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ABSTRACT

Examination of head shape during the fetal period is an important task to evaluate head growth and to diagnose fetal abnormalities. Traditional clinical practice frequently relies on the estimation of head circumference (HC) from 2D ultrasound (US) images by manually fitting an ellipse to the fetal skull. However, this process tends to be prone to observer variability, and therefore, automatic approaches for HC delineation can bring added value for clinical practice. In this paper, an automatic method to accurately delineate the fetal head in US images is proposed. The proposed method is divided into two stages: (i) head delineation through a regression convolutional neural network (CNN) that estimates a gaussian-like map of the head contour; and (ii) robust ellipse fitting using a registration-based approach that combines the random sample consensus (RANSAC) and iterative closest point (ICP) algorithms. The proposed method was applied to the HC18 Challenge dataset, which contains 999 training and 335 testing images. Experiments showed that the proposed strategy achieved a mean average difference of -0.11 ± 2.67 mm and a Dice coefficient of 97.95 ± 1.12% against manual annotation, outperforming other approaches in the literature. The obtained results showed the effectiveness of the proposed method for HC delineation, suggesting its potential to be used in clinical practice for head shape assessment.

Keywords: convolutional neural networks, fetal head, head circumference, registration, ultrasound

1. INTRODUCTION

Head growth during the fetal period is one of the bases for long-term health, determining life-long neurological competencies [1], [2]. The assessment and monitoring of the head growth is therefore a paramount task in clinical practice [3], [4], accomplished by measuring fetal biometrics, such as head circumference (HC), through ultrasound (US) imaging [5]. Currently, the estimation of HC is performed manually by overlaying an ellipse to the fetal skull, posing issues related to the observer variability [6]. Thus, the development of automatic methods to perform HC delineation can have added value in clinical practice. However, automatic delineation of the fetal head in US is not straightforward, due to its low image quality, speckle noise, and image artifacts inherent to the US imaging modality [2], [7], [8].

In the last decades, several methods have been proposed in the literature for HC measurement in US images [2]. The initial methods focused on simple image-based methods (e.g. threshold or mathematical morphology) to create a binarized image of the fetal skull, followed by Hough Transform or its variants to perform ellipse fitting [9]–[11]. To overcome the lack of robustness and sensitivity to noise of image-based methods, other approaches were also proposed, namely deformable models [12], [13] or machine learning techniques [14], [15]. In recent works, handcrafted-based learning approaches were overcome by deep learning strategies, but most of the strategies were used to create a segmentation of the entire fetal head

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instead of directly focusing on the head contour [16], [17]. More recently, HC delineation was interpreted in the literature as a regression problem that estimates a heat map representative of the head contour [18], [19]. However, issues related to the appearance of fragments in the heat map that do not belong to the fetal skull may remain.

In this paper, a novel method for HC delineation in US images is presented. Specifically, this work investigates the combination of a regression convolution neural network (CNN) with a registration-based approach to accurately estimate HC. The proposed method can be applied in clinical practice to aid clinicians to perform head growth assessments.

The main contributions in this article can be described as follows:

(1) A regression CNN to estimate a gaussian-like curve representative of the fetal head in US images is investigated;
(2) A new registration-based approach that robustly detects the HC from a heatmap of the head contour is proposed;
(3) An evaluation of the proposed method against literature approaches is presented.

This paper is organized as follows. In section 2, the proposed HC detection framework is described. In section 3, the experiments performed and obtained results are presented. In section 4, the performance of the method is discussed and in section 5 the main conclusions of this paper are given.

2. METHODS

Figure 1 shows an overview of the proposed framework for automatic HC estimation. Firstly, a CNN architecture is used to generate a gaussian-like heat map of the head contour (section 2.1). Secondly, a robust registration-based approach is used to fit an ellipse to the output of the network, mimicking the traditional clinical practice (section 2.2).

2.1. Head circumference regression

In US imaging, the fetal skull appears as a narrow continuous hyperechogenic structure interrupted only by few echolucent sutures, having higher intensities than its surrounding tissues and an ellipse-like shape [1]. Thus, in this work, we consider that the fetal skull can be represented as a gaussian-like curve around the head contour (Figure 2). In the first stage of the proposed method, a regression CNN is used to estimate this gaussian-like map representative of the fetal skull.

To perform the regression task, an U-shaped network was used [20]. The network architecture is constituted by the encoding and decoding path. The encoding network includes a stack of four encoding blocks, each one with two convolutional layers followed by a batch normalization layer and a leaky ReLU. The decoding path corresponds to a symmetric expanding path. Besides the two paths, skip-connections are used to allow that the encoder and decoder share information. In this work, a Sigmoid activation layer was added to the end of the network to achieve pixel-wise regression, considering that the gaussian-like function representative of the head contour presents a narrow spread.

To train the regression network, the ground-truth map was retrieved by applying a gaussian filter to the ellipse representative of the HC (Figure 2). This generates the gaussian-like curve with higher values at the fetal skull. To guide the network to predict the maps, a loss function f_{loss} that calculates the Euclidean distance between predicted heat maps and ground-truth maps was applied at the end of the network:

$$f_{loss} = ||L - L^*||_2^2, \tag{1}$$

where L and L^* are the prediction and ground truth maps of the fetal skull, respectively.

2.2. Ellipse fitting procedure

To perform the ellipse fitting, the heat map generated in 2.1 is firstly thresholded to obtain a binary map. However, the map may present outliers fragments that do not correspond to the head contour, which can lead to a sub-optimal representation of the HC. To solve this problem, the iterative Random Sample Consensus (RANSAC) method was used to remove outliers [21]. The RANSAC method consists of a model parameter estimation approach that robustly deals with outlier points on the data. Firstly, an initial ellipse model is fitted to a random subset of head contour points using the direct least squares ellipse fitting method. Afterward, all contour points are tested with respect to the initial ellipse model in terms of a cost function for outlier points identification. In this work, a weighted Euclidean distance was used as cost function. Let us define $P = \{p_1, \ldots, p_r\}$ as the set of pixels that belong to the estimated head contour, *i.e.*, the contour points, and $E = \{e_1, \ldots, e_q\}$ the set of points that belong to the ellipse model. For each point p, the loss function is given by:

$$d_p = w_p \times h(p, E), \tag{2}$$

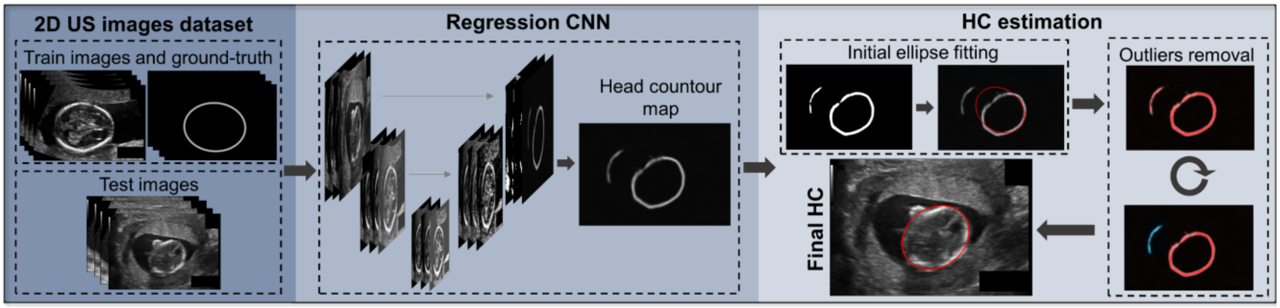

Figure 1 – Overview of the proposed method for HC delineation.

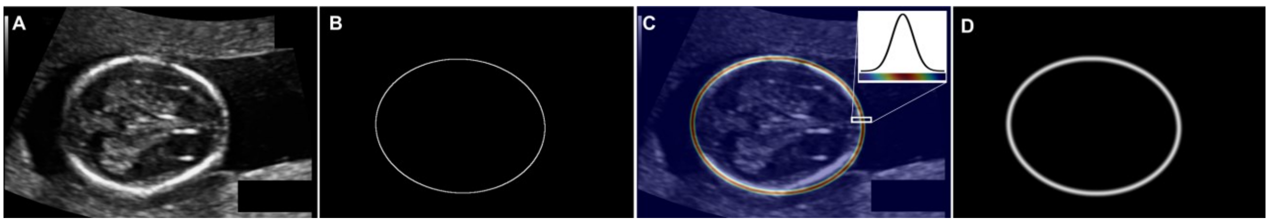

Figure 2 – Gaussian-like curve representative of the fetal skull. (A) Original 2D US image; (B) Manual ellipse as HC ground-truth; (C) Gaussian-like curve obtained from (B) overlayed on the original image; (D) Final ground-truth of the fetal head contour.

where $h(p, E) = min||p - e||_2^2$, with $e \in E$, represents the Euclidean distance between p and the closest point in E and w is a weight factor. Here, the weight factor for each point is given accordingly to the inverse of its intensity in the regression heat map, such as $w_p = 1/L^*(p)$. This strategy penalizes points with low values in the pixel-wise regression map. If $d_p > d_{th}$, the point p is considered outlier, with d_{th} being a defined threshold distance. Subsequently, at each iteration of the RANSAC approach, the ellipse model is refitted to the inlier points using the Iterative Closest Point (ICP) algorithm [22], updating the ellipse at each iteration. At the end of this registration-based process, the final ellipse used to estimate HC is found, along with its parameters, *i.e.,* the lengths of the semi-axes, the center position, and angle of orientation.

3. EXPERIMENTS AND RESULTS

3.1. Dataset

The proposed method was applied in the *HC18 Challenge* dataset, which contains 1334 2D US images of the standard anatomical plane used to measure the HC [15], [23]. The size of each image is 800 by 540 pixels with a pixel size ranging from 0.052 to 0.326 mm. The dataset is divided into training set, composed of 999 images, and testing set, composed of 335 images. The training set includes manual annotation of the HC as an ellipse fitted by one experienced sonographer.

To overcome overfitting problems during training, data augmentation techniques, including spatial and intensity-based transformations, were applied to the training images [24]. Spatial transformations included rotations, scaling, flips, and shear, whereas intensity transformations included Gaussian noise addition, brightness and contrast modification, and blur.

3.2. Implementation details

The regression network was trained during 500 epochs with a mini-batch size of 5 and using the Adam optimizer with an initial learning rate of 0.0001. At the end of each epoch, the learning rate was updated using a polynomial learning rate decay policy. The training was performed using the PyTorch python library. For the generation of the ground-truth map, a sigma of 5 was applied for the gaussian filter. After map estimation, a threshold value of 0.75 was used to create the binary map. Regarding the RANSAC method, the number of iterations was experimentally set to 10 and d_{th} was set to 15. Moreover, affine transformations of the ellipse were allowed during the ICP method (*i.e.,* translation, rotation, and resize).

3.3. Evaluation metrics

The performance of the proposed method was evaluated on the testing images of the *HC18 Challenge* dataset in terms of HC difference (DF), HC absolute difference (ADF), and Dice similarity coefficient (DSC), defined as:

$$DF = HC_{gt} - HC_{pred}, \tag{3}$$

$$ADF = |HC_{gt} - HC_{pred}|, \tag{4}$$

$$DSC = \frac{2 \cdot |area_{gt} \cap area_{pred}|}{|area_{gt} + area_{pred}|} \tag{5}$$

where HC_{gt} and HC_{pred} represents the manual and predicted HC, respectively, and $area_{gt}$ and $area_{pred}$ represents the area of the manual and predicted ellipses.

3.4. Results

Table 1 shows the performance of the proposed method in terms of the evaluation metrics. A mean DF of -0.11 ± 2.67 mm, a mean ADF of 1.92 ± 1.85 mm, and a DSC of 97.95 ± 1.12% were achieved, which can be considered very good results. Moreover, to evaluate the advantages of our HC ellipse estimation method (using RANSAC), a comparison against the standard direct ellipse fitting without outliers removal was performed. Figure 3 shows the added value of proposed methodology, showing higher robustness in cases where small fragments are found at predicted heat map.

Figure 3 also presents the comparison of the proposed method against literature approaches that also used the *HC18 Grand Challenge* dataset [15], [16], [18], [19], [25]–[27]. Here, it can be verified that the proposed approach outperforms literature methods, achieving the lowest value of DF and the highest value of DSC. Since HC estimation is a precursor for different clinical tasks, e.g., age prediction or fetal weight estimation, a higher accuracy of the HC estimation method is important in traditional clinical practice [28].

4. DISCUSSION

In this work, a deep learning approach to accurately segment the fetal head from US images was proposed. The proposed approach starts with a regression network to delineate the head boundaries, followed by an efficient ellipse fitting to find the final head contour. The proposed method was developed using the *HC18 Grand Challenge* dataset that presents variable images of the HC, including fetal heads with different sizes and locations and different gestational ages. Moreover, the images present the challenges inherent to the US modality, such as shadows, poor quality, and artifacts. Nevertheless, analyzing Table 1, it is possible to verify that the proposed approach achieved good results. Starting with the performance of the regression stage, a mean DF of 0.40 mm and a DSC of 97.61 were achieved, which can be considered good results. Regarding the performance of the network for different gestational ages, the results achieved by the network were not uniform across the three gestational trimesters. Specifically, slightly worst results were obtained for the first trimester, where a DSC of approximately 95.3% was achieved, against around 98% for the second and third trimesters. These results can be explained by the fact that the regression framework expects a head contour characterized by a gaussian-like curve, where the intensities of the skull are higher in comparison with the inner and outer surrounding tissues. In fact, in early stages of the development, the fetal skull may not be perfectly depicted and distinguished from the brain inner structures, which can lead that a gaussian-like curve being a suboptimal representation of the fetal skull. Moreover, in the first trimester, the fetal head only occupies a small part of the image, which can increase the probability of the presence of artifacts that are considered fetal skull by the network (please see the example in the sixth column of Figure 3). In the second and third trimesters, the fetal head represents a large part of the image, which can also lead to better results. Nevertheless, the results obtained showed the good performance of the regression framework even for images of the first trimester.

Analyzing the final results, *i.e*. the results after applying the proposed ellipse fitting method, it can be verified that the proposed second stage allowed to improve HC detection. In fact, an improvement of the DF and DSC was obtained in comparison with the results of only using the output of the regression network. Ultimately, a mean DF of -0.11 mm and a DSC of 97.95 were achieved. These results suggest the accuracy of the proposed ellipse fitting method to avoid the outliers generated by the regression network, which can be seen in Figure 3. Interestingly, when analyzing the final results for the different gestational ages, it was verified that the results were improved from 95.3% to 97% for the images of the first trimester, whereas the DSC for the images of the second and third trimester remained 98%. These results can corroborate that the regression network generated more outliers in the images of the first trimester, proving also the added-value of the HC refinement using the proposed ellipse fitting method for these images. Overall, the combination of the regression network with the proposed ellipse fitting method allowed to obtain accurate predictions.

Table 1- Performance of the proposed HC delineation approach and comparison with state-of-the-art methods (mean ± std)

	ADF (mm)	DF (mm)	DSC (%)
Heuvel et al., 2018 [15]	2.80 ± 3.30	0.60 ± 4.30	97.00 ± 2.80
Sobhaninia et al., 2019 [16]	2.12 ± 1.87	1.13 ± 2.69	96.84 ± 2.89
Rong et al., 2019 [25]	2.45 ± 2.55	−1.05 ± 3.38	95.49 ± 4.11
Al-Bander et al., 2020 [26]	2.33 ± 2.21	1.49 ± 2.85	97.73 ± 1.32
Li et al., 2020 [27]	2.03 ± 2.13	−0.28 ± 2.9	97.46 ± 0.86
Moccia et al., 2021 [19]	1.95 ± 1.92	−0.31 ± 2.73	97.90 ± 1.11
Fiorentino et al., 2021 [18]	**1.90 ± 1.77**	0.21 ± 2.58	97.76 ± 1.32
Proposed without RANSAC + ICP	2.10 ± 2.38	0.40 ± 3.16	97.61 ± 2.87
Proposed	1.92 ± 1.85	**−0.11 ± 2.67**	**97.95 ± 1.12**

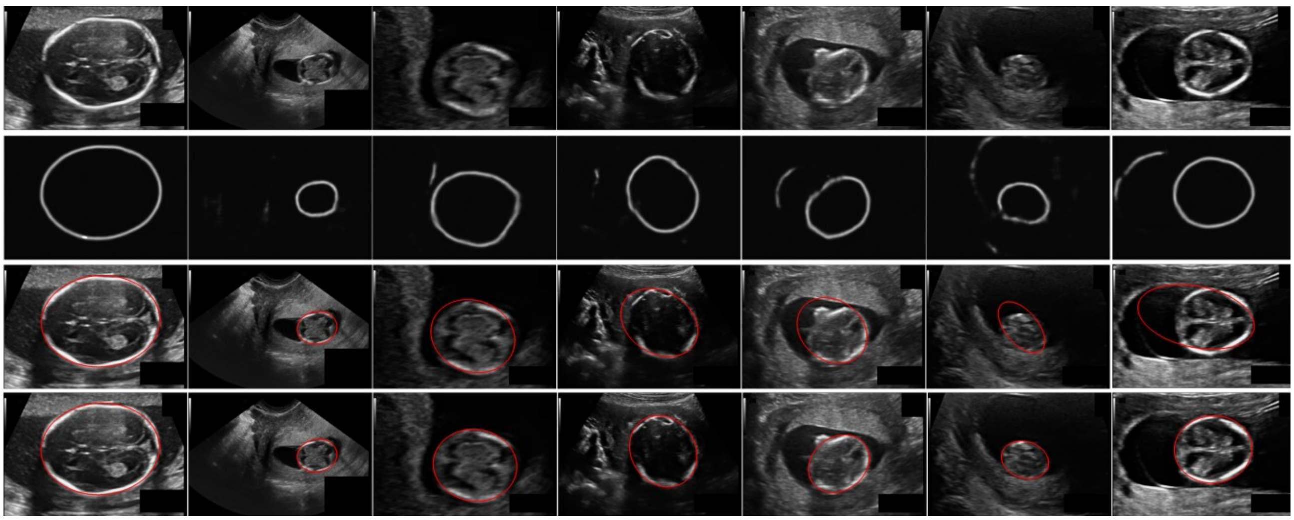

Figure 3 – Examples of HC detection using the proposed method. 1st row: original 2D US image; 2nd row: heat map generated by the regression CNN; 3rd row: ellipse fitting only using the direct least squares ellipse fitting method; 4th row: ellipse fitting using the proposed registration-based approach.

The results obtained by the proposed method were also compared with other literature methods for HC detection (Table 1). Here, it was possible to verify that the proposed method is competitive with the state-of-the-art, even outperforming other approaches. Specifically, a superior performance was obtained when compared with handcrafted-based or model-based strategies, such as the work of [15]. This is expected since deep learning-based strategies have the ability of being more robust and efficient for the task of US image segmentation, due to the capability of these strategies to obtain feature representations directly from the images. In fact, deep learning strategies have now superseded the image processing field. However, the proposed approach also showed to produce more accurate HC delineations in comparison with other deep learning-based strategies, including methods that perform HC delineation as a segmentation problem. Thus, the representation of the HC delineation as a contour regression problem seems to be a good approach.

As future work, an improvement of the proposed methodology is expected. Firstly, the use of a larger training dataset with images with higher variability and from different sources can improve the generalization of the network, allowing to achieve better predictions. Secondly, an improvement of the computational efficiency of the ellipse fitting method will be explored, in order to decrease the computational time and explore the real-time capabilities of US.

5. CONCLUSION

In this work, a new pipeline to automatically estimate HC from fetal US images was described. The method showed to be robust and accurate for head contour detection. Overall, the obtained results corroborated the potential of the proposed method to clinical practice, aiding the clinicians to perform head growth assessments.

6. ACKNOWLEDGEMENTS

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