Abstract: Fetal Magnetic Resonance Imaging (MRI) helps in learning about fetal brain development and has many advantages over ultrasound imaging technique. Such studies require segmentation of fetal brain. Manually segmenting the developing brain of a fetus is a challenging task and it necessitates anatomical knowledge. Hence, the proposed automatic method segment fetal brain region from fetal MRI. The pipeline of this proposed method comprises diffusion, morphological filtering, thresholding and connected component analysis. The proposed method is validated using sixteen retrospective T2-weighted fetal brain volumes. The segmented portions obtained by the method are compared with manually segmented gold standard, both qualitatively and quantitatively by estimating the Dice (D), Sensitivity (S), Specificity (Sp) and Hausdorff distance (HD). A highest value of 0.9268 for D, 0.9790 for S and 0.9983 for Sp are obtained by the method. For contour overlap, the method produced lowest value of 3.3 mm for HD value. Thus, our automatic algorithm to segment fetal brain from MRI gives competitive results compared to that of existing methods.

Keywords: fetal MRI, diffusion, morphological filtering, thresholding, fetal brain

I. INTRODUCTION

Magnetic Resonance Imaging (MRI) enables to study human brain development, brain abnormalities, brain tumor detection. Recent studies of MRI reported that how the methods are supported in early detection of brain tumor. Sharmila Agnal et.a. [1] worked on predictions towards the survival of brain tumor patients. In this work they used the properties such as structure, region labels, and feature extraction methods. They have done feature extraction by convolution neural network (CNN), and survival data classification by artificial neural network (ANN). Mrinal Paliwal [2] proposed brain tumor detection method in which the region is stated as unusual or dead cells. The author used machine learning (ML) and artificial neural network (ANN) to locate tumor region. The author also worked on injury images and tried to give precision-oriented results. In-vivo study of fetal brain is yet another emerging research area. The research requires segmented fetal brain which is surrounded with maternal tissues in fetal MRI. The process of manually segmenting fetal brain greatly takes time to complete and it is also dependent on the performance of the operator. In order to overcome these limitations, computer assisted segmentation methods were proposed. Numerous adult brain segmentation methods from MRI [3]-[8] and few segmentation methods for premature and developing neonates [9]-[13] and young children [14] are available. But automatic segmentation methods for adult brain and neonatal brain are not suitable for the study of fetal brain segmentations. since the fetal brain is much differ in size, shape and morphological changes in brain tissue. Hence few automatic [15]-[18], semi-automatic [19],[20] and atlas-based segmentation methods [21]-[23] to extract fetal brain from MRI were proposed. The existing algorithms are used different gestational week of fetal brain datasets and also varying in methodology. The analysis of ground truth results show that the cortex and cerebrospinal fluid (CSF) intensity distributions in some slices are melted (Fig.1) due to low contrast between fetal brain tissue types.

Fig.1 Fetal MRI with melted CSF and cortex

Hence fetal brain from all slices cannot be segmented by a single conventional segmentation algorithm alone. This leads to incorrect segmentation of fetal brain, which is anatomically wrong. Hence, we propose an automatic fetal brain segmentation method which involves anisotropic diffusion, filtering and improved maximum entropy thresholding.
II. MATERIALS AND METHODS

We have collected data sets of T2 – weighted single shot fast spin echo (SSFSE) MRI. Sri Ramachandra Medical University and Hospital, Chennai, India have provided the data sets for this research work. T2-weighted SSFSE is particularly enables to study about the structure of fetal brain and fetal brain abnormalities since the in-plane resolution is very high and provides appropriate contrast as well [24],[25]. The data set consist of sixteen volumes in which 10 are normal volumes and 6 are abnormal volumes. Table 1 shows the key constraints of fetal MRI which include the gestational week (GW), number of slices and slice thickness in millimeter. The other parameters are: repetition time (TR) ranges from 800 to 1,350 ms; echo time (TE) ranges from 86 to 91 ms; variable matrix size ranges from 160 to 512; and slice thickness of 3.5 – 6 mm. The range of gestational weeks for the fetal brain data sets varies from 20 to 36 weeks in axial, coronal and sagittal orientation and each volume with 20-24 slices. A medical expert segmented all the collected fetal MRI slices and thus we have used those slices as ground truth.

The following section describes the proposed method which involves diffusion, morphological filtering and thresholding and connected component analysis. The steps involved in this work is shown in Fig.2.

A. Edge preserving smoothing

We used two dimensional (2D) slice of fetal MRI as input image (I). To differentiate the fetal brain from surrounding maternal tissues in MRI, we applied smoothing and filtering in succession. First we diffused the input image to smooth the edges of fetal brain. The diffusion function is constantly decreasing the image gradient. Every pixel in the image is updated by the four nearest neighbours of the pixels. For diffusion, anisotropic diffusion filter is used which is formulated by Perona and Malik[26] to attenuate the diffusion, anisotropic diffusion filter is used which is updated by the four nearest neighbours of the pixels. For edges of fetal brain. The diffusion function is constantly updated for the fetal brain data sets varies from 20 to 36 weeks in axial, coronal and sagittal orientation and each volume with 20-24 slices. A medical expert segmented all the collected fetal MRI slices and thus we have used those slices as ground truth.

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\[ I_d = \frac{\partial}{\partial n} I(K, n) = \nabla \cdot (C(K, n)\nabla I(K, n)) \]  

where, K is the coordinate, n is the total iteration steps.
This morphological opening filter moreover facilitates to suppress many smaller areas of high intensity pixels in $I_d$, which are caused by surrounding maternal tissues in fetal MRI (Fig. 4(c)).

C. Improved Maximum Entropy Threshold (IMET)

The image $I_o$ which is filtered and further processed to obtain a binary image, in the subsequent step. For this we compute a maximum entropy threshold. The Maximum entropy $[27],[28]$ is obtained by the probability of gray level of the given image. Such intensity is used for segmentation. For estimating the entropy $H$, the filtered image $I_o$ is used as:

$$H = -\sum_{i=1}^{L} p_i \log(p_i) \text{ and } p_i = \frac{n_i}{N} \quad (4)$$

where $p_i$ is the probability of $i^{th}$ gray level and the gray level ranges from 1 to $L$, $n_i$ is calculated as pixel count with gray intensity $i$. The maximum entropy is obtained by selecting an intensity $i$ that makes $H$ maximum. We then estimate an optimum intensity threshold $T_{opt}$ using the maximum entropy ($H$), mean ($\mu_{Io}$) and standard deviation ($\sigma_{Io}$) of the filtered image as:

$$T_{opt} = H + \mu_{Io} + \sigma_{Io} \quad (5)$$

The optimum threshold $T_{opt}$ (IMET) is used to disconnect foreground objects from the background. Hence, we obtain a binary image $I_b$ using the optimum threshold $T_{opt}$ as:

$$I_b(i, j) = \begin{cases} 1 & \text{if } I_o(i, j) \geq T_{opt} \\ 0 & \text{otherwise} \end{cases} \quad (6)$$

The binary image $I_b$ is shown in Fig. 4(d).

D. Fetal brain mask

The binary image $I_b$ consists of several isolated regions. As the fetal head is localized during imaging process for this research, at least a part of the fetal brain lies at the middle of the scan. Hence, a connected region which covers the middle of the image is identified in $I_b$, through the intensity value 1. For this the 4 connected component analysis [29], is performed around the middle of $I_b$. That region is the final fetal brain mask $I_M$ and it is depicted in Fig. 4(e).

E. Segmentation of Fetal brain

The fetal brain portion $I_b$ is segmented from input image $I$ with $I_b$ as follows:

$$I_{br}(i, j) = \begin{cases} I(i, j) & I_M(i, j) = 1 \\ 0 & \text{otherwise} \end{cases} \quad (7)$$

Fetal brain extraction sample is shown in Fig. 4(f).

F. Evaluation Metrics

Apart from visual perception, the performance of the IMET method is estimated computed with Dice (D)[30], sensitivity (S) and specificity (Sp)[31] like previous works[35]-[40]. These evaluation results are also compared by Hausdorff distance (HD)[32-34] for better understanding towards the results.

The Dice ($D$) is given by:

$$D(A, B) = \frac{2|A \cap B|}{|A| + |B|} \quad (8)$$

where, A and B are comparable two datasets.
The sensitivity (S)[31] is the percentage of fetal brain pixels identified by the IMET method and specificity (Sp)[31] is the percentage of fetal non-brain pixels identified in the IMET method. Sensitivity and Specificity are computed using the correct identifications such as True Positive (TP), False Positive (FP). Where the TP and FP are the number of pixels correctly classified as fetal brain tissue by the IMET algorithm. Same time, the incorrect identifications such as True Negative (TN) and False Negative (FN) are the number of pixels related to incorrect classifications by the IMET algorithm. TN and FN are representing the total pixels correctly and incorrectly classified as fetal non-brain tissue by the IMET algorithm (Fig.5).

\[
S = \frac{TP}{TP + FN} \\
Sp = \frac{TN}{TN + FP}
\]

Hausdorff distance (HD)[32]-[34] computes the distance between manual segmented region (A) and automatic segmented region (B). HD is computed in a two phase process. The initial phase, every pixel in manual segmented region and the minimum distance to every one point of IMET method segmented region is calculated. \(d_{H_{ab}}\) providing the maximum of this group of minimum distances between the manual segmented region and the proposed IMET segmented region.

Let the minimum distance for the ith exterior pixel in Manual segmented (A) region to the group of exterior pixels in IMET segmented (B) region is \(d_{i}^{ab}\), therefore \(d_{H_{ab}}\) is the maximum value of distance of all exterior pixels in A and is given by:

\[
d_{H_{ab}} = \max\{d_{i}^{ab}\}, i = \{1..n_{a}\}
\]

Similarly let \(d_{H_{ba}}\) be distance between B and A. In the second stage, the HD between A and B is obtained as:

\[
HD = \max\{d_{H_{ab}}, d_{H_{ba}}\}
\]

D, S and Sp are closer to 1 at the same time as the IMET segmented results (B) are closer to Manual segmented results (A). When the same values move towards 0, they show disagreement. A low HD value shows good contour overlap.

III. RESULTS AND DISCUSSION

The data set which captured at different gestational weeks were tested through the proposed IMET method. We used the gold standard images for comparing our results or we can try to improve our results to get closer to those standard. The experts were validated our results with the gold standard images and appreciated that our image results are agreed well with gold standard images. For illustration, a dataset of fetus with normal brain imaged at GW 20 (Fig.7), abnormal brain imaged at GW 29 (Fig.9) and the brain segmented by our method are shown in Figure 8 and Figure 10 respectively. The Fig. 8 and 10 shows the proposed IMET method’s extraction towards the fetal brain in most MRI slices. For slices 1-3 in Fig.8 and slices 1-7 in Fig.10, few pixels were detected as brain since the lower slices are not included in the brain region.
Fig. 8 Segmented fetal brain portion in the volume from in Fig. 7.

Fig. 9. A volume of Fetal MRI of abnormal brain (GW 29)

Fig. 10 Segmented fetal brain portion in the volume from in Fig. 9.

For qualitative evaluation, fetal brain portion segmented by IMET method and manually segmented are shown in Fig. 11, 12 and 13. The original slices obtained in MRI orientations such as Axial type, Coronal type and Sagittal type planes are given in first row of Fig.11, 12 and 13 respectively. The results of gold standard images and the results of IMET method are exposed in the successive rows. We can observe the Fig. 11, 12 and 13 that the results of the method produced acceptable results for the given input MRI fetal slices.

Fig. 11. Segmented Fetal MRI in Axial view. Row 1 illustrates the original images, the row 2 illustrates manual segmentation and row 3 illustrates the proposed IMET method.

Fig. 12. Segmented Fetal MRI in Coronal view. Row 1 illustrates the original images, the row 2 illustrates manual segmentation and row 3 illustrates the proposed IMET method.

Fig. 13. Segmented Fetal MRI in Sagittal view. Row 1 illustrates the original images, the row 2 illustrates manual segmentation and row 3 illustrates the proposed IMET method.

The evaluation metrices D, S, Sp and HD are done by comparing the gold standard and the proposed IMET method. Those results are furnished in Table 2.
The observation of the results as of Table 2 proves that, for 5 volumes the D value lies between 0.91 to 0.922 and for the remaining volumes, the value lies between 0.86 to 0.89. The average value of S is 0.9264 and the value of Sp is 0.9940. This shows that the IMET method gives the segmented result better by including fetal brain pixels (S) and excluding fetal non-brain pixels (Sp). The low HD value 3.3mm for volume 3, produced by our method shows that the good agreement between manual and proposed segmentation results.

The significance of the Improved Maximum Entropy method (IMET) will be found by comparing the recent methods such as Kainz[22] and Tourbier[23]. The dataset used by the mentioned methods are different from the dataset used by the proposed method. But the Table 3 gives a comparison on the Kainz[22] and Tourbier[23] Dice values with the IMET method. The quantitative measure D obtained by the cortex segmentation method by Kainz et al is 0.90 for 50 data sets. The method by Tourbier et al. is 0.93 for 10 fetus data sets. The observation from the Table 3 shows that the D values obtained by the IMET method are very close to Kainz[22] and Tourbier[23] quantitative analysis values. This comparison table also shows that the IMET method is close to the accuracy level regarding fetal brain segmentation.

Table II. D, S, Sp and HD values of the IMET method

| Vol. Labe | Dice (D) | Sensitivity (S) | Specificity (Sp) | Hausdorff Distance (HD) |
|-----------|----------|-----------------|-----------------|------------------------|
| 1         | 0.863704 | 0.97903         | 0.986419        | 4.326236               |
| 2         | 0.873066 | 0.969113        | 0.990777        | 5.257418               |
| 3         | 0.890672 | 0.956469        | 0.991493        | 3.888627               |
| 4         | 0.884471 | 0.925769        | 0.989998        | 4.246712               |
| 5         | 0.883347 | 0.925222        | 0.992374        | 3.988844               |
| 6         | 0.910887 | 0.883238        | 0.998316        | 3.401193               |
| 7         | 0.896807 | 0.866542        | 0.997593        | 3.56109                |
| 8         | 0.925323 | 0.93578         | 0.997266        | 3.366594               |
| 9         | 0.926892 | 0.939002        | 0.99617         | 3.936031               |
| 10        | 0.895019 | 0.933352        | 0.993378        | 3.79299                |
| 11        | 0.872149 | 0.919121        | 0.994321        | 3.72683                |
| 12        | 0.86198  | 0.93796         | 0.99252         | 3.480413               |
| 13        | 0.877004 | 0.876842        | 0.996404        | 3.549923               |
| 14        | 0.914107 | 0.914733        | 0.996428        | 3.848556               |
| 15        | 0.910516 | 0.910405        | 0.996342        | 3.549135               |
| 16        | 0.893317 | 0.930939        | 0.994581        | 3.501135               |
| Avg.      | 0.892454 | 0.92647         | 0.994024        | 3.838858               |

Regarding segmentation, we can find small drawback in Kainz et al method. This method fails to segment the fetal brain region. Even though there is large anatomical abnormality, the IMET method identified the region. Kainz et al can detect only a few voxels as brain portion near the border slices. The method of Tourbier et al.[23] using the multiple Atlas Fusion and produced better Dice value rather than single-atlas strategy given by Caldairou[18].

Table 4 shows the average value of distance measure HD, for the proposed method and that of Jeremie et al[15]. Again the datasets used by the two algorithms are different and exact comparison is not possible. Table 4 shows that the proposed method also gives a HD value 3.8 lower than that of Jeremie et al.[15].

The proposed automatic fetal brain segmentation is an intensity based method. This method makes use of the applications of diffusion, morphological filtering and maximum entropy thresholding in a sequel. The computed values of similarity indices and qualitative results of the proposed method are closer to that of earlier fully automatic method, atlas based method and manually segmented gold standard results. Hence the extraction of fetal brain of our method is helpful in the study of evolution of brain structure in vivo.

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