Nakagami-Based Choroid Plexus Detection in Fetal Ultrasound Images using AdaBoost

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Abstract

In obstetrical ultrasound examinations, the appropriate fetal biometry plane is identified by the presence and absence of key anatomical landmarks within the image [3]. In the 20 to 22 weeks of gestation, the transthalamic plane becomes of particular importance, as it is the stage at which early signs of trisomy 18 can be detected by the presence of cysts in the choroid plexus (CP) [5]. We propose a method to detect the presence of the CP in 2D ultrasound images of the fetal brain using an AdaBoost learning algorithm. We compared the performance of the detection using three different feature sets: intensity-based, and empirically-fit Nakagami μ and ω parameter features. We found that the accuracy of the Nakagami ω parameter had the highest detection accuracy (72.73%).

1 Introduction

Obstetrical ultrasound examinations form an integral part of standard prenatal monitoring. It serves for the purpose of pregnancy dating, fetal growth monitoring, and detection of abnormalities throughout gestation. During the examination, the ultrasonographer collects scans from the fetal head, abdomen, and thigh such that the standard fetal biometric measurements can be obtained [3]. These measurements are then plotted on population-based growth charts to assess the normality of fetal growth. Our interest is assessing fetal development from analysis of the fetal brain. In the standard neurosonography examination, an axial plane (the *transthalamic* plane) is used for assessing the fetal head, as it is believed to contain the significant anatomical landmarks (Fig. 1), yet it is the most challenging plane to locate [3]. The biometric measurements of the fetal head (namely the biparietal diameter (BPD) and occipital-frontal diameter (OFD)) are acquired in this plane and are plotted on the growth curves to determine gestational age of the fetus [3].

1.1 Transthalamic Plane and the Choroid Plexus

In the transthalamic plane, the choroid plexus appears as an echogenic glomular region in ultrasound images, and it has slight variations in size and shape across gestational age [1]. The basic scan is performed at 20 to 22 weeks [3] in which the appearance of the CP is of

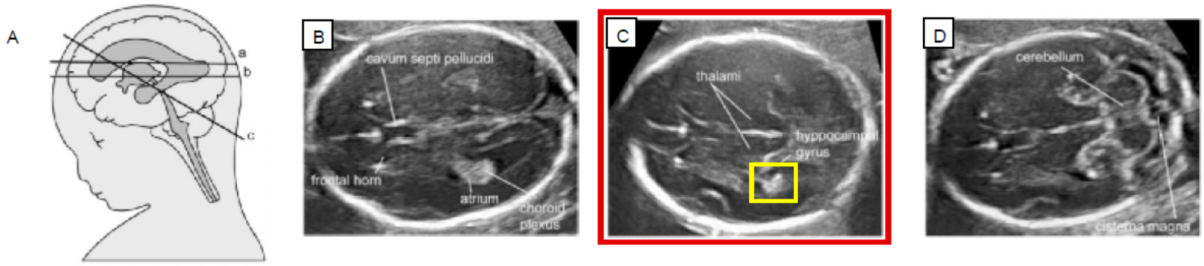

Figure 1: Three axial ultrasound planes used in standard fetal neurosonography examination (A): transventricular plane (B), transthalamic plane with yellow box around the choroid plexus(C), transcerebellar place (D). (Adapted from [3])

particular importance in determining the presence of cysts within the CP (which are indicative of early signs of trisomy 18) [5]. The current practice in an obstetrical examination is for the ultrasonographer to determine whether a suitable transthalamic plane has been selected for biometrical measurements by looking for a number of visual cues including texture, size, shape, and boundary characteristics, which means that the diagnostic decisions are influenced by the experience of the ultrasonographer.

Another difficulty with the detection of structures in ultrasound images is their susceptibility to data drop-out noise commonly described as speckle. Particularly if the plane is selected based on the appearance characteristics of the object of interest within the image, it seems appropriate to design an automated classifier that depends on the backscatter properties of the choroid plexus. Recent studies have shown that statistical processing is beneficial for characterizing tissues in ultrasound images, namely the Nakagami distribution and its parameters [7]. In the current study, we have empirically fit a Nakagami distribution to ultrasound image regions and used the information in an object detection framework.

1.2 Related Work

In the work of Rahmatullah et al. [4], a machine learning technique was proposed for checking that a given image plane has key structures in it for biometric measurements. They used an AdaBoost object detection framework which was robust to size, shape, and position variations of the object of interest in an obstetrical ultrasound image, which suggests it may be suitable for the detection of the choroid plexus.

Traditionally, the AdaBoost-based detection framework has been implemented using intensity-based features. In this study, we instead use an empirical model of ultrasound image formation to account for the speckle within the image and to determine whether the scatter profile of a tissue can be used as a form of tissue characterization. We used the local-based estimation of Nakagami parameters proposed by Wachinger et al [7]. We compared the performance of features extracted from the statistical parameter plots of the images to those of intensity images in the detection of an object in an ultrasound image.

To the best of our knowledge, the automated detection of the choroid plexus has not been attempted before. Thus, the contributions of this study are *a*) to present a method for detecting an anatomical landmark in the standard transthalamic fetal brain scan; *b*) to introduce a novel feature set (Nakagami) in the machine learning framework for object detection in ultrasound images; *c*) to determine the performance of the Nakagami-based feature set in comparison with the currently-used intensity-based ultrasound object detection.

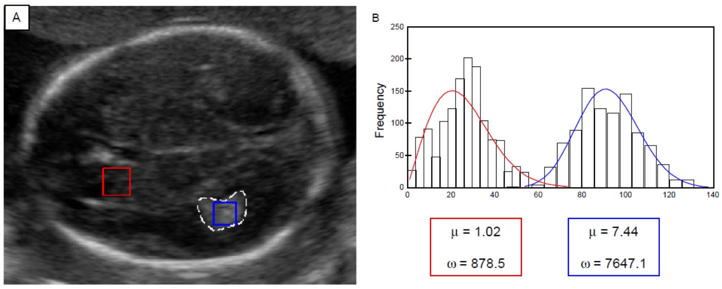

Figure 2: Empirically-fitted histograms and Nakagami parameters for rectangular regions inside the choroid plexus (in blue) and in a background region (in red). The choroid plexus is outlined by a white dotted line.

2 Methods

Two-dimensional ultrasound images of the standard transthalamic plane of the fetal brain were randomly selected from the ongoing Intergrowth-21st study database. For this work, the images were acquired between 19^{+6} to 22^{+6} weeks of gestation. All women were screened based on a set of criteria that define them as having low risk of impairment of fetal growth or fetal abnormality. The images were all acquired using a 2D linear probe (Phillips HD9) at a 2-5MHz wave frequency and saved in a DICOM format of size 1024×728 pixels.

2.1 Nakagami Distribution Approximation

Tissue characterization and detection in ultrasound images is particularly challenging due to the presence of speckle and inhomogeneities within the images. In recent years, segmentation and classification studies have investigated a multitude of distributions for modelling ultrasound scattering for varying amounts of scatterer per resolution cell, with the Rayleigh distribution being the most commonly applied. The Nakagami distribution (which has the properties of an incomplete Gamma function) is of particular interest because it benefits from the fact that by varying its shape parameter, it is possible to emulate other distributions that have been used to model ultrasound RF data and its ability to distinguish between scatterers of different concentrations and arrangements within the tissue [7]. In this work, we used it for the detection of the choroid plexus, a glomerular mass comprised of connective tissue.

The Nakagami distribution, $N(x|\mu,\omega)$, is one of the exponential probability distributions and it can be defined by two parameters: the shape (μ) and scale (ω) parameters.

$$N(x|\mu,\omega) = \frac{2\mu^{\mu}}{\Gamma(\mu)\omega^{\mu}} x^{2\mu-1} exp(\frac{-\mu}{\omega}x^2), \forall x \in \mathbb{R}_{\geq 0} \tag{1}$$

The parameters are approximated by determining the Nakagami maximum likelihood estimation (MLE) of a histogram of pixels intensities in a small rectangular region within the image. Figure 2 shows the MLE fits for a rectangular region within the choroid plexus and for a background region outside. The variation in the distribution parameters is indicative of the speckle statistics characteristic to the different tissues within the fetal brain, as it corresponds to the inhomogeneities of the tissues. The size of speckle is related to the sound wavelength, λ, and it has been found to occur in the range of approximately $0.1 \leq \lambda \leq 1.0mm$ [7].

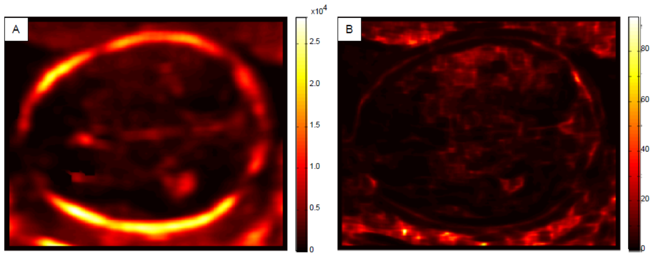

Figure 3: Nakagami μ (A) and ω (B) parameter plots for a 2D fetal brain ultrasound image.

In our images, the resolution is approximately $1.37 \times 1.37mm$, so we selected a patch of 16×16 pixels from which the distribution parameters were estimated and assigned to the center pixel of the patch, and the patch was shifted across the entire image to produce μ and ω parameter plots. Representative examples of parameter plots are shown in figure 3.

2.2 Local Feature Extraction

The objective of this study was to detect the rectangular region (subwindow) of the transthalamic plane (TP) with the highest likelihood of containing the anatomical object of interest (the choroid plexus). This subwindow is identified as the region with the maximal score determined by the classifier. In order to classify each subwindow as foreground (containing the choroid plexus) or background, we opted for the Haar-wavelet based approach for the selection of features to best discriminate between the positive (foreground, ζ) and negative (background, χ) subwindow from the image, I, such that $\zeta \cup \chi \subseteq I$ and $\zeta \cap \chi = \oslash$.

The feature score is determined by subtracting the sum of pixels in a rectangular region from the sum of pixels in an adjacent rectangular region of the same dimensions. This process was described in detail in [6].

2.3 AdaBoost Classifier

We used the AdaBoost algorithm [2] to select the features and to train the classifier, as it has proven to be effective in similar problems of object detection in fetal ultrasound images [4]. The AdaBoost algorithm linearly combines a collection of weak classifiers (i.e. the set of extracted features) to form a strong classifier, such that it boosts the performance of the weak classifiers. During training, the weight distributions of the features are modified after each iteration such that the error of classification is lower than that of the previous iteration.

The training data consisted of a set of positive and negative examples that were passed through the AdaBoost learning framework. The positive subwindow examples (containing the choroid plexus) were manually cropped from the ultrasound images and scaled to 100×100 pixels and the process was repeated for the negative samples. We obtained the training examples from three different feature sets: *a*) the intensity values of the ultrasound image pixels, I, *b*) the shape parameter, μ, and *c*) the scale parameter of the local Nakagami distribution, ω.

2.4 Data Acquisition

The training set for the choroid plexus detection consisted of 190 positive and 380 negative examples for each of the training sets. We found that the choroid plexii in the standard transthalamic plane occupies approximately 2014±88.5 pixels which can be adequately encompassed by subwindows ranging from 75×75 to 117×117 pixels.

3 Results and Discussion

The AdaBoost training algorithm was implemented in MATLAB 7.13. The program was validated on 61 images and trained on 44 images of fetuses between 19^{+6} and 22^{+6} weeks of gestation.

3.1 Evaluation of Validation Data

The AdaBoost algorithm required the tuning of two parameters:*a*) the number of iterations that produce T weak learners (WL), and *b*) the final classifier threshold that yields the highest sensitivity and specificity. These parameters were selected based on Receiver Operating Characteristic (ROC) curves for each of the feature sets for a selected number of T weak learners. Table 1 summarizes the results from the ROC analysis.

Table 1: ROC Results for Different Number of Weak Learners (WL)

No. of WL	Intensity			Nakagami μ			Nakagami ω		
	AUC	Acc	Thresh	AUC	Acc	Thresh	AUC	Acc	Thresh
300	0.785	0.7213	0.6415	0.666	0.6393	0.6437	0.802	0.7049	0.6518
500	0.807	0.6557	0.6299	0.695	0.5738	0.6598	0.807	0.7213	0.629

A higher area under the ROC curve (AUC) yields a better object detector test producing fewer false positives, and vice-versa. Based on the results displayed in table 1, we selected 500 WL due to the fact that the highest accuracies are seen with this number of weak learners (particularly for intensity and Nakagami ω, highlighted in gray) with the respective thresholds for each of the feature sets (Table 1).

3.2 Evaluation of Independent Testing Data

The testing dataset consisted of 44 2D fetal ultrasound scans of gestational ages ranging between 20^{+0} and 22^{+6} weeks. The choroid plexus detection was considered to be positive when it occupied more than 50% of the automatically found subwindow by visual inspection. The performance of the three features sets (i.e. Intensity, Nakagami μ, Nakagami ω) was compared using ROC curves shown in figure 4, and the statistical results are summarized in table 2.

Table 2: ROC Results for Different Number of Weak Learners (WL)

Feature Set	AUC	Balanced Accuracy (%)
Intensity	0.889	61.36
Nakagami μ	0.678	65.91
Nakagami ω	0.862	72.73

Based on the findings, it is evident that the proposed Nakagami ω feature was able to outperform the intensity and Nakagami μ feature sets in the detection of the choroid plexus

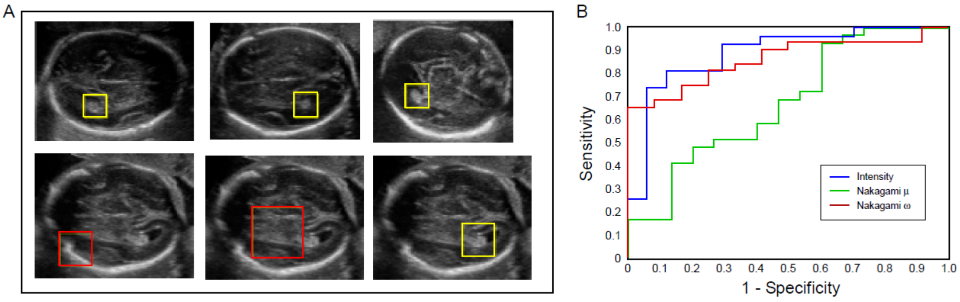

Figure 4: Choroid plexus detection results. The positively detected choroid plexuses are bounded by a yellow box, and the false positives are bounded by a red box (A). The ROC curves for 500WL are also shown (B).

with an increase in accuracy of 11.37% over the intensity feature and 6.82% over the Nakagami μ feature. This is possibly due to the fact that the scale (ω) parameter captures the characteristic spread of the speckle noise within the choroid plexus, which encapsulates textural properties as opposed to the energy of the pixel intensities captures by the shape (μ) parameter.

4 Conclusion

This paper presents a novel method for the detection of the choroid plexus in the standard transthalamic scan of the fetal head. We have tested three different feature sets on the AdaBoost object detection framework and found that the statistical model approximation yielded the best results in detection accuracy. This result can be extended to other ultrasound object detection applications, and for quality control of plane selection during the obstetrical exam.

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Classification of Microcalcification Clusters Using Topological Structure Features

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Abstract

The presence of microcalcification clusters is a primary sign of breast cancer. It is difficult and time consuming for radiologists to diagnose microcalcifications. In this paper, we present a novel method for the classification of malignant and benign microcalcification clusters in mammograms. We analyse the topology of individual microcalcifications within a cluster using multiscale morphology. A microcalcification graph is constructed to represent the topological structure of the cluster and two properties associated with the connectivity are investigated. A multiscale topological feature vector is generated from a set of microcalcification graphs for classification. The validity of the proposed method is evaluated based on the MIAS database. Using a k-nearest neighbour classifier, a classification accuracy of 95% is achieved for both manual annotations and automatic detection results. The obtained area under the ROC curve is 0.93 and 0.92 for the manual and automatic segmentation, respectively.

1 Introduction

The presence of microcalcification clusters is a primary sign of breast cancer. The radiological definition of microcalcification clusters is that at least three microcalcifications are present within a 1 cm^2 region [7, 12]. Due to its high spatial resolution, mammography enables the detection of microcalcifications at an early stage, however, it is difficult and time consuming for radiologists to distinguish malignant from benign cases. This results in a high rate of unnecessary biopsy examinations [4, 12].

In order to improve the performance of radiologists and reduce the false positive rate, computer-aided diagnosis (CAD) systems have been applied [4]. A variety of approaches have been developed for the characterisation and classification of microcalcifications. Shen *et al*. [10] and Ma *et al*. [7] developed a set of shape features to quantitatively measure the