Optimal Segmentation Framework for Detection of Brain Anomalies

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Abstract

This work presents an enhancement in accuracy for brain disorder detection using optimal unification. The strategy for detection of segments and brain regions causing medical conditions are described. This work demonstrates the application of multilateral filter and applied watershed method with EM-GM method. The most popular existing techniques of brain tumor detection are not optimal compared to this combination of Watershed and EM-GM technique with the proposed optimal unification technique. The result is optimally unified and achieved high accuracy. The multilateral filter enhances the image edges for better segmentation using signal amplitude moderation of the pixel. In the unification process, the optimal sets of segments are divided and finest merged results are considered with the brain regions detected with anomalies. Henceforth the number of possible medical investigations will be reduced.

Index Terms: Brain MR Images, T1 Images, HMA, Watershed Method, EM-GM Method, Multilateral Filter, Optimal Unification.

1. Introduction

Over the last few decades, the massive growths in the brain imaging technique have explored the extended possibilities of brain anatomy analysis. In order to maximize the accuracy of detection for brain anatomy, the imaging techniques have extended the quality of the images. Thus the analysis of this complex and high quality images became the most tedious task for the technicians [1]. Moreover, due to the human intervention the investigations are bound to be erroneous. Also these manual analyses are often time-consuming and limited in finding difficulties in brain data analysis compared to the computerized methods for anomalies detection [1].

The widely used technique for analysis of medical images is segmentation based imaging in clinical analysis. For the medical purposes like analysis of brain cell distortion, regions with damaged cells, anatomical visualization and planning for brain surgery image segmentation is used. Though limitations identified from the

study demonstrate various segmentation techniques are restricted in generating high accuracy and mostly focused in brain tumor detection. The recent researches also fail to achieve the unsurpassed accuracy [2].

Henceforth the rest of the paper is furnished with the focus to exhibit the improvement in accuracy of disorder detection for T1 type MR Images.

2. Related Works

The extraction of the features from the medical images makes the major outcome of the analysis. The segmentation techniques of the medical image are the most widely used for medical analysis [2]. The parallel researches have proposed multiple significant algorithms for image segmentation in 3D image visual analysis for detecting medical disorders. The researches carried out in image segmentation are classified into two major categories as supervised and unsupervised. The supervised techniques are automatic and outcomes into a high density output images and in the other hand the unsupervised techniques extracts the features and results into a feature extracted image. A wide variety of medical image segmentation techniques are been deployed to detect the brain tumors from the MR images. Some of the techniques [3] are compared here [Fig -. 1].
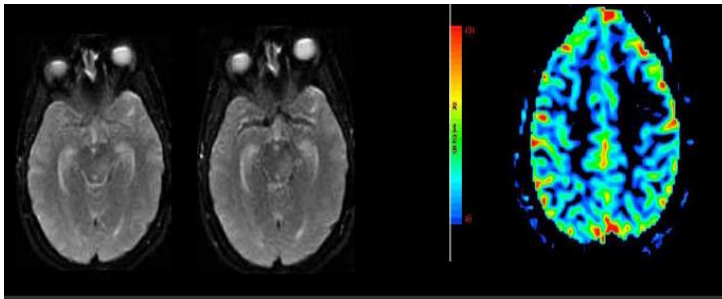

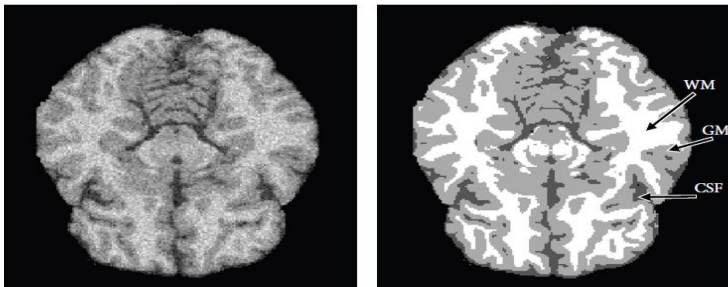Fig.1. (a) Brain Image Analysis using Histogram

Fig.1. (b) Brain Image Analysis using Segmentation

Hence with this understanding, the next research direction is clear to have some segmentation technique to improve the possibilities of the accuracy with the scope of reduced time complexity.

Thus this work proposes an optimal unification of the results obtained from the watershed method and expectation maximization of Gaussian mixture segmentation techniques with a proposed Multilateral filtering to improve the accuracy of the brain disorder detection.

3. Brain Anomalies Detection using the Proposed Method

The major focus of this work is to increase the accuracy of the detection of brain anomalies for MR Images. The magnetic resonance techniques for generating the visual representation of brain images result in two

different types of images as T1 image and T2 image. The studies demonstrate the accuracy of T1 images is higher for detecting the anomalies. Hence in this work we focus on T1 images to carry out the proposed method. The core framework is been demonstrated here [Fig. 2].
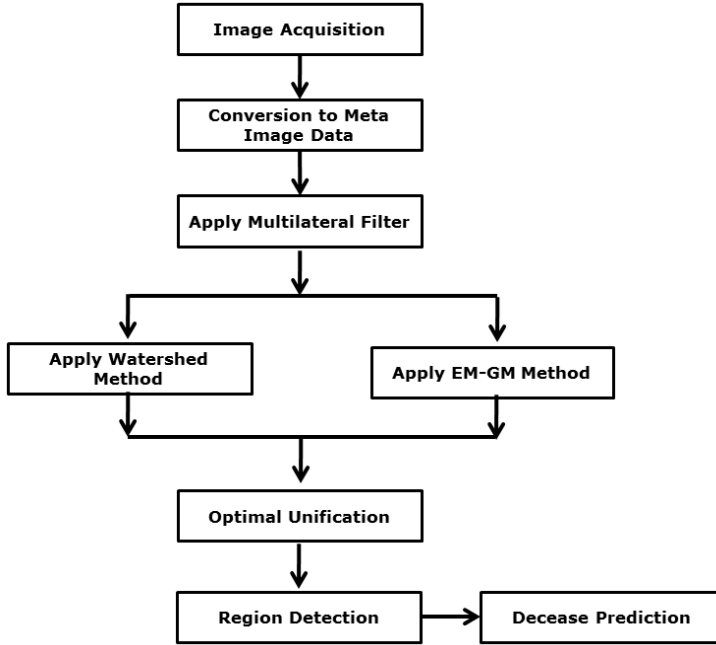

Fig.2. Proposed framework for Brain Anomaly Detection

3.1. Proposed Multilateral Filter

The Proposed multilateral filter is based on the existing bilateral filter for improving the input image variance and standard deviation [4] [11].

The bilateral filter explained as

$$\overline{IMG}(Co_1) = \frac{1}{N(Co_1)} \sum_{Co_1 \in Px} IMG(Co_2).g(Co_1, Co_2).P(IMG(Co_2), IMG(Co_1)) \tag{1}$$

Where,

IMG denotes the original image, $\overline{IMG}$, denotes the filtered and noise removed image, Co_1 and Co_2, denotes the spatial coordinates of the image, Px, denotes the collection of pixels around the noise, $N(Co_1)$, denotes the normalization constant for each pixel to restrict the value after normalization within geometric and photonic range denoted by Px and g and p, denotes the geometric and photometric similarities of the image.

Hence the enhancement of the image is proposed to regularize the local signal amplitude of every pixel value:

$$\overline{IMG}(Co_1) = \frac{1}{N(Co_1)} \sum_{Co_1 \in Px} IMG(Co_2).\theta(Co_1, Co_2, t) \tag{1}$$

As,

$$\theta(Co_1, Co_2, t) =$$
$$(1 - a(Co_1)).g(Co_1, Co_2)$$
$$+ a(Co_1).g(Co_1, Co_2).P(IMG(Co_1), IMG(Co_2)).\sum_{i=1}^{D-1} d_i(Co_1, Co_2) \qquad (2)$$

Where,

$a(Co_1)$, denotes the regularized local signal amplitude of the pixel, d_i, denotes the image dimensions for during noise removal.

The improvement in the input images are been recorded [Table – 1] and the improvement in variance and standard deviation is been observed.

Table 1. Improvement in the Input Data by Multilateral Filter

Image Dataset In MHA	Actual Image Variance	Filtered Image Variance	Improvement	Actual Image Std. Deviation	Filtered Image Std. Deviation	Improvement
Dataset 1	4426745	19162216	3.3	72	104	0.44
Dataset 2	8406091	26021378	2	74	99	0.33
Dataset 3	16958827	19501273	0.14	100	103	0.03
Dataset 4	17772628	19802241	0.11	99	102	0.03
Dataset 5	13768559	14906214	0.08	93	95	0.02

Applied Watershed Method

The applied watershed [3] [12] [13] method is described as morphological gradient-based segmentation for this work [Fig.3]. The minimal watershed method is:
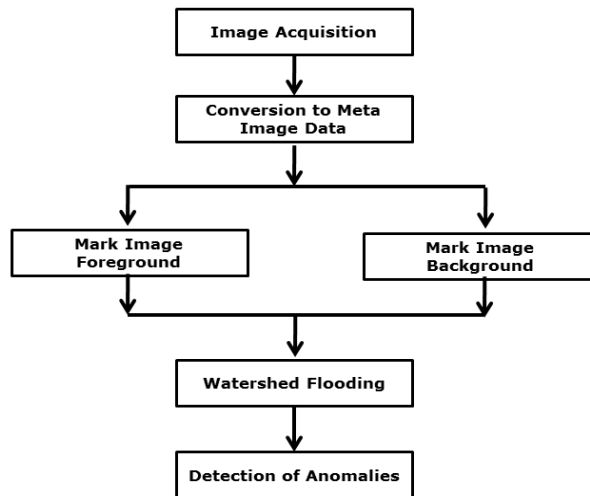

Fig.3. Applied Watershed Method Framework

Considering the β(a,b) with (a,b) $\in$ I^2 as a scalar representation of the image IMG, hence the morphological gradient is

$$\partial_M \beta = (\beta \oplus M) - (\beta \oslash M) \tag{3}$$

Here,

$(\beta \oplus M)$ denotes the dilation, $(\beta \oslash M)$ denotes the erosion and M denotes the structuring element. Hence the Morphological Laplacian is

$$\Delta_M \beta = (\beta \oplus M) - (\beta \oslash M) \tag{4}$$

Hence, the segments to be classified as maxima can be identified as

$$\Delta_M \beta < 0 \tag{5}$$

And the segments to be classified as minima can be identified as

$$\Delta_M \beta > 0 \tag{6}$$

Thus the edge of the segments can be identified as

$$\Delta_M \beta = 0 \tag{7}$$

Henceforward with the maxima, minima and edges now the watershed method can recursively identify the segments in the image.

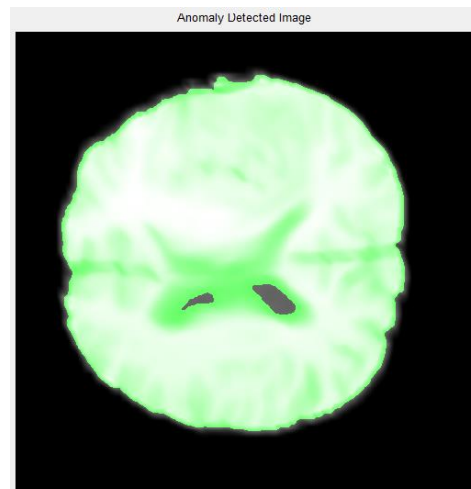The Applied Watershed Method detects the brain anomalies [Fig.4].

Fig.4. Applied Watershed Method Results

Applied Expectation Maximization and Gaussian Mixture Method

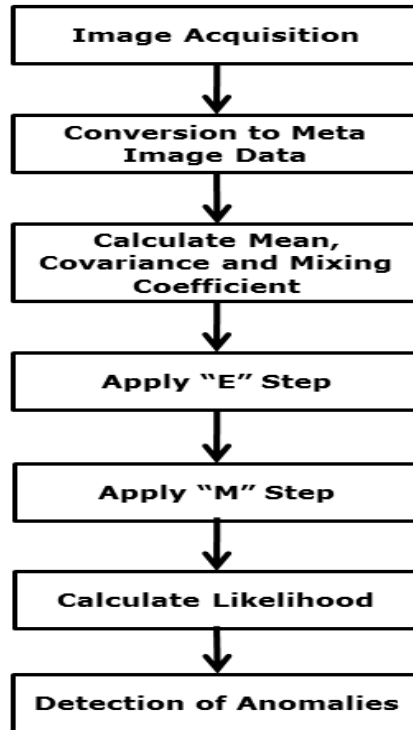The Gaussian mixture method [Fig.5] [5] [6] [10] for each pixel value for input image is described as:

Fig.5. Applied Gaussian Mixture Method Framework

$$G(i) = N(i \mid \mu, \Sigma) \tag{8}$$

Where

N denotes the Gaussian normal distribution, μ denotes the mean and Σ denotes the variance
The inclusion of the multiple neighboring pixel will result in

$$G(i) = N(i \mid \mu_1, \Sigma_1) + N(i \mid \mu_2, \Sigma_2) \tag{9}$$

Henceforth, applicability of mixing coefficient will result in

$$G(i) = \pi_1 N(i \mid \mu_1, \Sigma_1) + \pi_2 N(i \mid \mu_2, \Sigma_2) \tag{10}$$

Thus the Gaussian mixture for the complete image will result in

$$G(i) = \sum_{z=1}^{K} \pi_z N(i \mid \mu_z, \Sigma_z) \tag{11}$$

Where K denotes total number of pixels in the input image

After application of Gaussian mixture method, the expectation maximization needs to be applied Expectation step as score for each pixel:

$$i : \gamma_z \tag{12}$$

Then, the Gaussian parameters to be mapped into the score point:

$$\pi_z, \mu_z, \Sigma_z \rightarrow \gamma_z \tag{13}$$

And Finally, the likelihood to be calculated to converge.

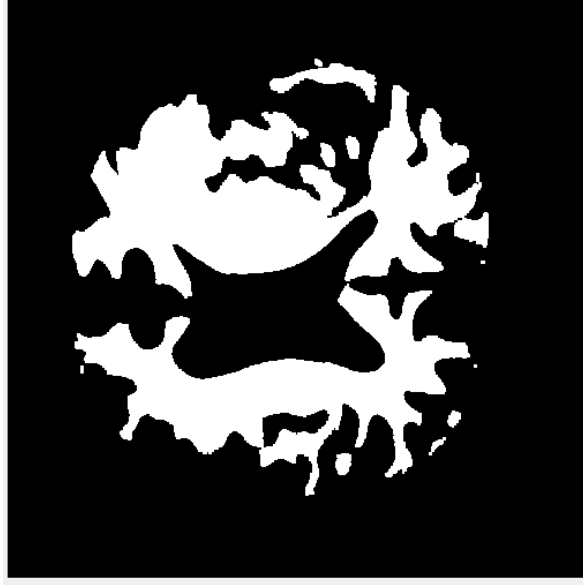The Applied EM-GM Method detects the brain anomalies [Fig.6].

Fig.6. Applied EM-GM Method Results

Proposed Optimal Unification

The optimal unification of the result images are carried out in two phases. In the first phase, the images are been divided into segments and in the next phase from the input images the segments are been merged. The approach is demonstrated here:

Optimal Segment Dividing Algorithm: Image1 and Image2 are the results from Watershed and EM-GM method respectively

Step-1.1. Calculate the number of regions for Image1 and Image2 and store in n and m respectively

$$\Psi[IMG_1] \rightarrow n, \Psi[IMG_2] \rightarrow m \tag{14}$$

Step-1.2. Repeat Till n+m, where m=n denotes the size of the SegmentList arrays

$$\forall\{\Psi[IMG_1], \Psi[IMG_2]\} \tag{15}$$

Step-1.3. Compare All SegmentList1[n] and SegmentList2[m] to find the unique region

$$\exists[\forall\{\Psi[IMG_1]\}]_{\forall!n_i \neq n_j}, \exists[\forall\{\Psi[IMG_2]\}]_{\forall!m_i \neq m_j} \tag{16}$$

Step-1.4. If SegmentList1[n] and SegmentList2[m] are unique, then Store the segmented regions into the SegmentList1, SegmentList2 from Image1 and Image2 respectively

$$\exists[\forall\{\Psi[IMG_1]\}]_{\forall!n_i \neq n_j} \rightarrow SegmentList_1$$
$$\exists[\forall\{\Psi[IMG_2]\}]_{\forall!m_i \neq m_j} \rightarrow SegmentList_2 \tag{17}$$

Optimal Segment Combining Algorithm: SegmentList1, SegmentList2 are obtained from the Eq. 13

Step-2.1. Calculate the number of regions for SegmentList1, SegmentList2 and store in n and m respectively
Step-2.2. Repeat Till n+m, where m=n denotes the size of the SegmentList arrays
Step-2.3. Compare each Segment from SegmentList1 and SegmentList2 to find the similar regions
Step-2.4. If the regions are nearing neighbors, then combine the regions
Step-2.5. Mark the regions with anomalies

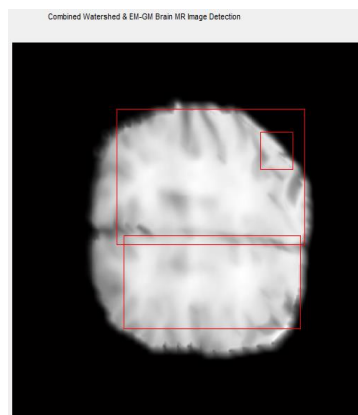The proposed method identifies the region for disease prediction [Fig.7].

Fig.7. Optimal Unification Method Results

Based on the region marks, this technique will predict the possible diseases [Table – 2] [9] [7] [8].

Table 2. Brain Anomalous Area and Prediction of Diseases

Brain Region	Predictable Diseases
Amygdala	Memory Loss, Anxiety, Phobia, Post – Traumatic Disorder
Prefrontal Cortex	Stress
Anterior Cingulate Cortex	ADHD, Schizophrenia, Depression
Hippocampus	Mood Disorder

4. Results and Discussion

The applied Watershed [Table – 3] and EM-GM [Table – 4] method is been applied on the dataset to compare the achieved results of the Optimal Segmentation Technique [Table – 5] and achieved a comparative result improvement.

Table 3. Accuracy Analysis of Watershed Method

Image Dataset In MHA format	Number of Images in the Dataset	Number of Correctly Identified Images	Accuracy (%) for Identified Images
Dataset 1	10	6	98.13
Dataset 2	10	8	98.12
Dataset 3	10	6	97.99
Dataset 4	10	8	98
Dataset 5	10	6	95.36
Dataset 6	10	7	92.69
Dataset 7	10	6	97.98
Dataset 8	10	6	97.98
Dataset 9	10	8	85.43
Dataset 10	10	6	97

The obtained average accuracy is 95.868%, the mean accuracy is 95.868% and the median accuracy is 97.98% for Watershed Method.

Table 4. Accuracy Analysis of Expectation Maximization – Gaussian Mixture Method

Image Dataset In MHA format	Number of Images in the Dataset	Number of Correctly Identified Images	Accuracy (%) for Identified Images
Dataset 1	10	7	96.97
Dataset 2	10	8	98.12
Dataset 3	10	8	91.53
Dataset 4	10	7	91.67
Dataset 5	10	6	95.63
Dataset 6	10	8	93.04
Dataset 7	10	7	94.25
Dataset 8	10	7	92.03
Dataset 9	10	7	85.43
Dataset 10	10	7	97.54

The obtained average accuracy is 93.621%, the mean accuracy is 93.621% and the median accuracy is 93.645% for EM-GM Method.

Table 5. Accuracy Analysis of Proposed Optimal Unification Method

Image Dataset In MHA format	Number of Images in the Dataset	Number of Correctly Identified Images	Accuracy (%)
Dataset 1	10	8	99.13
Dataset 2	10	9	99.12
Dataset 3	10	10	98.99
Dataset 4	10	8	99
Dataset 5	10	9	96.65
Dataset 6	10	9	94.04
Dataset 7	10	8	98.98
Dataset 8	10	9	98.98
Dataset 9	10	8	86.43
Dataset 10	10	10	98.54

The obtained average accuracy is 96.986%, the mean accuracy is 96.986% and the median accuracy is 99% in the proposed method.

Hence this work shows significant improvement of accuracy for all the tested datasets for 300 patients [Fig.8].
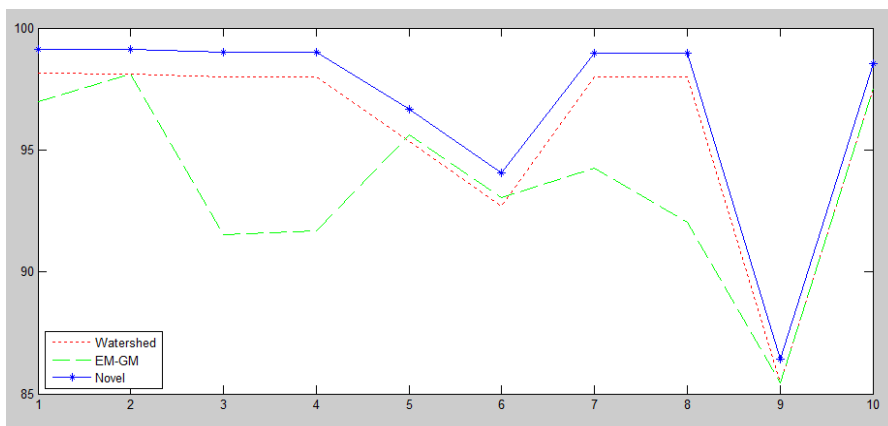

Fig.8. Accuracy Comparison of Applied Watershed Method, Applied EM-GM Method and Optimal Unification Method

5. Conclusion

Quantitative analysis of brain MR images allows a greater understanding of the nature of the diseases. The proposed algorithm in this work has been tested on BRATS 2012 (Nice), BRATS 2013 (Nagoya) and BRATS 2014 (Boston) challenge datasets and demonstrates higher accuracy. The work also concludes the optimal technique for medical image segmentation and detection of brain anomalies. Compared to the existing research outcomes, this work proposes the mapping of possible disease with the brain anomalous regions. With the final outcome of accuracy improvement and disease prediction, the work certainly and satisfyingly extends the possibilities of better medical image processing.

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