Evolutionary Techniques on Fetal Head Segmentation

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Abstract

In Obstetrics, Ultrasound is used to access fetus growth which can be measured by Head Circumference. Accurate segmentation of fetal head is important for calculating Head Circumference. As Deep Learning is gaining popularity because of its state of the art performance, the various Deep Learning techniques for the segmentation of fetal skull are discussed in this article.

Keywords: Segmentation, Deep Learning, CNN, fetal head, medical image

1 Introduction

ULTRASOUND (US) is widely accepted in clinical practice. As compared to other imaging modalities like Computed Tomography, Magnetic Resonance etc.. It is safe, painless, low cost, portable and radiation free [1]. But it has some disadvantages like speckle noise, artifacts [2], shadows, missing boundaries, low SNR, low contrast and long-spun-occlusion [3].

In prenatal screening, US is used to check fetus growth, estimate Gestation Age and detect growth abnormalities [4]. In [5], AIUM gave guidelines for performing high quality Obstetrics US exams for measuring different bio-metric measures like Bi-parietal Diameter (BPD), Head Circumference (HC), Abdomen Circumference (AD), Femur Length (FL), Crown Rump Length (CRL) etc. For first trimester, CRL is important for estimating Gestational Age (GA). After that GA is calculated by other measures like HC and FL [4].

According to [6], variation in caliper placement between sonographers is the largest error source for fetus bio-metric measurement. Patient anatomy and fetal orientation also causes error in measurement. Moreover, measurement is time consuming and tiring [7]. So, there is a need for an automatic solution of segmentation of fetal head boundary from US images and then calculating different bio-metrics.

1.1 Segmentation

Segmentation is a process of sub-dividing an image into objects having homogeneous features like color, intensity [8] etc. Different features for segmentation can be divided into four categories: features based on descriptor, based on model, based on texture like Wavelets and LBP (Local Binary Patterns) [9]. In [10] Random Forest classifier was used with Haar like features for fetal skull localization. Log. Gabor was used in [11] for measurement of fetal bio-metrics. It can be considered as a pixel wise classification task i.e. to classify a given pixel in different classes. For 2D US head segmentation, the task is to classify a pixel as belonging to fetal head region or not.

1.2 Traditional Machine Learning

In Traditional Machine Learning, feature extraction (man crafted features) and selection are important. First, the pre-processing of acquired images is done followed by feature extraction and then the features are fed to the machine learning model for classification of pixels into different categories.

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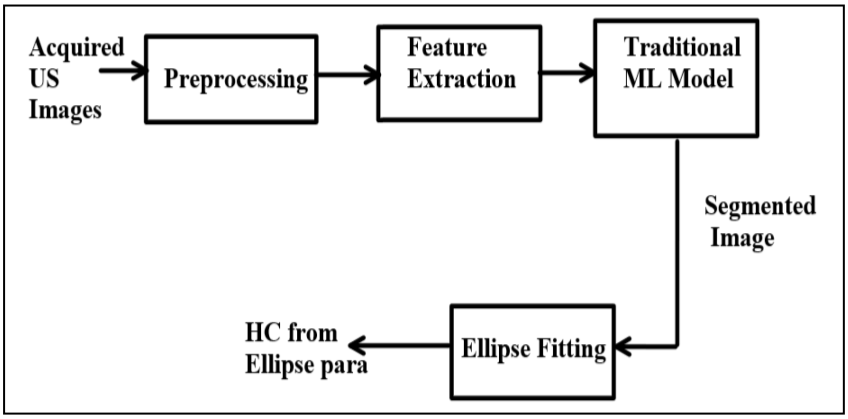

Fig. 3. Machine Learning Approach

In [12], texton is used with Support Vector Machine to detect fetal head. Constrained Probabilistic Boosting Trees with Haar features were used in [13]. In [14], Haar Cascade is used for automatic fetus skull detection.

1.3 Deep Learning

For Deep Learning, the pre-processed images are directly fed to the Deep Learning model without any need of extracting features by human. The model extracts relevant features which are more efficient than hand-crafted features along with segmenting the image into different objects. Fig. 2. shows the common approach used to measure fetal HC using Deep Learning. Segmented image after thresholding is fed to an ellipse fitting algorithm like Dogell [15], Hough Transform, Ellifit [16], Least Square Ellipse fitting [17] etc. which gives ellipse parameters (semi minor axis, semi major axis, angle between x-axis and the semi major axis, center co-ordinates) from which Ellipse Circumference can be detected. Ramanujan approximation II [18] is one common approximation to estimate ellipse circumference.

Different Deep Learning architectures are described in Section III. CNN architectures have convolution layers, pooling layers and fully connected layers. Often in deep learning, over fitting problem is there. To tackle this, batch normalization, data augmentation and drop out is used. Drop out is mainly used with fully connected layers. For convolution layers, Dropblock [19] is used for regularization. For network to converge faster, proper weight initialization is needed. There are many initialization schemes like He initialization, Glorot initialization, Xavier initialization [20]. Common loss functions for segmentation are Cross Entropy loss and Dice loss. The weights are updated such that the loss is minimized.

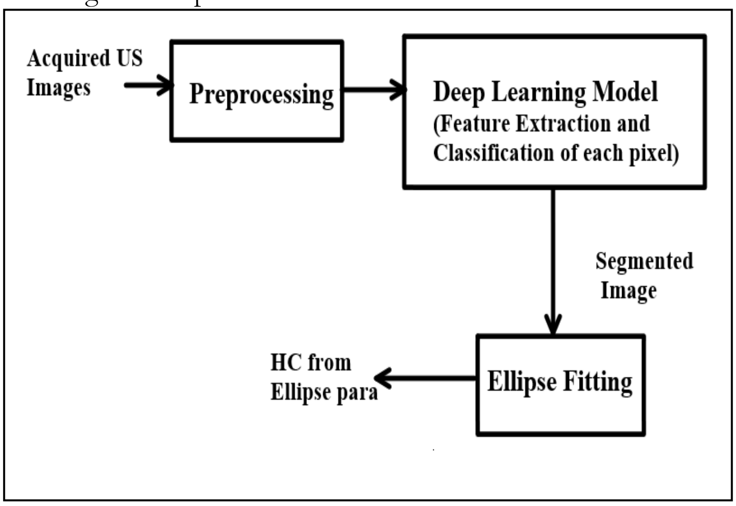

Fig. 4. Deep Learning Approach

2 HC18 Dataset

HC18 [21], a Grand Challenge dataset that came in year 2018. It contains 1334 two dimensional standard plane fetus head Ultrasound images of image size 800X540 pixel. The dataset has images of all three trimesters. No abnormal fetal head images were provided. It was collected from Medical Center at Radboud University, Nijmegen, the Netherlands with General Electric's Voluson 730 and Voluson E8 Ultrasound machines [17]. The pixel size ranges from 0.052 mm to 0.326 mm. Train set of the dataset has 999 images along with corresponding annotated masks. The Head Circumference (in mm) and Pixel Size (in mm) information is given in a .csv file for train set. The test set consists of 335 images with no information of ground truth Head Circumference and annotated masks. Heuvel et al. [17] proposed three systems (A, B, C) and trained Random forest on Haar like features to detect fetal skull pixels. HC was calculated with dynamic programming, Hough transform and ellipse fit. System C gave better results than system A and B which shows the importance of separating results for each trimester.

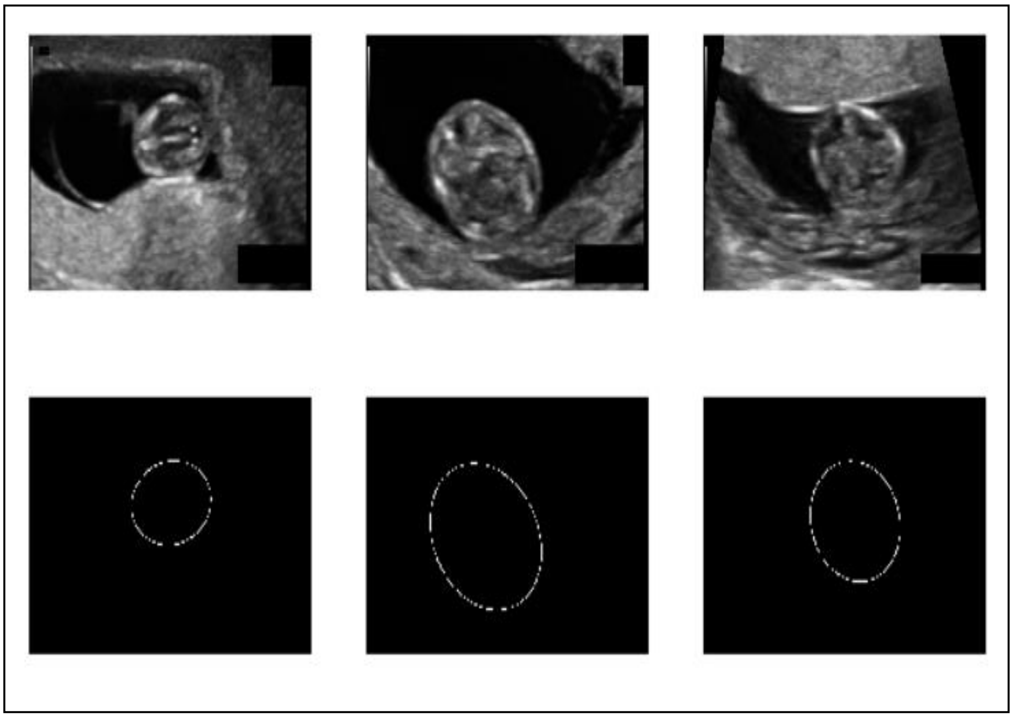

Fig. 5. HC18 [17] [21] dataset images along with annotations

3 Deep Learning Based Architectures used with 2D Fetal US Images

Various variants of Fully Convolutional Networks (FCN), UNet and LinkNet architectures proposed in literature for fetus head segmentation are described in this section.

3.1 FCN

Fully Convolutional Network (FCN), proposed by Long et al. [22] replaces fully connected layer of CNN with fully convolutional layer. With this the network achieved dense pixel wise prediction.

In 2017, Wu et al. [7] proposed casFCN, which is a lite FCN with Auto Context scheme. Instead of parallel join, summation was proposed in Auto Context. This gave refined fetal head boundary in segmented image which was not there with FCN model. 900 training images and 236 test images of 19-40 week GA were used in the study.

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In 2018, Sinclair et al. [23] proposed VGG16-FCN with 16 conv layers and initial weights of ImageNet. HC calculation with Ramanujan approximation II [18] was done. Study on Inter Observer and Model Expert was done. Near real time model performance was observed similar to human expert.

3.2 UNet

UNet [24], proposed by Ronneberger et al. has 31 Million parameters. The contracting path in UNet is used to capture context and the expansion path is used for precise localization. It uses filters for up-sampling because Transposed convolution is used. As we go down the contracting path, the feature channel number gets doubled. The number of channels become half as we go up the expansion path. The cropped encoder features are concatenated with the features of the corresponding decoder. In [25] different fine tuning strategies of UNet for ultrasound images are discussed.

In [26], a UNet architecture having input layer size 512X512 was used. US image pixels were classified into three classes i.e. maternal tissue, fetal head and background or others. It gave large error as compared to previous studies because learning did not reach convergence.

In 2019, MPF-UNet, a UNet inspired model having bottleneck linked to Feature Pyramid Network was proposed by Oghli et al. [27]. Segmentation of head, abdomen and femur was done with a single model.

In [28], DU-Net, a UNet with Scattering Coefficients that preserve frequency was proposed. SC (derived from Morlet Wavelet and ScatNet) and image is separately encoded and the encoded feature maps were fused and decoded to get segmentation map. It has high confidence while making predictions as compared to UNet which is shown by a sharp segmentation map.

Budd et al. [29] evaluated Probabilistic UNet, MC Dropout and proposed a Variance score for rejecting images that produce sub-optimal HC measure.

In [30] a three encoder-decoder layer UNet with Squeeze Excitation (SE) blocks on skip connection for channel attention called SE-UNet was proposed. In bottleneck of SE-UNet, dilated convolution having dilation factor 1, 2, 4, 8, 16 and 32 is used. The model could predict fetal head and boundary, even when the boundaries were missing in the ultrasound images.

YOLO for fetal head localization was used in [31]. Masks were preprocessed based on distance field concept. UNet was trained to reduce MSE loss. Tanh activation function was used at the output layer of UNet. Outliers were detected and removed. Outlier detection improved the model performance and the approach gave highest performance compared to other state of the art techniques for HC18 dataset.

3.3 LinkNet

LinkNet proposed in [32] is a network consisting of 11.5 Million parameters. A 7X7 convolutional layer with stride 2 is present at the start of the LinkNet encoder. A 3X3 spatial max pooling operation with stride 2 is performed. Residual blocks are present in later encoding blocks which use ResNet18 encoder.

In [32], full conv is proposed which is used in the decoder LinkNet. The positional information which is lost is recovered with the bypassed encoder link to corresponding decoder. The decoder can use this recovered information. The resultant network is efficient and can be used in real time. The decoder shares knowledge learnt at each stage.

In 2019, Sobhaninia et al. [33] proposed a multi scaled input LinkNet (MTNL) with ResBlock in encoder and skip connections for encoder decoder connection. Ellipse tuner which consists of three Fully Connected layers having five neurons in the last layer for calculation of five ellipse parameters. Segmentation loss (BCE and 1-Dice) and Tuner Loss (Mean Square Error) were reduced as an optimization process. This Multi task network with Tuner gave better results than single task deep learning network without Ellipse Tuner.

In 2020, a LinkNet inspired Multi Scale Mini LinkNet was introduced by Sobhaninia et al. [34]. It has low complexity. Instead of 4 encoder blocks of LinkNet, 3 were used and multi scale images were fed to the network. Reduction of training time (reduced by half) and parameters was observed as compared to LinkNet.

3.4 2D VNet

3D VNet was proposed in [35] for the segmentation of Prostate MRI images. In [36], 3D VNet was adapted to segment 2D US fetus head standard TV plane images. Instead of softmax, sigmoid activation function was used in its 2D adaptation. In the proposed VNet-C, ELU activation was used in intermediate layers, hard sigmoid was used at the output layer, batch normalization was used after activation function, network depth was increased from 5 to 7 and Tversky loss was used.

3.5 CNN

In 2020, Zhang et al. [37] compared four different regression CNNs - CNN 1M, CNN 263K, ResNet50 and VGG16 having linear activation function in the end for HC measurement directly. CNN's were trained with three different regression losses (huber loss, mean absolute error and mean square error) and their analysis was done. Reg-ResNet50 with the MSE loss gave better results out of all the models. The regression CNNs have high error and standard deviation than segmentation based networks.

In 2020, the first method for HC measurement from standardized sweep protocol was done in [38]. A CNN inspired by VGG-Net with 3 neurons in the last layer detects fetal skull from 3 sweep OSP [39]. UNet inspired model was used for identification of fetal head pixels and Direct Least squares [40] was used for ellipse parameters. The approach showed decrease in network complexity because of down-sampling of input images. The proposed approach can be used in low cost environments.

3.6 YOLO

In 2017, Irene et al. [15] used YOLO for localization of fetal skull and abdomen from dataset containing images having both abdomen and fetal skull. The fetal head and abdomen area was cropped along the bounding box given by YOLO, The work compared Dogell and Hough Transform methods for detection of ellipses. Dogell algorithm gave better accuracy and performed faster than Hough Transform.

4 Conclusion

In this paper, different Deep Learning techniques for the segmentation of head of a fetus from 2D US images is briefly reviewed. Head Circumference (HC) is an important parameter to find the growth of the fetus. Because of low signal to noise ratio, blur, missing boundaries etc., the manual calculation of HC is tedious, time consuming and is error prone. It needs expert Sonographers which are not readily available in developing countries and rural area. So, we need models for automatically calculating HC from given US image. Deep Learning is widely studied these days but in case of 2D Ultrasound, it is in developing stage. There is a need to transfer existing approaches in other modalities to 2D US domain. Work can be done on attention mechanism, deep supervision, GANs for generating artificial images for data augmentation [41] and adversarial training [42]. Plane acceptance check along with segmentation can also be considered for future work [43].

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