Context Independent Expectation Maximization Algorithm for Segmentation of Brain MR Images

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Abstract

For analyzing neurological disorders, realistic analysis of brain MRIs serves as a prerequisite step. This realistic analysis can be best described by segmenting the image into its constituent parts. Unfortunately, segmentation carried out by human visual system (HVS) is always influenced by certain factors. For example, inter-observer, intra-observer variability and large medical datasets. These factors make routine clinical applicability of HVS, a non practical way of examining MRIs. Therefore, to address this problem a fully automatic method is need of the hour. This paper discusses a highly efficient method i.e. the Expectation Maximization (EM) that precisely separates various parts of brain from a brain MRI. It works on the phenomenon of pixel labeling. The results obtained through this method are quite encouraging and are likely to contribute significantly in analyzing brain MRIs.

Key Words: MRIs, Segmentation, Medical Images, EM Algorithm.

1 Introduction

Medical Image segmentation is a highly contested field where quite a number of state-of-the-art methods are existing. These methods have their own merits and demerits [1]. The current section addresses the limitations of some of the important methods and eventually brings to light, the choice of pixel labeling i.e. EM to be a well suited method for addressing the important issues of navigating and analyzing large datasets, controlling inter-observer and intra-observer variability.

Some of the important contemporary methods include, thresholding, edge detection, fuzzy c means, region growing, snake based method, deformable method, level set methods, ANN based methods etc. a brief discussion Each of these methods is briefly discussed in the following paragraphs.

Thresholding Method: Among one of the pioneering methods, it used to hold a significant position in the area of image processing [2-3]. The method is suitable for solving two class segmentation problems. Since MR images are multispectral, therefore, their segmentation through this method is unrealistic. Secondly, the method is noise sensitive as a result of which it looses its performance in such environment.

Edge Detection Methods: This method finds edges of objects found in an image [4]. It maintains its performance when it is used for analyzing noise free images.

Fuzzy Logic Based Methods: This approach aims to group pixels on the basis of some well defined fuzzy rules [5-7]. This precise definition of fuzzy rules emerges from a fundamental assumption that image pixels belonging to certain regions share common characteristics. However, there are certain factors that make the precise definition of these fuzzy rules a difficult job. For example, intensity non-uniformity (INU), partial volume effect (PVE) and noise. In the presence of these difficulties straight forward application for precise segmentation of multispectral MR images doesn't seem to work reliably.

Region based Methods: Region based methods include methods like region growing, Snake based method, deformable models, level set methods etc.

Region Growing Method works by exploring the similarity in the characteristics of the pixels constituting an image [8]. Generally, manual interaction is required for selection of seed points. The selection of these seed points from complex multispectral brain MR images is sensitive and difficult job. This job becomes even challenging when the images under observation are affected with some quality degradation factors, like noise INU or PVE. Therefore under the influence of these characteristics i.e. the presence of image quality degradation factors and the compulsion of manual selection of seed points, make it significantly hard to get realistic results by the straight forward employment of this approach.

Snake Method: This is also considered as region based method [9]. This method too, gives appreciative performance when the intensities are uniformly distributed. An important limitation of the method was its inability to capture topological changes. This limitation was partially addressed by gradient vector flow method and subsequently the

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model was further improved by introducing geometric active contour model.

Deformable Method: As mentioned before, brain MRIs are complex images and carry irregular patterns. To deal with this complexity and to capture irregular patterns, deformable curves were employed. This is a closed curve which has the ability to deform itself according to the shape and size of object of interest [10-11]. So its adaptive ability served as the main cause for extracting regions of interest from complex images. Certainly, the adaptive nature of the model attempts to establish similarity with the neighboring pixels. A higher degree of similarity can be obtained if the quality of the image is good and the pixel intensities are uniformly distributed. However, this approach too requires a human expert that decides about the initial curve. We have seen in the beginning that brain MRI analysis is influenced by human experts. As a result of which the results obtained by employing deformable model are likely to carry variation for regions where the images are affected by INU, noise or PVE problems.

Level Set Methods: Level set methods bears similarity with snake method and deformable models [12]. As a result of which, more or less, they carry same sort of limitations as mentioned above. The imposition of connectivity constraints during the process curve's movement is the difference that distinguishes level set method from the aforementioned methods.

Artificial Neural Network (ANN): ANN is a well established technique for dealing with medical image processing [13]. It requires two sets of data. One for training and the other for testing. The accuracy and reliability of the results depends upon the training of the data. If the training patterns are carefully prepared and an extensive training is done by taking into account all possible configurations of the data then it is likely to produce good results. A straight forward difficulty in the employment of ANNs for the purpose of brain MRI segmentation is that, what method should be relied upon for defining the precise training patterns. Secondly it needs to have a lot of data for its training only; in that case it is expected to provide stable performance. The situation in which the training data is insufficient and where training patterns are not defined according to the desired level, the results produced by employing ANN may not be helpful. Because of its demand for having an extensive training, one may find this approach slower when seen in comparison to the other approaches. Besides, the approach may affect the optimized utility of the machine because it demands resources during the training process.

Though the previous approaches like FCM, thresholding, snake based methods, active contours etc., performed well and attracted a lot of attention when there is clean image to process or when there is fewer number of classes to be separated. Therefore, there straight forward application is not well suited for the extraction of information from complex medical images where a mixture of various densities is not precisely separated. Therefore, in order to deal with the complex medical images, we need to have an automatic method that ensures reliability and enhances accuracy. The desired method should be competent enough to tackle the problems of large MRI data sets and should be able to efficiently control the variations reported due to inter-observer and intra-observer variability. Besides, the potential method should efficiently maintain its performance in real life situations and should not compromise over the optimized utility of the machine resources. All of these desires push us to introduce a state-of-the-art algorithm, i.e. the EM algorithm [14]. The EM or EM based approaches ensure an improvement over the aforementioned methods because of the following important features.

Ability to work in noisy environment. An important feature of EM is its ability to produce a consistent performance even in the presence of noise and INU. It works on the paradigm of modeling mixture densities and uses the strength of expectation and maximization phenomenon through which it predicts a data value over the basis of observed data value.

Reduced requirement of input data. The EM has significantly contributed in reducing the size of dataset. The size of data is in-significant for this method. The performance, stability and reliability of the method remain same in variable data sizes. The EM algorithm follows pixel labeling. It investigates every single pixel, looks at the prior probability, computes the posterior probabilities and then decides about the membership of a pixel with a specific class thus reducing the requirement of large datasets for training.

Increased time efficiency. EM statistically addresses the problem by modeling mixture of densities and applying the estimation theory. Through this estimation it establishes relationship of every single pixel with a distinctive class. This is how it is efficient. Weather we are testing a single image or a large dataset, it maintains its efficiency.

Addressing the issue of intensity non uniformity. The previous methods were not designed by taking under considerations, the noise, the bias field or patient specific intensity non uniformity which is likely to be found in MR imaging. Due to noise, the intensity of the pixels is likely to get affected which in turn becomes responsible for producing erroneous results. The EM algorithm addresses this problem by computing prior and posterior probabilities. This computation is followed by estimating maximum a posteriori approach.

Handling complex images. Brain MR images are complex in nature. Though the previous methods did make significant contributions in analyzing MRIs but still they were not flexible enough to comprehensively deal with complexities. EM is one such method, which is simple, straight forward and has the ability to precisely and conveniently process complex medical data. Besides in comparison to the conventional techniques, it ensures a higher degree of accuracy for the data whose mixture densities are not well separated.

2 EM Algorithm

This method assumes data as mixtures of Gaussians (GMM). The GMM can be described by the following equation.

$$f(x) = \sum_{i=1}^{K} w_i \, N\left(x \mid \mu_i, \sigma_i^2\right)$$

Where K represents the number of desired classes, w_i represents the mixing weights. The mixing weights should not be equal or less than 0. It should be greater than 0 and the overall sum of all the mixing weights should be equal to one, i.e.

$$w_i > 0$$

$$\sum_{i=1}^{K} w_i = 1$$

A GMM depends upon parameters therefore it is a parametric model. This set of parameters include mixing weights, mean and variance of the data, i.e.

$$\theta = \{w_i, \mu_i, \sigma_i^2\}$$

$N\left(x \mid \mu_i, \sigma_i^2\right)$ Represents the data distribution which is 'normal' in this case. Statistically, this distribution is modeled with the help of following equation.

$$N\left(\mu_i, \sigma_i^2\right) = \frac{1}{\sigma\sqrt{2\,w_i}} \exp \frac{-(x-\mu_i)^2}{2\,\sigma^2}$$

Step 1: Read an image from database and vectorize it, i.e. x_j such that $j = 1,2,3, \dots, n$. the labels which correspond to the classes of this image are indexed by i such that $i = 1,2,3, \dots, k$

Step 2: Initialize set of parameters $\theta = \{w_i, \mu_i, \sigma_i^2\}$ for the desired number of classes. In our case this is three.

Step 3: Compute the E-Step.

$$w_{ij}^t = \frac{w_i^{(t)} N\left(x_j \mid \mu_i^t, \sigma_i^{2^t}\right)}{\sum_{i=1}^{K} w_i^t N\left(x_j \mid \mu_i^t, \sigma_i^{2^t}\right)}$$

Where x_j represents pixel at j^{th} location and i represents label for cluster.

Step 4: Compute M-Step

$$w_i^{(t+1)} = \frac{1}{n}\sum_{j=1}^{n} w_{ij}^t$$

$$\mu_i^{(t+1)} = \frac{\sum_{j=1}^{n} w_{ij}^t \, x_j}{\sum_{j=1}^{k} w_{ij}^t}$$

$$\sigma_i^{2^{(t+1)}} = \frac{\sum_{j=1}^{n} w_{ij}^t \left(x_j - \mu_i^{(t+1)}\right)\left(x_j - \mu_i^{(t+1)}\right)^T}{\sum_{j=1}^{k} w_{ij}^t}$$

Step 5: Keep on iterating between the above mentioned step and step 4 until a convergence criteria is met i.e. when the ratio of $(t+1)^{st} : t^{th}$ iteration becomes less than a certain predefined threshold value.

3 Flow Chart for Segmenting Images

The steps to obtain the results are shown in Figure 1. According to this figure, the images are read from a database. The number of clusters in which the image is supposed to be divided, is settled manually. The algorithm then computes the E-Step and the M-Step and finally produces segmented results. In order to check the accuracy of the segmented image, peak signal to noise (PSNR) of the segmented image was computed. However, it was observed that with increasing the number of clusters the PSNR value keeps on increasing.

In subsequent stage, the same procedure was repeated but a certain amount of noise was added. Again, the achieved segmented results were studied in the light of PSNR. It was found that, though by adding noise, the system loses its precision but it is not that much huge.

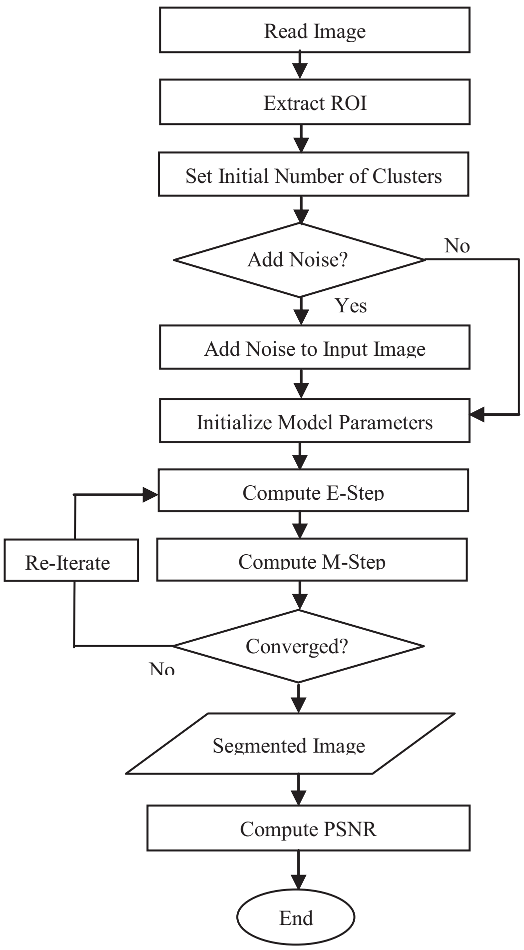


Figure 1: Flow Chart of the Method Used in This Study

The PSNR was computed by using the following relations

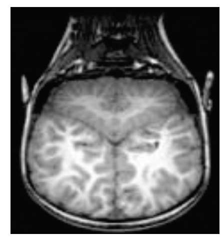
$$MSE = \frac{1}{MN}\sum_{i=0}^{M-1}\sum_{j=0}^{N-1}|I(i,j) - segImage(i,j)|^2$$

$$PSNR = 10 * log_{10}\left(\frac{255}{MSE}\right)$$

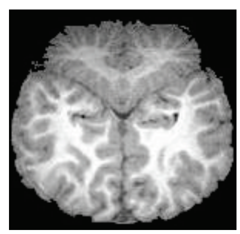
Where M and N are maximum gray values, $I(i,j)$is the input image and *segImage* is the output segmented image.

3 Results

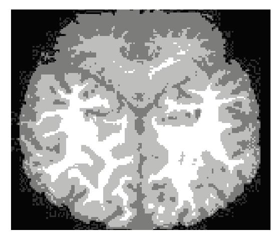
For achieving the desired results an input image is taken as shown in Figure 2. From this input image all the information presented is not relevant. Therefore, an ROI was extracted by eliminating the unwanted portions of the input image.



Original Image



Extracting ROI

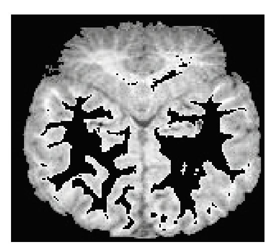


Segmented Image

Figure 2 : Original Input Image, Extracted ROI and the Ultimate Segmented Image

From the aforementioned segmented image shown in Figure 2, certain portions of brain MR image were extracted. The only objective for extracting these regions is to conduct a precise analysis Figure 3 shows these extracted regions.

White Matter (WM)



Remaining Image Without WM

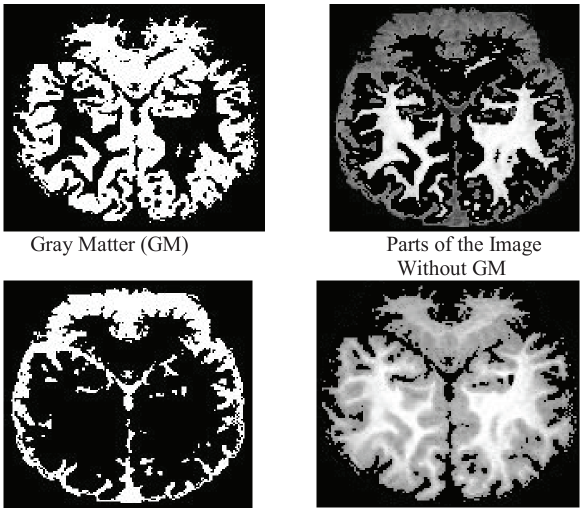


Figure 3: Distinctive Portions of Segmented Brain MR Image

In order to check the performance of the segmentation method followed in this study, two things were done. One, noise free images were segmented and their PSNR was computed and second, noisy images were segmented by taking different number of initial clusters through the same procedure and their PSNR was also computed. Table 1 depicts the results obtained for noisy and noise free images. For noisy images 'salt and pepper' noise was used with standard deviation 0.02 and 0.04 respectively.

Noise Free Image		Noisy Image, Std. Dev= 0.02 and 0.04	
No. of Clusters	PSNR	PSNR for (0.02)	PSNR for (0.04)
5	+ 9.82	+ 9.51	+ 9.23
7	+ 9.89	+ 9.58	+ 9.30
9	+ 9.96	+ 9.67	+ 9.34

Table 1: Comparison of PSNR for noisy and noise free images.

4 Conclusion and Future Directions

This paper has discussed an un-supervised method for extracting various structures from an MR image. The method disregards the size of the data. It works with equal efficiency with small and large datasets. This is an independent method. It does not require the services of human expert for completing the segmentation process. On top of it, the method follows the paradigm of soft segmentation. This significantly contributes in raising the segmentation accuracy. However, the method do not takes into account the information about neighboring pixels. Of course, this information serves as the cornerstone requirement of image segmentation. Therefore, for further raising the accuracy level, some computationally inexpensive and a highly compatible method is needed to be integrated with this method. Besides, Table 1 leads us to an important conclusion ; that higher number of clusters produces higher level of accuracy. Therefore, we need to have true information about suitable number of clusters on the bases of which segmentation process can be carried out. So it is badly needed to establish the definition of suitable number of clusters. Once it is precisely established then segmentation task would be easier, realistic and practical which is likely to make significant contribute in achieving a higher level of precision.

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