Segmentation of Neonatal Brain using MR Images in an Efficient Manner

Puja Shashi, Suchithra R

Abstract: Image analysis using updated technology of magnetic resonance for finding, measuring and studying various tissue related structure of brain and thus discovering its medical region is an important application of segmentation process. In order to analyze the specific regions of brain, brain image segmentation plays a significant role for researchers and clinicians. In this work, we make an attempt to design an efficient segmentation model of neonatal brain MRI images of preterm infants. Initially, the dataset is collected from an eminent public repository that composes of numerous training and testing datasets. The proposed framework comprises of six phases, viz, pre-processing using FANFMF, Contrast enhancement using AAIHE, Feature extraction using PBDLFL, Affinity information using SCMMAL, Dictionary creation using DCAD and clustering using SSMLC. The main aim of this paper is to increase segmentation accuracy in the given MR images. The extraction of local features is a complex task which is simply achieved by the proposed PBDLFL via DCAD. The formation of self-similarity map from the probabilistic dictionary creation helps for better segmentation process. Finally clustering based segmentation process using SSMLC algorithm is used that that helps in decreasing uncertainty and sparsity of data so that an efficient diagnosis system can be obtained. Segmentation process that is proposed in this paper can be proved as accurate and efficient by various experimental result.

Keywords: Image segmentation, Segmentation accuracy, Contrast enhancement, Dictionary creation and Self –similarity map.

I. INTRODUCTION

In modern diagnosis systems, the analysis of medical images plays an important role in healthcare systems. Diagnosis systems can be made more reliable by the help of computer based image analysis. Accumulating efficient and relevant information from anatomical structure of the brain neonatal is of challenging and difficult tasks. Magnetic Resonance (MR), Computed Tomography (CT), digital tomography and other imaging facilitate for better understanding of anatomical structure of a subject. Computer algorithm performing medical task can be made more automated by finding region of interest that plays a key role for studying the anatomical structure of brain. In order to perform delineation, characterization and visualization of the given ROI[1], image segmentation plays a vital role as their result will affect all the given process of analysing the image.

It is clearly mentioned by many researchers that in medical field segmentation process is very difficult owing to pixel complexity.

An accurate ROI is not detachable because of grey level uncertainties and inconsistent boundary detection. Usually, the medical images contain noise that modifies the pixel information and thus, classification becomes uncertain [2]. Due to accumulation of irrelevant noises, the non-uniformity may cause low interaction among the tissues. Thus, the segmentation algorithms should cope up with these challenges to yield acceptable results of every medical image. Segmentation algorithms are classified into three sorts, viz, supervised, unsupervised and interactive. Supervised segmentation requires a labelled data for identifying the particular region of interest. Unsupervised segmentation facilitates the segmentation outcomes without context – aware information which yielded low outcomes when pixel complexity increases. In the interactive environment, precision, accuracy and efficiency are achieved from complex segmentation tasks [3]. Thus, researchers are interested to design and develop an interactive environment for medical image segmentation process. Developing an automated segmentation, of neonates MR imaging is the chief contribution of this study. According to previous and current study segmenting neonatal brain is much more complex than adult brain mainly because of following reasons:

- ➢ Lower CNR ratio
- ➢ rapid brain development during neonatal stage.
- ➢ Signal intensity are inverted in white matter(WM) causes partial volume effect.

Segmentation approach are mainly of three categories:

- ➢ Segmentation based on atlas
- ➢ Segmentation based on augmented atlas
- ➢ Segmentation based on atlas free approach

The main difference between atlas and augmented atlas based approach is that previous technique mainly rely on atlases that are derived manually and also on probabilistic tissues.Priors to this whereas in case of augmented atlas-based strategies are mainly dependent on longitudinal type of data and subject that are specific representation for segmentation. Main disadvantage of given two techniques when we apply them on test image then construction and registration becomes very difficult. Therefore, in order to remove these disadvantage there has arisen a necessity of atlas free approach. Major advantage is that they do not depend on manual data or longitudinal data. Other part of paper is organised as follows: literature survey is given in section II, proposed work is presented in section III, experimental analysis and results are given in section IV and final conclusion is given in section V.

II. LITERATURE SURVEY

There are various pros and cons of neonatal brain image segmentation techniques that are existing. These pros and cons are briefly summarised in this section.

Researches considers MR images as on of the most reliable method that can produce data spatial resolution that are extremely high and can be estimated in non-invasive manner for various technique in medical imaging [4]. Hence MR image segmentation are drawing lots of attention of researchers now a day mainly in the field of biomedical image processing. Tumour classification based on neuroscience researches and practice in clinical field requires major role of image segmentation. In order to face the challenges that occurs during quantifying the segmentation process [5], brain and its anatomical structure are studied on a huge scale. Brain image is comprised of three matters namely grey matter, white matter and CSF. Most important prerequisites of brain image segmentation is pixel distribution in grey matter. Major problem related with manual segmentation is time consumption and hence researchers get motivated to design brain segmentation that is fully or partially automated that can further recognize the brain tissue in much more accurate manner.

Segmentation of MR images can be done by various techniques. Two main concept of segmentation is to recognize either discontinuity or similarity among the pixel of same or different region. Finding the isolated points like thresholding[6], detection based on edge[7] and region growing[8] is the main motive of first algorithm. Efficiency in thresholding can be obtained by analysing histogram and ROI with great efficiency. Excessive use of thresholding may degrade brain segmentation owing to their complexity in pixel distribution. Similarly, when edge detection methods are used for finding edge or boundary in order to get accurate segmentation, it fails. Mostly pixels are very sparse that may make segmentation task very complex. Splitting, merging and region growing [9] is included in second set of algorithm. Two main factor in segmentation process are

- ➢ Homogeneity and
- ➢ connectivity

Region based method may be applied for image segmentation that mostly deals with homogeneities and pixels intensity [10,11].In case of approaches that are pixel based, segmentation process can be performed efficiently by pixel-based approaches[12]. Grouping of same types of points into given subsets or clusters is known as clustering approach. Fuzzy clustering techniques [13], maximization and k-means [14] are some of the examples of segmentation clustering methods. Efficient clustering methods were suggested to overcome the issues of active contour segmentation and watershed marker approaches. Both approaches failed to analyse the local features which degrade the accuracy of the segmentation process. Indeed, several works are suggested for segmentation quality assessment, the tuning parameters [15] of segmentation process were not successfully achieved. It is evident that only a few works are available to analyse the MR images for segmentation results.

III. PROPOSED WORK

In this section, working model of an efficient segmentation of the neonatal brain is presented.

A. Problem Statement:

As the anatomical structure of brain shows high variability, hence segmentation analysis of neonatal brain is very complex. Many researchers have developed variants segmentation models, in specific, active contour segmentation and marker-based watershed algorithms were eminent. During watershed process, the issue of over-segmentation process incurs higher computational efforts. Though it is robust, it works on closed contours with efficient boundary definitions. In general, active contour method operates by capturing the local shape features.

B. Proposed work:

The problems mentioned in section A are resolved by a novel segmentation approach, Collaborative Affinity Dictionary Clustering (CADC). Segmentation accuracy is the main parameter which defines the success rate of the proposed segmentation approach. Thus, it's being enhanced using deep learning concepts. The below fig 3.1 presents the workflow of the proposed study. The proposed phases are explained as follows:

a. Dataset acquisition:

It is the foremost step that depicts the details of collected datasets. The dataset is collected from a public repository given in [16]. It composes of both training and testing images.

b. Image pre-processing:

The collected dataset is subjective to irrelevant and relevant noises. It deteriorates the quality of the segmented images. Here, Fuzzy Adaptive Non-Local Mean Filter (FANLMF) is employed to remove the noises. This model preserves the edges by computing output pixel as weighted sum of input pixels. In a larger region, the input pixels contributing to output pixels are known as non-local. Similarly, it finds the similar measure in fuzzy domain field and hence correct and clar similar measure may be obtained. Hence image can be normalised by intensity level mapping of images to given images $[I_{min}, I_{max}]$.

$$I_{nor} = I_{min} + \frac{(I_{max} - I_{min}) * (I_0 - I_{0\,min})}{(I_{0\,max} - I_{0\,min})} \quad (3.1)$$

Where,

$I_{0\,min} \& I_{0\,max}$ are the least and the highest intensity of the given original image.

$I_{min} \& I_{max}$ are the least and highest intensity level of the given normalized images

I_{nor} and I_0 is considered as grey levels before and after normalization.

c. Contrast enhancement:

Contrast of an image is then increased by using obtained pre-processed image. The image visual quality is done byAdaptive Average Intensity Based Histogram Equalization. The contrast limited AHE algorithm in range of 0 -1 is applied. Then, finding the maximum intensity regions of a contrasted image and intensity of each pixel is also estimated from 3 * 3 window sliding neighbourhood operation.

The new intensity of the pixels is estimated from the average pixels of the tile's window. Each window is further updated by the new intensity pixels.

d. Feature extraction:

After improving the image visual quality, the features are extracted using Patch based deep local feature learning that defines the local features of an image. The contrast enhanced image is converted into m *m patches in accordance to the label on each pixel.

E. Affinity Extraction:

Spatial coherence Multi-Modal Affinity learning isperformed for leveraging all modalities.
Weighted undirected graph which is affinity matrix is formed as a result of variety of ranges having similar intensity. This further relates to same features between the patches. Initially, patch pixel are transformed into form that is vector in nature. Patches appears as point representation of intensity values of feature space in the given system. The similarity between two vectors p_i and p_j are given as:

$$\omega(p_i, p_j) = <p_i, p_j \geq \sum_{k=1}^{K} \quad p_{i,k} p_{j,k} \quad (3.2)$$

Where k is the index of a pixel related to grid in patch and size of patch is reprsented by K (no. of pixels in a patch)

f. Dictionary Creation:

Based on affinity matrix representation of selected features, a dictionary is created using Deep Collaborative Affinity Dictionary (DCAD) model. For each feature, with the help of alternative decision, entire dictionary can be created that keeps on modifying sparse coefficients and dictionary in repeated manner. Various dictionary atoms are then combined and are used for reconstruction ofclusters. Segmented image is finally constructed by aggregation of patches obtained by reconstruction. Here, the affinity matrix is decomposed into a linear function of a codebook (dictionary). The coherent variations of similar pixel location of a cluster are represented in the dictionary. Once the dictionary is created for particular cluster, orthogonal matching is done for sparse representations. This process is applied for all clusters and then aggregated using strong collaborative constraint. It is applied for both filtered and non-filtered images. .

g. Brain Segmentation:

Here, a Self- Similarity Multi-Level Clustering (SSMLC) is employed for segmenting the neonatal regions of brain. Initially, the local similarity value and the mapping structure are taken to estimate the local weight probability map. Thus, the accuracy in similarity measure of local weight is defined by the help of probability map accuracy. Probability map can be calculated by the help of introducing and also distance field are used for maping the label image. Weighting of distance field is determined by the help of positioning in map level image. Based on self-similarity features, image pixel are then segmented. It also optimizes the local weight probability map. Thus, the formation of self-similarity helps for segmenting the images
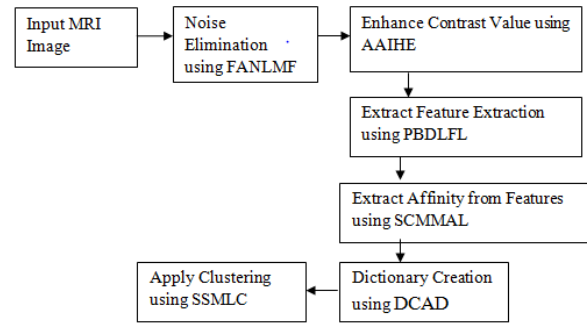

Fig 3.1 DFD of proposed work

IV.   EXPERIMENTAL RESULTS

In this section, given framework is analysed by experimental manner. Initially, the experimental dataset is collected from [16] which is composed of numerous training and testing images for analysis purposes. The followings are the output images achieved using our proposed framework. The fig.4.1 represents the sample input image.
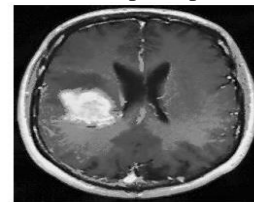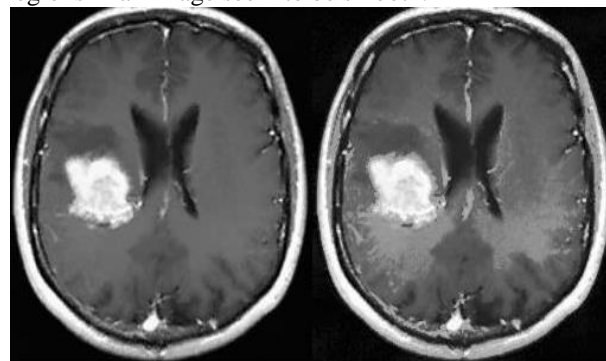

Fig.4.1 Sample Input Image
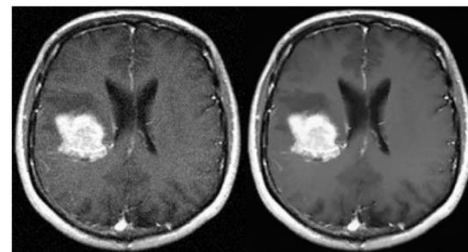
Fig.4.2 Pre-processed Image

The fig 4.2 represents the pre-processed images. It is observed that the proposed pre-processing technique works efficiently to remove irrelevant noises in image. Most of the regions in an image seem to be smooth.

Fig.4.3 Contrast enhanced image

The fig 4.3 presents the contrast enhanced image. The visual quality of an image is being improved for better anatomical structural analysis of a medical image.
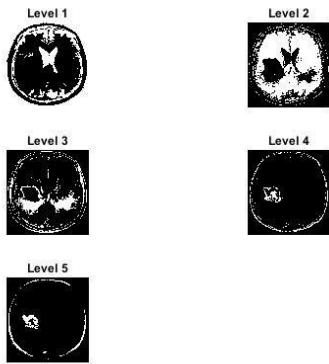
Fig. 4.4 Patch level

The fig 4.4 presents the patch level based feature extraction process. Once after the structural analysis, sparse representations of an image are being explored.

Fig. 4.5. Segmented Image

The fig 4.5 presents the segmented image. Based on probability of the weight map, the segmentation process is done with collaborative constraint.
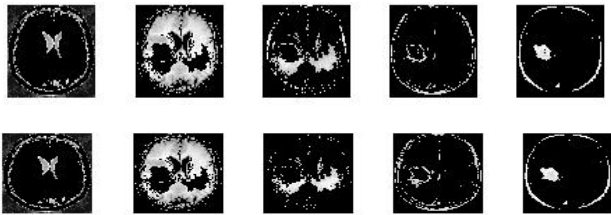

Fig. 4.6 Clustering process at iteration 17.

The fig 4.7 presents the clustering process at iteration 17. A self-similarity map formation at multi-levels clusters the images based on their dictionary deep learning model. By doing so, the segmentation accuracy is maintained for all images.

The performance indices analysed are discussed as follows:

A.   Dice Similarity Index (SI):

It measures the spatial overlap on target regions among the segmented images. This index estimation defines the accuracy of segmentation process. It is given as:

$$DSI = \frac{2|a \cap b|}{|a| + |b|} \qquad (4.1)$$

Where,
a and b are the two segmented images.
|a| and |b| are the cardinality sets of two segmented images.

B.   Correct Estimation Index (CEI):

It measures the structural information of an image during the segmentation process. It is given as:

$$CEI = \frac{(2\mu_x\mu_y + c_1)(2\sigma_{xy} + c_2)}{(\mu_x^2 + \mu_y^2 + c_1)(\sigma_x^2 + \sigma_y^2 + c_2)} \qquad (4.2)$$

Where,
$\mu_x \& \mu_y$ are the average of two images a and b.
$\sigma_x^2 \& \sigma_y^2$ are the covariance of two images x and y.

C.   Over Estimation Index (OEI):

It measures the actual ground truth of segmented image. It is given as:

$$(OEI) = Actual\ Ground\ truth\ (X) - Observed\ ground\ truth\ (X) \qquad (4.3)$$

D.   Modified Hausdorff Distance (MHD):

It measures the segmentation method make use of distance transform of the segmentation boundary. It defines the morphological erosion on deviation between actual and observed segmentation maps. It is given as:

$$A_\delta = \{x \in D: |x - a| \leq \delta\ for\ some\ a\ \in A \qquad (4.4)$$

Where D is the non-empty sets of image A.

E.   Average Symmetric Distance (ASD):

It measures the distance from each pixel to the nearest non-zero pixel during patch based feature extraction process. It is computed as:

$$ASD = \sqrt{(X_2 - X_1)^2} = |X_2 - X_1| \qquad (4.5)$$

F.   Under Estimation Index (UEI):

It measures the observed ground truth of segmented image. It is given as:

$$E = -\sum_{i=1}^{a} e_i \log e_i \qquad (4.6)$$

Where E is the representation of under estimation index. The intensity value of pixel is 'i'.

Table 4.1 Performance results

Performance metrics	Outcomes
Dice Similarity Index	0.6682
Correct Estimation Index	0.9998
Over Estimation Index	0.5018
Modified Hausdorff distance	0.8438
Average Symmetric Distance	0.5017
Under Estimation Index	1.0000

V.   CONCLUSION

Accuracy in segmentation performs a crucial role in medical field. Pixel distribution in grey level images causes sparsity, homogeneity, uncertainty and non-uniformity which reduced the accuracy of the segmented images. To resolve these challenges, an efficient segmentation model is proposed on MR brain images of pre-infants. To the best of our knowledge, the research in this field needs to be more concentrated.

Henceforth, we proposed a novel clustering based segmentation approaches via dictionary creation for local features extraction. Prior active contours and watershed approaches have achieved better segmentation results, but the focus on accurate extraction of the local features is a pending task. The proposed clustering based segmentation approaches operates on basis of self-similarity map and dictionary creation functionalities that develops an accurate medical diagnosis system. Performance metrics such as dice similarity index, correct estimation index, over estimation index, modified hausdorff distance, average symmetric distance and the under estimation index were analyzed. The results states that the modified hausdorff distance has achieved 0.8438 which proved better accuracy. Likewise, 0.6682 of dice similarity index also states efficient dictionary creation. The proposed framework will help the medical researchers to use cluster based segmentation approaches for resoving the non-uniformity and uncertainty at some extent.

REFERENCES

1. Forghani, N; Teshnehlab, M; Forouzanfar, M Parameter optimization of improved fuzzy c means clustering algorithm for brain MR image segmentation Eng Appl Artificial intelligence 2010,23,160-168.
2. Gore, J.C.; Metaxas, D.N.; Gatenby, J.C.; Ding, Z; Huang, R; Li,C. A level set method for image segmentation in the presene of intensity homogeneity with application to MRI. IEEE Trans. Image Process 2011,20,2007-2016.
3. Ciecholewski, M. An edge based active countour model using an inflation/deflation force with a damping coefficient. Expert Syst. Appl. 2016,44,22-36.
4. Zhang, L; Zhag,K. Active countour driven by local image fitting energy. Pattern Recognition. 2010,43,1199-1206.
5. [5] Y.J,Chanu;Dhanachandra, N A survey on image segmentation methods using Clustering technique. Eur. J. Eng. Res. Sci. 2017,2,15-20.
6. Dora,L.; Agarwal, S A study on fuzzy clustering for magnetic resonance brain image segmentation using soft computing approaches. Appl. Soft Comput. 2014,24,522-533.
7. Nematollahy,P; A, Talebi; Vard,A; Ghane,N. Segmentation of white blood cells from Microscopic Images using a Novel combination of K-means Clustering and modified Watershed Algorithm. J. Med. Signals Sens. 2017,7,92-101.
8. Poornima, N.; Karthikeyan, T. Microscopic Image Segmentation using Fuzzy C Means for Leukemia Diagnosis. Leukemia 2017,4, 3136-3142.
9. Belloni, C; Aouf, N; Kechagias-stamatis, O;. Automatic X-ray Image Segmentation and Clustering for Threat Detection. In target and Background signature III, 1043200; SPIE: Bellingham, WA, USA, 2017.
10. Tuan; Son, L.H. Dental segmentation from X-ray images using semi-supervised fuzzy clustering with spatial constraint. Eng. Appl. Artificial intelligence 2017, 59, 186-195.
11. Chen, Q; Ji, Z.; Liu, J; Cao, G. Robust spatially constrained fuzzy c means algorithm for brain MR image segmentatio. Pattern Recognition. 2014, 47, 2454-2466.
12. Ren, T.I.; Cavalcanti, G.D.C.; Portela, N.M. Semi-supervised clustering for MR brain image segmentation. Expert Syst. Appl. 2014, 41, 1492-1497.
13. Ding, W; Zhang, Y. Based on rough set and fuzzy clustering of MRI brain segmentation. Int. J. Biomath. 2017, 10, 1750026.
14. Ibrikci, T; Sekizkarde, S; Pehlivanli, A.C; Kaya, I.E. PCA based clustering for brain tumour segmentation of T1W MRI images. Comput. Methods Progr. Biomed. 2017, 140, 19-28.
15. Tarantino, E; Aguilar, F.J.; Aguilar, M.A.; Novelli, A. AssesSeg-A Command Line tool to Quantify Image Segmentation Quality : A Test Carried Out in Southern Spain from Satellite Imagery. Remote Sens. 2017,9,40.
16. Dataset Link: http://neobrains12.isi.uu.nl/register.php.

AUTHORS PROFILE

Puja Shashi, currently pursuingPhd research in the domain of computer application under the main title **Image processing** from Jain deemed to be University, Bangalore. She is having ten years of teaching and administrative experience in various reputed institutions. She is working under Dr. SuchithraR Nair, Associate professor, HOD MSc IT, Jain University as mentor and guide. This Paper is a part of the research work on automated segmentation of neonatal brain.

Dr.Suchithra R, is the director of MCA department in Jain Deemed to be University, Bangalore . She has 16 years of experience in teaching and research. She has published more than 24 papers in reputed journals and her area of specialization is on cloud computing, machine learningand data science. She is guiding research scholars in the PhDprogramme.

Retrieval Number: B3489129219/2019©BEIESP
DOI: 10.35940/ijeat.B3489.129219
Journal Website: www.ijeat.org

1300

Published By:
Blue Eyes Intelligence Engineering
& Sciences Publication