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An Analytical Study on 2D Ultrasound Fetal Anatomy Measurement

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ABSTRACT: The modern medical technologies have developed such that most of the diseases are curable if diagnosed at their early stage. Segmentation of the fetal anatomy plays an important role in such detection. This paper mainly reviews some of the efficient automatic and semi automatic techniques proposed in the past years for the segmentation of fetal head and femur.

KEYWORDS: fetal anatomies, fetal head circumference, femur length, fetal measurement

I. INTRODUCTION

Medical trends show great development in all its wings. Pregnancy can generally be divided into three trimesters – the first trimester(1 week to 12 weeks) , the second trimester(13 weeks to 28 weeks) and the third trimester(29 weeks to 40 weeks). The fetus develops almost all major organs – heart, brain and spine in the first trimester itself. Similarly each trimester has its own way of development of the fetus. Periodic consultation with the physician helps diagnosing and treating the major anomalies even before the baby's birth. Ultrasound scanning is the widely used medical equipment for the picturization of the fetus. Not many but a few tools are available which automatically detects the fetal organs. AUTO OB is one such commercial tool in use. The fetal organs are detected in prior and the following fetal measurements are made which help diagnosing the anomalies

(i) Bi-parietal diameter (BPD)
(ii) Head circumference (HC)
(iii) Abdominal circumference (AC)
(iv)Femur length (FL)
(v) Humerus length (HL)
(vi) Crown-rump length (CRL)

Several techniques have been proposed by several people for the segmentation and analysis of the fetus. The techniques proposed in [13] and [14] focus on fetal facial detection. [13] proposed a learning based approach which combines both 2D and 3D information for automatic fetal face detection; [14] proposed a feature-based method to automatically detect 3D fetal face and accurately locate key facial features from the 3D US images. The fetal abdomen is analyzed in [15] which proposed an automated method of detecting two important anatomical landmarks (stomach bubble and umbilical vein) from the fetal ultrasound abdomen scan. Works done on fetal cardio have been proposed in [16]-[18]. Fetal cardiac structures are delineated in [16]; a noninvasive method for automated estimation of fetal cardiac intervals from Doppler Ultrasound (DUS) signals was proposed in [17] and an automated identification of the fetal cardiac valve opening and closing from Doppler Ultrasound signal was proposed in [18].

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In this paper we will know about a few of the segmentation techniques that help detecting the fetal head and the femur from ultrasound images. Section II overviews fetal head detection algorithms, Section III discusses fetal femur detection algorithms and Section IV deals with the measurement of the anatomies.

II. FETAL HEAD DETECTION

A. Hanna in [1] proposed a segmentation technique based on morphological operators. The ultrasound image obtained is made free from the echoes of skin reflections by applying a threshold and thus converting the input image to binary. An approximate circle is fit over the head to attain a preliminary assessment of it. Then, a 4D Hough transform is used to find a perfect elliptical fit of the head. Any curve fitting algorithm is applied to smooth the obtained head contour. Thin cracks and holes in the head contour which is due to the noise elimination is managed by applying a morphological closing which recovers the original bone thickness and boundaries.

B. In [2] Jardim and Figuoredo proposed an automatic technique to estimate the contours of the cranial cross section. The technique is a region based maximum likelihood formulation of parametric deformable contours method. The algorithm begins with representing the head as a closed 8-point interpolating spline. Initially with a single interpolating point as the input, the algorithm determines the maximum variance in the region. It then updates the contour parameters as per the following equation (1)

$$p_i^{(q+1)} = \arg\max_{p_i \in N(p_i^{(q)})} \log p(z \mid [p_1, p_2^{(q)}, \ldots, p_8^{(q)}], \hat{\varphi}) \qquad (1)$$

In this equation $N(p_i^{(q)})$ represents the set of 8 nearest neighbors of $p_i(q)$. When the stopping criterion is met the algorithm stops. Otherwise it begins another iteration. The main aspect of this algorithm is that, as the head contour estimation is more prone to false results due to the presence of many intracranial structures, it uses a ML function of the form

$$(\hat{\theta}, \hat{\varphi}) = \arg\max_{(\theta, \varphi)} \{\log p(z \mid \theta, \varphi) + \lambda b(\theta)\} \qquad (2)$$

where $b(\theta)$ is the balloon term increasing the contour area. The value of λ is found to be 0.15 which serves as a good general purpose value. This technique has the advantage of working with low quality ultrasound images.

C. The paper [3] proposed a novel method for the automatic segmentation of fetal anatomical structures. This technique uses a classifier to perform the segmentation. A trained classifier is used to minimize the probability of misclassification.

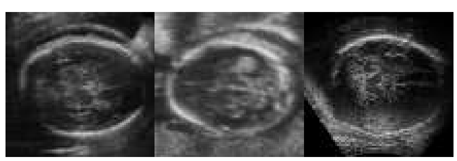

Fig. 1 Training examples

In order to reduce the training and detection time, a Constrained Probabilistic Boosting Tree (CPBT) algorithm is used. Training the CPBT involves two classification problems – a *coarse stage* robust to false negatives and a *fine stage* robust to false positives. The detection algorithm also works in the above two stages. The coarse detection stage samples the image space using a coarse sampling interval and generates hypotheses whereas the fine detection stage samples the hypotheses at fine sampling interval. This technique has the advantage of automatically segmenting the head, femur and the abdomen and computes the head circumference, bi-parietal diameter, abdomen circumference and femur length.

D. The method proposed in [7] is a fully automatic method to compute the BPD (bi-parietal diameter) and OFD (occipitofrontal diameter). The main strategy used here is that an ellipse is fit, modeling the head contour of the fetus by minimizing the parameters of the cost function. Generally the ultrasound images may be of varying contrasts and hence a two-step preprocessing is done. The first step is to extrapolate the original scan image to fit the background using iterative low pass filtering in Discrete Cosine Transform domain.

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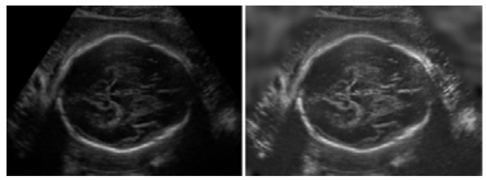


(a) (b)

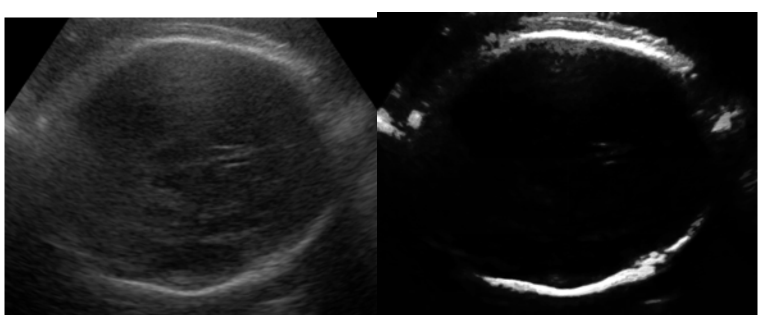
Fig. 2 (a) original image (b) after preprocessing

The second step is to regularize the intensity and the contrast. This is achieved by leveraging the DCT domain smoothing. Fig. 2 (a & b) shows the original US image and the preprocessed image.The algorithm begins with initiating three nested ellipses over the ultrasound head image where the innermost ellipse represents the skull exactly, i.e., the region with high intensity and the other two representing the outer regions with relatively lower intensity. The ellipses are parameterized with 5 parameters which are organized into a vector a = (c1,c2,r1,r2, θ) where (c1,c2) is the center co-ordinates; (r1,r2) is the semi axis lengths; θ is the rotation angle. The following cost function (3) is implemented then.

$$C(z,a,s) = \iint \frac{z(x1,x2)\, g(x1,x2,a,s)\, dx1\, dx2}{M(a)^{0.5}} + 0.5\left(\max\left\{0, \frac{\max(r1,r2)}{\min(r1,r2)}\right\} - 1.4\right)^2 \quad (3)$$

where 'g' represents the Gaussian function ; M(a) represents the circumference of the ellipse. This cost function is further optimized using Nelder – Mead optimization algorithm. Thus this technique automatically computes the OFD and BPD and provides a good coincidence with fetal biometry.

E. The algorithm in [8] presented a machine learning approach which is a combination of local statistics and shape information about pixel clusters.



(a) (b)

Fig. 3 (a) original 2D US image (b) Intensity and shape based probability plot

Each image pixel is assigned to an overlapping cluster center through the minimization of modified Euclidean distance metric. This technique well discriminated the structures within the head. For every cluster i, (i€K) of image I, the shape feature associated with it is determined by computing the cluster shape descriptor as

$$f_i^{Shape}(I,K) = [f^{(\mu int)}, f^{(area)}, f^{(maj)}, f^{(min)}, f^{(ecc)}, f^{(circ)}]^T \quad (4)$$

The feature vector is then trained using the random forest classifier[11]. The trained random forest classifier provides the probability of a pixel belonging to the cranial sections.

F. In [9] an automatic method is proposed to detect the cranial portion of the fetus. The basic idea behind the method is to compute the Chamfer distance of the skull bones.

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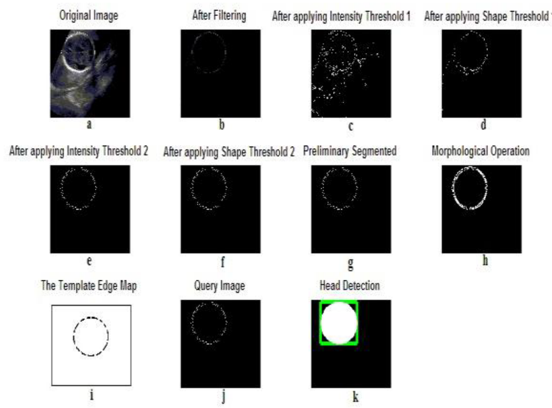

Fig. 4 Head segmentation using Chamfer Matching Method

As a preliminary segmentation, a multilevel intensity thresholding is applied to the original ultrasound image to get multiple binary images. In the next step, shape based (thinness, elongation and size) thresholds are applied to recognize the skull bones. The multiple binary images obtained in the previous step that passed the shape thresholds are collectively formed into a single binary image[proceeding]. The Chamfer matching technique compares the single binary image just obtained to various template ellipses in the following manner.

1. Extract the edge of the query image and the target image.
2. Consider one pixel of the edge in the query image and find the distance of a closest point of the edge in the target image.
3. Sum the distances for all edge points of the query image.

The lower the Chamfer distance metric, the higher the similarity between the images. Hence the best matching ellipse delineates the skull. The result is compared with the skull segmented using Hough transform and results show that Chamfer distance works well than the Hough transform.

III. FETAL FEMUR SEGMENTATION

A. The technique proposed by Jardim and Figueirdo[2] explained in section I-B can be used for femur segmentation too. It uses the same parameter function and the Maximum Likelihood function (equation 2) except that, a 3 point interpolation spline is used for femur segmentation instead of the 8 point interpolation spline to define the contour. The major positive fact about the method is that it produces results with equal accuracy for youngest femur which is straight and also for elder femur which is curved.

B. A fully automatic method to deduce the femur based on morphology was proposed by Wang [4]. The method mainly relies on the entropy of the image. The first step is to apply median filter to the original image to nullify the noise and then entropy based segmentation is applied. This gives the candidate pixels in the image.

(a) (b) (c)

Fig. 5 (a) original image (b) Entropy based segmentation (c) Final selected pixels

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The final femur segments are obtained by applying morphological dilation to the image complement and then by extracting the long and slim connected portion (Fig. 5). This is achieved using the density and height –to – width ratio information.

C. In [5], the automated method proposed works in the following way. The US fetal femur image is grayscale opened with a structuring element (generally >15) wider than the femur. An appropriate threshold is applied and regions smaller than 25 pixels are removed to generate an enhanced binary image. The region with largest length is the femur since other bright areas are subtracted as the background.

(a) (b)

Fig. 6 (a)Original image (b)Thinned femur segment

Finally, the segment is skeletonized (single pixel thickness) to obtain the end – to – end length as shown in Fig. 6

D. The method [6] proposed by Ponomarev is based on detecting the femur with the key concept that the femur pixels are brighter and have contrasting edges than other portions after extracting the binary image from the original image. Also the femur is always the central portion of a region. With this concept a Support Vector Machine is trained to detect the fetal femur. The whole dataset was divided into 10 parts of equal size. For each iteration, the method was trained on the concatenated set of nine parts and tested on the remaining part. The segmented objects were manually classified into positive and negative classes to train the SVM classifier. This resulted in a scoring function, encoding the recognition model.

(a) (b) (c)

Fig. 7 (a) Original image (b) Segmented object (c) Recognized femur object

The femur length was then calculated as the longest distance between any pair of pixels for the selected binary object.

E. The paper[10] proposed a fully automatic method to measure the femur length using shape based thresholds. The US image is converted to binary image using intensity thresholding. This intensity thresholding is applied at N levels to produce N binary images. These binary images are then subjected to shape thresholds – size, thinness and elongation. Binary images that overcome all the shape thresholds are collected into a single image. Support Vector Machine is used to classify the femur object from the binary image. The SVM is trained with 'Femur' and 'Non femur' objects and the results are shown in Fig. 8

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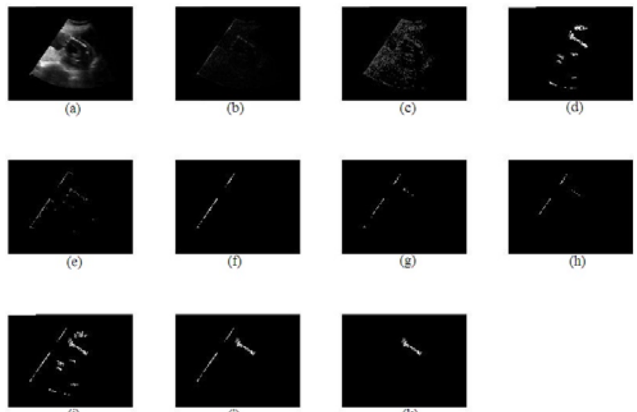
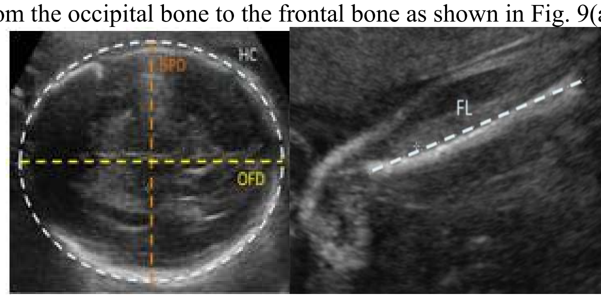


Fig. 8 (a) Original Image. (b) Filtered Image. (c) After applying Intensity Threshold 1. (d) After applying Shape Threshold 1. (e) After applying Intensity Threshold 2. (f) After applying Shape Threshold 2. (g) After applying Intensity Threshold 3. (h) After applying Shape Threshold 3. (i) Composite Image. (j) SVM based Classification. (k) Segmented Femur.

IV. FETAL ANATOMY MEASUREMENT

The above sections discussed various automatic and semi-automatic techniques to segment the fetal head and femur from 2D ultrasound images. With these segmented images the measurement of those fetal organs shall be computed mathematically. This section provides the formulae for the measurement of the Head Circumference (HC) and the Femur Length (FL).

A. The HC is the circumference of the fetal skull bone which is computed from the BPD and the OFD. BPD, the Bi-parietal Diameter is the diameter of the skull from one parietal bone to the other. OFD, the Occipito-Frontal Diameter is the diameter of the skull from the occipital bone to the frontal bone as shown in Fig. 9(a) [12]



(a) (b)

Fig. 9 (a)Head Circumference, Bi-Parietal Diameter & Occipito-Frontal Diameter (b) Femur length

The segmented skull would generally be elliptical and hence the major and the minor axis represents the OFD and the BPD respectively. From these measurements the HC is calculated as per the equation 5.

$$HC = \pi\,(BPD + OFD)/2 \qquad (5)$$

B. The femur is the longest part of the fetal body. The femur length is calculated as

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p_i, p_j]} (6)
where [p_i, p_j] is the pixel pair in the segmented binary image as depicted in Fig. 9(b)

V. CONCLUSION

This paper discussed various automatic and semiautomatic fetal anatomy segmentation (fetal head and femur) techniques using present day Computer Aided Diagnosis(CAD).These measurements are very much useful for the early detection of anomalies. It also helps doctors save the time required for analysis of 2D ultrasound fetal images.

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