International Journal of Innovative Technology and Exploring Engineering (IJITEE)
ISSN: 2278-3075 (Online), Volume-9 Issue-3, January 2020

Fetal Brain Segmentation using Improved Maximum Entropy Threshold

Gayathri S P, Siva Shankar R, Somasundaram K

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 l[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.

Revised Manuscript Received on January 30, 2020.
***** Correspondence Author
Gayathri S P*, Dept. of Comp. Sci. and Appl., The Gandhigram Rural Institute – Deemed to be University (MHRD-Govt. of India), Gandhigram – 624302, Tamil Nadu, India. Email:gayathrisp12@gmail.com
Siva Shankar R, Dept. of Computer Applications, Madanapalle Institute of Technology & Science , Madanapalle – 517325 Andra Pradesh , India. Email:arjhunshankar@gmail.com
Somasundaram K, Dept. of Comp. Sci. and Appl., The Gandhigram Rural Institute – Deemed to be University (MHRD-Govt. of India), Gandhigram – 624302, Tamil Nadu, India. Email: ka.somasundaram@gmail.com

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.

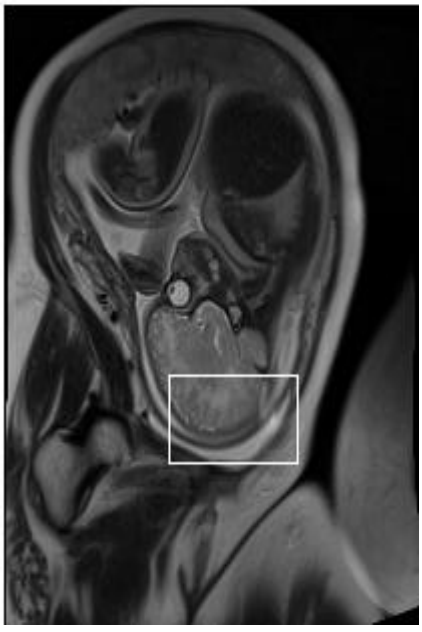

Fig.1 Fetal MRI with melted CSF and cortex

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.

Table I. Key constraints for fetal MRI slices

Vol. Label	GA	No. of slices	Slice thickness (mm)
1	20	21	3.5
2	29	22	4
3	29	24	4
4	29	24	4
5	29	20	4
6	31	23	6
7	31	20	6
8	31	20	6
9	20	23	6
10	20	23	6
11	20	20	6
12	20	20	6
13	36	23	6
14	36	20	6
15	36	20	6
16	36	20	6

The following section describes the proposed method which involves diffusion, morphological filtering and thresholding and connected component analysis. The steps invlolved 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 surrounded maternal tissues in MRI, we applied smoothing and filtering in succession. First we diffuse 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 non-brain part. The diffused image I_d is obtained as :

$$I_d = \frac{\partial}{\partial n} I(K,n) = \nabla \cdot (C(K,n) \nabla I(K,n)) \qquad (1)$$

where, K is the coordinate, n is the total iteration steps.

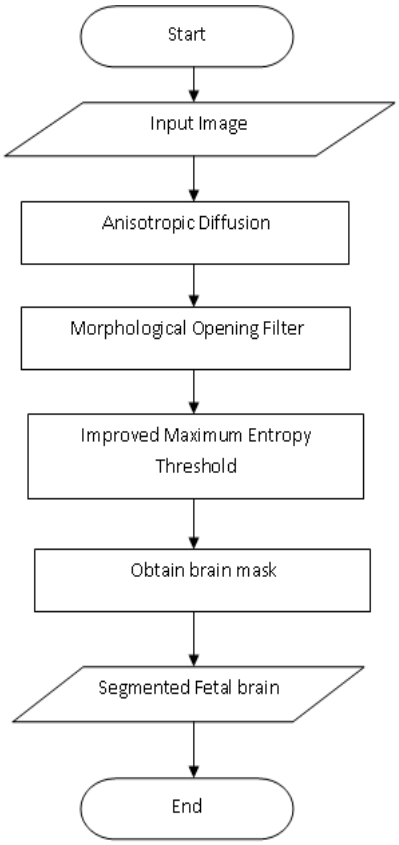

Fig. 2. The steps involved in the proposed method

$C(K,n)$ is the diffusion function and is given by :

$$C(K,n) = \exp\left(-\left(\frac{\nabla I(K,n}{p}\right)^2\right) \qquad (2)$$

where, p is the diffusion constant. The behaviour of filter depends upon the value of k. We have used 10 for p, which is nominal for the edge gradient for maternal tissues and fetal head. Fig.4(b) shows the diffused image I_d

B. Morphological Opening

In fetal MRI, there are some intensity overlap between fetal cortex and fetal brain white matter. Hence further smoothing process is essential to do an accurate segmentation. In view of the fact that the fetal cortex is a slim layer, morphological opening filter is required to apply for smoothing the edge pixels at the interface of CSF-skull. The morphological opening process is applied to obtain I_o , as:

$$I_o = (I_d \Theta B) \oplus B \qquad (3)$$

where, Θ is dilation and $\oplus$ is erosion . The structuring element B with radius 3 is given in Fig.3.

Retrieval Number: B7706129219/2020©BEIESP
DOI: 10.35940/ijitee.B7706.019320
Journal Website: www.ijitee.org

Published By:
Blue Eyes Intelligence Engineering
& Sciences Publication (BEIESP)

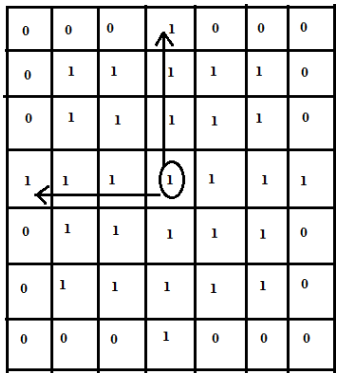

Fig.3 Structuring element (B) of three pixel radius size

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 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 (μ_{Io}) and standard deviation (σ_{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 :

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

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

D. Fetal brain mask

The binary image $I_{\bar{B}}$ 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 $I_{\bar{B}}$, through the intensity value 1. For this the 4 connected component analysis [29], is performed around the middle of $I_{\bar{B}}$. That region is the final fetal brain mask I_M and it is depicted in Fig.4 (e).

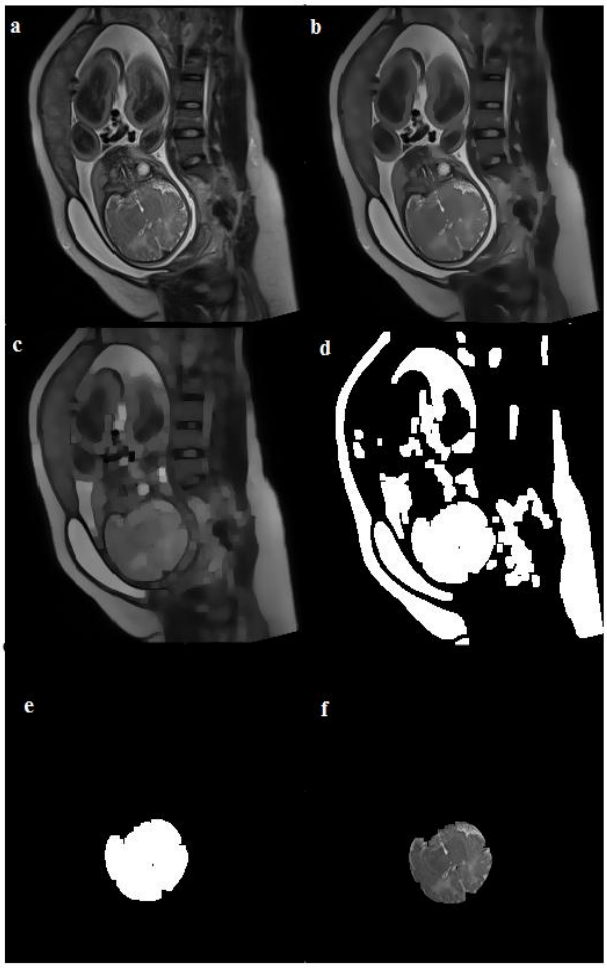

Fig.4. (a) Original Input mage (b) Diffused Image (c) Filtered Image (d) Conversion of Binary (e) Brain Mask I_M (f) Segmented Fetal Brain

E. Segmentation of Fetal brain

The fetal brain portion I_{br} is segmented from input image I with I_M as follows:

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

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).

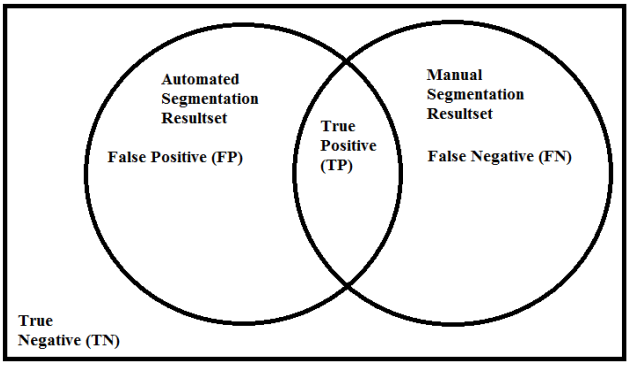

Fig.5. Overlap Metric

The sensitivity (S) and specificity (Sp) are given by:

$$S = \frac{TP}{TP + FN} \tag{9}$$

$$Sp = \frac{TN}{TN + FP} \tag{10}$$

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. dH_{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^{ab}_i, therefore dH_{ab} is the maximum value of distance of all exterior pixels in A and is given by :

$$dH_{ab} = \max\{d_i^{ab}\}, i = \{1...n_a\} \tag{11}$$

Similarly let dH_{ba} be distance between B and A. In the second stage, the HD between A and B is obtained as:

$$HD = \max\{dH_{ab}, dH_{ba}\} \tag{12}$$

where a is manual segmented (A) region and b is IMET segmented (B)region. The visual perception may given us better idea in Fig.6.

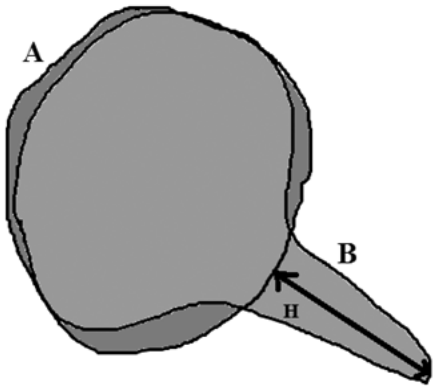

Fig.6 Haustroff Distance

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.

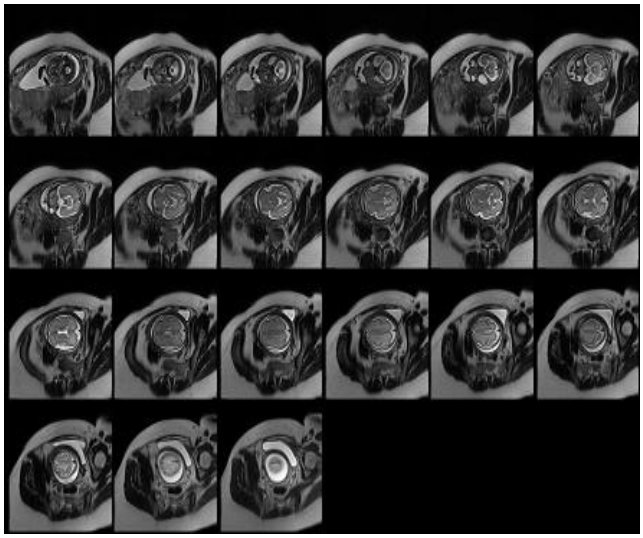

Fig.7. A volume of Fetal MRI of normal brain (GW 20)

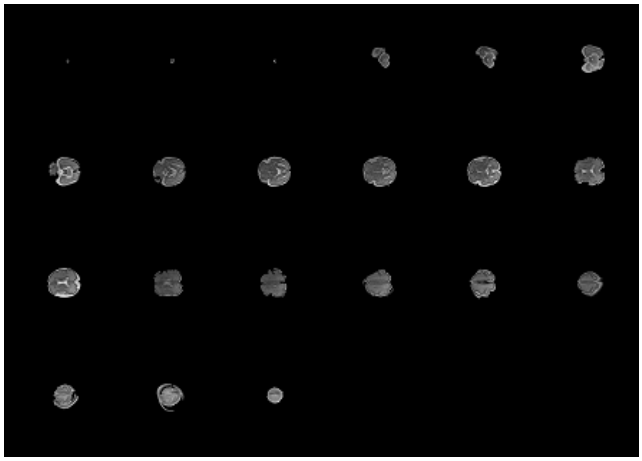

Fig.8 Segmented fetal brain portion in the volume from in Fig.7.

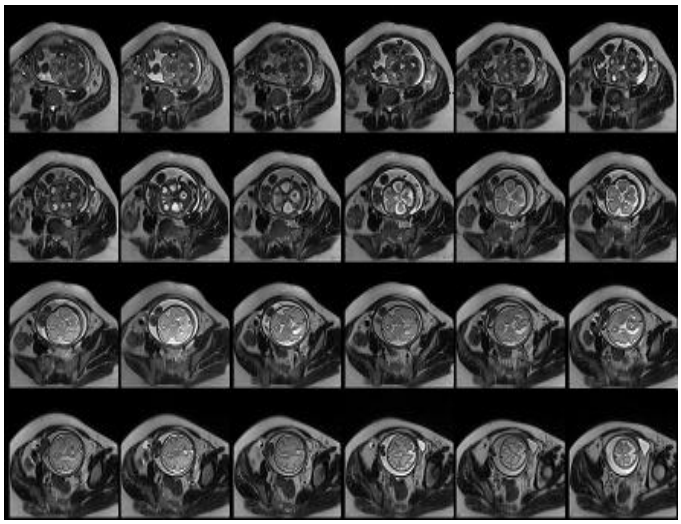

Fig.9. A volume of Fetal MRI of abnormal brain (GW 29)

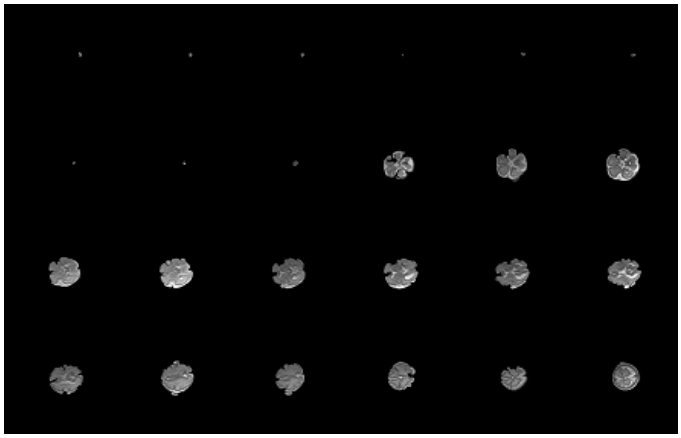

Fig.10 Segmented fetal brain portion in the volume from in Fig.9.

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.

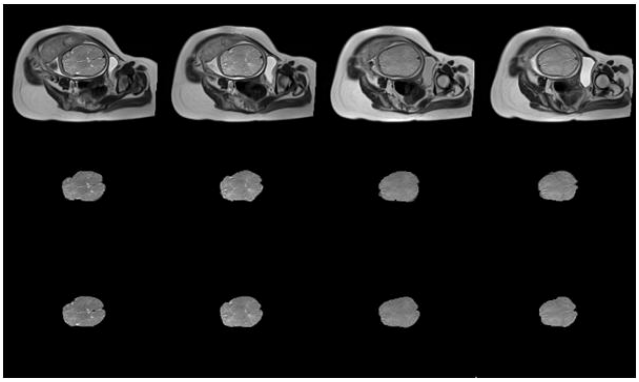

Fig.11. Segmented Fetal MRI in Axial view. Row 1 illustrates the original images, the row 2 illustrates manual segmentation and row 3 illustrates the proposed IMET method.

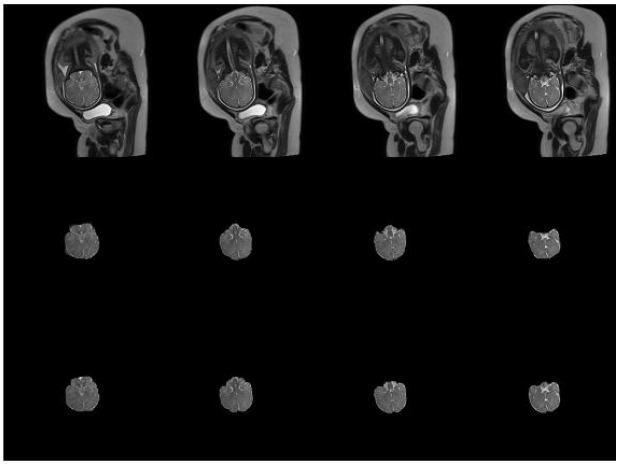

Fig.12. Segmented Fetal MRI in Coronal view. Row 1 illustrates the original images, the row 2 illustrates manual segmentation and row 3 illustrates the proposed IMET method.

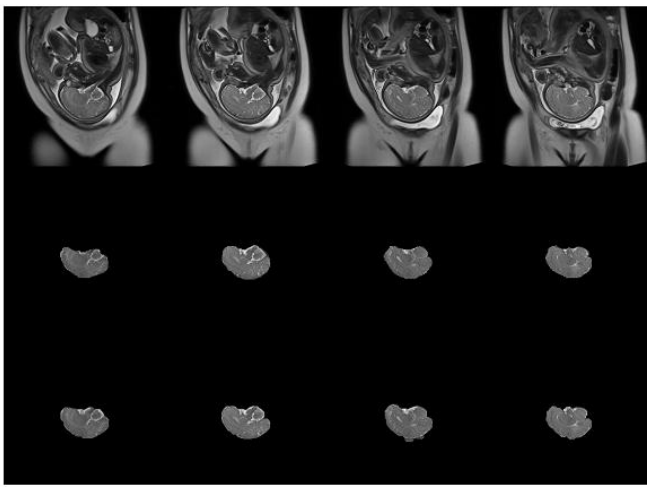

Fig.13. Segmented Fetal MRI in Sagittal view. Row 1 illustrates the original images, the row 2 illustrates manual segmentation and row 3 illustrates the proposed IMET method.

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.

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

Vol. Label	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	0.886542	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

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 III Comparison of Dice of recent methods with IMET

Author	No.of Datasets	Best Dice value
Kainz et al	50	0.90
Tourbier et al	10	0.93
Proposed method	16	0.89

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].

Table IV Computed Hausdorff distance

Algorithm	No.of cases	HD value (mm)
Jeremie et al.	24	3.9
Proposed method	16	3.8

IV. CONCLUSION

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.

ACKNOWLEDGMENT

The authors thank Dr.R.Rajeswaran MD, Ph.D, Radiologist, Radiology & Imaging Sciences, Sri Ramachandra Medical College, India. Dr.Rajeswaran validated the results of the proposed method. The authors also thank Dr. Manjiri Dighe M.D., Dept of Radiology, University of Washington Medical Center, Seattle, USA., for her support in this research. This work is done at Gandhigram Rural Institute – Deemed University [MHRD - Govt of India], under the MoU - 20.02.2014, between Gandhigram Rural Institute and Sri Ramachandra Medical College, India.

REFERENCES

1. Sharmila Agnal A, Arun Deepak C, Venkatesh J, Sudarshan S, Pranav A, Predicting Survival of Brain Tumor Patients using Deep Learning.International Journal of Innovative Technology and Exploring Engineering (IJITEE), 2019, 8, 1441-1448.
2. Mrinal Paliwal,Brain Tumor Detection by Fusing Machine Learning and Neural Network Practices.International Journal of Innovative Technology and Exploring Engineering (IJITEE), 2019, 8,108-111.
3. Mikheev, A., Nevsky, G., Govindan, S., Grossman, R. and Rusinek, H., Fully automatic segmentation of the brain from T1-weighted MRI using Bridge Burner algorithm. J. Magn. Reson. Imaging, 2008, 27, 1235-1241.
4. Somasundaram, K. and Kalaiselvi, T., Fully automatic brain extraction algorithm for axial T2-weighted magnetic resonance images. Comput. Bio. Med., 2010, 40, 811–822.

5. Somasundaram, K. and Kalaiselvi, T., Automatic brain extraction methods for T1 magnetic resonance images using region labeling and morphological operations. Comput. Bio. Med., 2011, 41, 716-725.
6. Somasundaram, K. and Siva Shankar, R., A novel Skull Stripping Method for T1 Coronal and T2 Axial Magnetic Resonance Images of Human Head Scans Based on Resonance Principle. International conference on Image Processing, Computer Vision and Pattern Recognition organized by WORLDCOMP'12, Las Vegas, Nevada, USA, 2012,16-19.
7. Somasundaram, K. and Ezhilarasan, K., Automatic Brain Portion Segmentation From Magnetic Resonance Images of Head Scans Using Gray Scale Transformation and Morphological Operations. J. Comput. Assist. Tomogr., 2015, 39, 552-558.
8. Galdames, F. J., Jaillet, F. and Perez, C. A., An Accurate Skull Stripping Method Based on Simplex Meshes and Histogram Analysis in Magnetic Resonance Images. J. Neurosci. Methods, 2012, 2,103–119.
9. Wang, L., Shi, F., Lin, W., Glimore, J. H. and Shen, D., Automatic segmentation of neonatal images using convex optimization and coupled level sets. Neuroimage, 2011, 58, 805–817.
10. Prastawa, M., Gilmore, J. H., Lin, W. and Gerig, G., Automatic Segmentation of Neonatal Brain MRI. in: Proc. of the 7th Int. Conf. on Medical Image Computing and Computer-Assisted Intervention, Part I, 2004, 10-17.
11. Prastawa, M., Gilmore, J. H., Lin, W. and Gerig, G., Automatic segmentation of MR images of the developing newborn brain. Med. Image Anal., 2005, 9, 457–466.
12. Glasel, H., Leroy, F., Dubois, J., Hertz-Pannier, L., Mangin, J. F. and Dehaene-Lambertz, G., A robust cerebral asymmetry in the infant brain: The rightward superior temporal sulcus. Neuroimage, 2011, 58,716–723.
13. Chiverton, J., Wells, K., Lewis, E., Chen, C., Podda, B. and Johnson, D., Statistical morphological skull stripping of adult and infant MRI data. Comput. Biol. Med., 2007, 37, 342 – 357.
14. Murgasova, M., Dyet, L., Edwards, D., Rutherford, M., Hajnal, J. and Rueckert, D., Segmentation of brain MRI in young children. Acad. Radiol., 2007, 14, 1350-1366.
15. Jeremie, A., Elsa, D.A. and Isabelle B., Automatic Segmentation of Head Structures on Fetal MRI. Biomedical Imaging: From Nano to Macro, IEEE International Symposium, 2009, 109-112.
16. Cuadra, M.B., Schaer, M., Andre, A., Guibaud, L., Eliez, S. and Thiran, J.P., Brain tissue segmentation of fetal MR images. 12th International Conference on Medical Image Computing and Computer Assisted Intervention, 2009, EPFL-CONF-141281.
17. Ferrario, D. et al., Brain Surface Segmentation of Magnetic Resonance Images of the Fetus. 16th European Signal Processing Conference, 2008, 1-8.
18. Caldairou, B. et al., Segmentation of the cortex in fetal MRI using a topological model. Biomedical Imaging: From Nano to Macro, IEEE International Symposium, 2011, 2045-2048.
19. Claude, I., Daire, J. L. and Sebag, G., Fetal brain MRI: segmentation and biometric analysis of the posterior fossa. IEEE Trans. Biomed. Eng., 2004, 51, 617–626.
20. Gholipour, A., Estroff, J.A., Barnewolt, C.E., Connolly, S.A. and Warfield, S.K., Fetal brain volumetry through MRI volumetric reconstruction and segmentation. Int.J. Comput. Assist. Radiol. Surg., 2011, 6, 329-339.
21. Habas, P.A. et al., A Spatiotemporal atlas of MR intensity, tissue probability and shape of the fetal brain with application to segmentation. Neuroimage, 2010, 53, 460-470.
22. Kainz, B., Keraudren, K., Kyriakopoulou, V., Rutherford, M., Hajnal, J.V. and Rueckert, D., Fast fully automatic brain detection in fetal mri using dense rotation invariant image descriptors. In Biomedical Imaging (ISBI), IEEE 11th International Symposium on, 2014, 1230–1233.
23. Tourbier, S. et al., Automatic Brain Extraction in Fetal MRI using Multi-Atlas-based Segmentation. SPIE Medical Imaging, International Society for Optics and Photonics, 2015, 9413, 94130Y1-94130Y7.
24. Rousseau, F. et al., Registration-based approach for reconstruction of high-resolution in utero fetal mr brain images. Acad. Radiol., 2006, 13, 1072–1081.
25. Jiang, S., Xue, H., Glover, A., Rutherford, M., Rueckert, D. and Hajnal, J., MRI of moving subjects using multislice snapshot images with volume reconstruction (SVR): application to fetal, neonatal, and adult brain studies. IEEE Trans. Med. Imaging, 2007, 26, 967–980.
26. Perona, P. and Malik, J., Scale-Space and Edge Detection using Anisotropic Diffusion. IEEE Trans. Pattern Anal. Mach. Intell., 1990, 12, 629-639.
27. Wong, A.K. and Sahoo, P.K., A gray-level threshold selection method based on maximum entropy principle. Systems, Man and Cybernetics, IEEE Transactions on, 1989, 19, 866-871.
28. Mcgibbon, A. J., Pennycook, S.J. and Jesson, D.E., Crystal structure retrieval by maximum entropy analysis of atomic resolution incoherent images. J. Microsc., 1999, 195, 44-57.
29. Sonka, M., Hlavac, V. and Boyle, R., Digital Image Processing and Computer Vision, Cengage Learning, India, 2008, 1st edn, p.273-275.
30. Dice, L.R., Measures of the Amount of Ecologic Association between Species. Ecology, 1945, 26, 297-302.
31. Altman, D.G. and Bland, J. M., Diagnostic tests. 1: Sensitivity and specificity. BMJ: British Medical Journal, 1994, 308, 1552.
32. Babalola, K. O. et al., An evaluation of four automatic methods of segmenting the subcortical structures in the brain. Neuroimage, 2009,47,1435-1447.
33. Alansary, A. et al., MAP-based framework for segmentation of MR brain images based on visual appearance and prior shape. MIDAS J., 2013, 1, 1-13.
34. Hausdorff, F., Grundzuege der Mengenlehre, Leipzig, 1914.
35. K. Somasundaram, S. P. Gayathri, R. S. Shankar, R. Rajeswaran,"Fetal head localization and fetal brain segmentation from MRI using the center of gravity",
36. K.Somasundaram, S.P.Gayathri, R.Rajeswaran, Manjiri Dighe, "Fetal Brain Extraction from Magnetic Resonance Image (MRI) of Human Fetus",The Imaging Science Journal (SCI Journal), Vol. 66, No. 3, pp.133–138, 2018.
37. International Computer Science and Engineering Conference (ICSEC), Chiang Mai, Thailand, pp. 1-6., 2016. DOI:10.1109/ICSEC.2016.7859866.
38. S.P.Gayathri, K.Somasundaram, R.Siva Shankar,"Fetal brain border detection from MRI using Chain code algorithm", International Journal of Compter Sciences and Engineering(IJCSE),Vol.6(4)pp.236-238,2018
39. S.P.Gayathri, S.Praveenkumar, K.Somasundaram, R.Siva Shankar, T.Kalaiselvi, S.Magesh, "Estimation of Fetal Brain Volume from MRI of Human Fetus", Biomedical Journal of Scientific & Technical Research (BJSTR),Vol.9(2),pp.1-4,2018.
40. K.Somasundaram, S.P.Gayathri,"Automatic Segmentation of Fetal Brain from MRI of Human", International Journal of Computational Intelligence and Informatics, vol.4, pp.287-292, 2015.ISSN: 2349-6363.

AUTHORS PROFILE

Dr.S.P.Gayathri, received her Master of Computer Science from Seethalakshmi Ramasamy College of Arts and Science, Trichy, India. From 2004 to 2007, she was a Lecturer in Department of Computer Science, Ramaprabha College of Arts and Scinece, Dindigul, TN, India. From 2007 to 2011 December, she was a Assistant professor in Department of Computer Science and Applications in Gandhigram Rural Institute(DU), Dindigul, TN, India. She finished her Ph.D in Segmentation and Volume Estimation of Fetal Brain from T2-W Magnetic Resonance Images (MRI) of Human Fetus in the Department of Computer Science and Applications, Gandhigram Rural Institute - Deemed University, Dindigul, India.She also worked in Sakthi College of Arts and Science for Women,Oddanchatram and PSGR Kishnammal College for Women , Coimbatore ,TN,India. Currently she is working in the Department of Computer Science and Applications, Gandhigram Rural Institute - Deemed University, Dindigul. She has published many research articles on Fetal Brain Segmentation of Human Fetus in reputed journals. Her research interest is Digital and Medical Image Processing

Dr.R.Siva Shankar, did MCA and Ph.D. from Gandhigram Rural University[MHRD-India], Tamil Nadu, India. He worked in National Institute of Technology-Trichy-620015, India. He is a Life Member of "Computer Society of India" and "International Association of Engineers". He is currently working in Madanapalle Institute of Technology and Science, Andhra Pradesh, India. His main research work focuses on Medical image segmentation and his recent research area is IOT, Automation in Agriculture.

He can be reached through arjhunshankar@gmail.com

Dr.K. Somasundaram, received his MSc degree in Physics from the University of Madras, Chennai, India, in 1976, a PhD degree in Theoretical Physics from Indian Institute of Science, Bangalore, India, in 1984, and a Post Graduate Diploma in Computer Methods from Madurai Kamaraj University, Madurai, India, in 1989 . He is presently a Professor at the Department of Computer Science and Applications, Gandhigram Rural Institute, Gandhigram, India. From 1976 to 1989, he was a Professor with the Department of Physics at the same institute. He was previously a Researcher at an International Centre for Theoretical Physics, Trieste, Italy, and a Development Fellow of Commonwealth Universities at the School of Multimedia, Edith Cowan University, Australia. His research interests are in image processing, image compression,medical image processing, magnetohydrodyanmic surface waves and astrophysical plasmas. He is a Life member of the Indian Society for Technical Education and Telemedicine Society of India. He is also an annual member in ACM, USA and IEEE Computer Society, USA.