data quality and the operator's skills during and after a scan. Factors such as speckle, shadows, signal drop-outs and attenuation [7] are amongst the inherent characteristics of US images that can affect the quality of data. In addition, other aspects such as orientation of the transducer during image acquisition and low contrast rates between areas of interest will significantly affect the overall image quality. It is important to note that currently the low-cost portable probes that can be powered from the USB port of a laptop are simpler, with less sophisticated beamforming and post-processing which means the images can look quite different and potentially for some tasks diagnostically inferior. However for certain other applications such as fetal head detection, we would argue that this is not the case, as argued in this paper the algorithms currently available have produced equally accurate results on data acquired from a low cost and a mid range probe.

### 1.2 Pregnancy Complications: Breech Delivery

Breech presentation is defined as a fetus in a longitudinal lie with the buttocks or feet closest to the cervix and occurs in 3-4% of all deliveries [5]. The percentage of breech deliveries decreases with advancing gestational age from 22% of births prior to 28 weeks gestation to 7% of births at 32 weeks gestation and 1-3% of births at term [3, 4, 5, 6]. Previous studies have shown that vaginal birth of prenatal fetus at a breech position is associated with an increased risk of adverse neonatal outcomes and even death [6]. The US scan detection of the fetal head and its relationship with the uterine major axis is essential in diagnosing the fetal lie and therefore the breech presentation. Furthermore, the detection of the fetal head is the prerequisite for the fetal head biometry evaluation which is useful for the gestational age and fetal growth estimation. Hence we were interested in assessing how well the fetal head can be detected using image analysis solutions on images from a low cost probe.

We follow a machine learning approach for head circumference detection. Carniero et al. has carried out some related work using Probabilistic Boosting Tree (PBT) [1, 2]. Also a 2012 ISBI challenge composed a number of methods for head circumference detection on high-quality data of which the boundary fragment model produced very strong results and therefore has been used in this study.

## 2 Materials and Methods

### 2.1 Data Acquisition

The 2D fetal ultrasound images used in this study were acquired from subjects participating in a fetal growth study [12]. Data acquisition was carried out using a mid-range ultrasound machine, Philips HD9 with a V7-3 transducer denoted as A, and a low-end portable USB ultrasound machine, Interson Seemore denoted as B, by an obstetrician trained to follow standardized procedures [9]. The participants are fifteen healthy pregnant women, aged 20 to 38 with the fetus at a gestational age of 16 to 39 weeks. For data acquisition probe A was


(a) (b)

Figure 1: (a) Philips V7-3 on the top and the Interson Seemore transducer on the bottom. (b)2 sample images from the Philips HD9 and the $V7-3$ transducer (top) and Interson SeeMore probe(bottom).

used twice for each participant resulting in a total of 30 images obtained using A. Similarly probe B was also used twice for each participants resulting in another 30 images acquired using B.

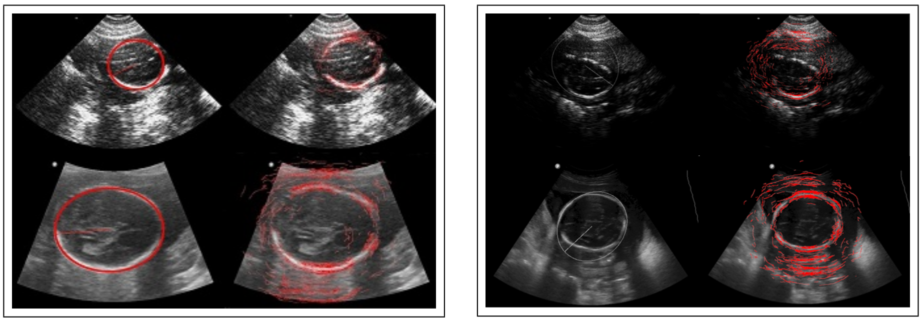
Image acquisition was carried out by the same obstetrician and during the same session. The participants were scanned with the two ultrasound probes with the intention to include the same anatomical features while keeping external conditions constant. Figure 1 illustrates a sample image obtained using the two ultrasound probes.

## 2.2 Analysis

The Boundary Fragment Model (BFM) utilised in this study [10] allows an object to be represented by its scale-normalised edge responses. An initial step towards the construction of the model is to determine the position and orientation of each edgel in the input images. An edge fragment library is then constructed for the fetal skull by manually labelling the inner and outer edgels on the edge maps. The resulting edge fragment library is composed of fragments that jointly describe the boundary of the fetal skull. Finally a boosted classifier is used to identify the scale and center of the fetal skull in the training images. The trained classifier is then used to detect the fetal skull in unseen images by firstly detecting the scale and centroid of the skull and using fragments from the edge fragment library to weakly describe the shape of the skull. An iterative ellipse fitting algorithm [11] is then used to fit an ellipse on the identified skull edges. The reader is referred to [10] and [11] for an extensive explanation of the two methods.

## 2.3 Validation Methods

The images were graded using a Likert-scale system as previously reported in the literature. The Likert-scale used in this study is set from $1-3$ where the grades represent *poor*, $fair$ and *good* respectively from 1 to 3. The results were graded with the assumption that all the grades have the same weight. Thus images are divided into two classes; class 1 includes



(a) (b)

Figure 2: (a)The Interson Seemore and Philips images are shown on the top and bottom rows respectively with the Ellipse fitting results on the left and BFM on the right - The fitted ellipse has been highlighted for clarity. (b)The edge detection has not worked well due to the bright attenuation marks.

images which are rated as *poor* and class 2 includes images rated *fair* or *good*. To analyse the results, the images were assessed prior to any processing. This is to measure 1) sharpness of the images and 2) the visibility of the region of interest (*ROI*) to get a better insight into the accuracy of the model, given the initial difference in appearance between the images obtained from the two probes. This assessment was carried out by the author with visual checks by an obstetrician. A two tailed Wilcoxon signed-rank test with a 95% confidence interval was used to indicate if there was statistically a significant difference between the result of the head detection algorithm on images acquired using A and B.

# 3 Results

## 3.1 Head Detection Performance

### 3.1.1 Pre-processing Analysis

The Likert-scale grading results show that from the 30 images that are acquired from A in this experiment, 6 and 2 images are graded as poor in terms of visibility and sharpness respectively, before the head detection algorithm is applied. In comparison the results obtained from B suggest there is a clear difference in the appearance and visibilty of the ROI as 19 images are rated as poor and the rest are rated fair.

### 3.1.2 Head Detection Analysis

The results show that 7 images acquired via A are in class 1 and the other 23 in class 2 suggesting an overall success of 76.7 % in identifying the head boundaries. The results for B are also very high with 6 images in class 1 and 24 images as class 2, indicating an accuracy of 80%. The results suggest that the sharper appearance of the edges of the skull in images obtained from B are a great contribution factor for the high accuracy in the results. Figure 2 illustrates the result of the BFM and Ellipse fitting algorithm on an image obtained from the two probes, A and B. Also an example where the algorithms have not worked so well can be seen in Figure 2.

Table 1: The Results of Visibility & Sharpness of the ROI in images obtained with the A and B probes, before and after head detection.

| | Good No% | Fair No% | Poor No% | $p$ Value Wilcoxon Rank Test |
|---|---|---|---|---|
| Visibility[a] | 40.0 | 20.0 | 20.0 | $6.69 * 10^{-4}$ |
| Visibility[b] | 0.0 | 36.7 | 63.3 | |
| Sharpness[a] | 46.7 | 46.7 | 6.6 | $1.23 * 10^{-4}$ |
| Sharpness[b] | 0.0 | 43.3 | 56.7 | |
| Head Detection[a] | 46.67 | 30.0 | 23.33 | 0.2012 |
| Head Detection[b] | 73.33 | 6.67 | 20.0 | |

*a*. Philips Probe
*b*. SeeMore Probe

The Wilcoxon Signed-Rank test results from Table 1 show that statistically no significant difference between the accuracy of the results were found (p=0.2012). However there is a significant difference in the sharpness (p=0.00067) and visibility (p=0.00012) before the images are processed, as expected. This is a positive result which suggests that although the visibility and sharpness of the images from a low-cost probe might not be as high as a mid-range probe, the performance of the head detection algorithm may not be effected by the source of the images as shown in this study.

# 4 Conclusions

We have described a new application of a Boundary Fragment Model on images obtained from a low-cost USB ultrasound probe, with the aim to utilise this in resource-constrained regions for detection of breech labour position. The statistical analysis shows that the fetal head detection and segmentation algorithms work well with the images obtained from the low-cost USB probe. In future work we will analyse more data with validation by obstetricians. Also we will be looking at gestational age estimation using the images obtained from the USB probe. A limitation of the study is that the data obtained from the two probes is not from the same virtual slice. The effect of this however is minimized by following a defined protocol carefully and thus this does not seem to have affected the results.

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