Bivariate Gaussian Mixture Model Based Segmentation for Effective Identification of Sclerosis in Brain MRI Images

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***Abstract*— The focal point in this paper is to develop an effective segmentation model for brain images and in particular to identify the sclerosis in brain images. Bivariate Gaussian mixture model is utilized in this paper and the entire image is assumed to be a mixture of multiple Gaussians that are oriented spatially. The experimentation is conducted on brain web images. The results are tested using metrics like image fidelity, mean square error, and signal to noise ratio, average distance and structural similarity.**

***Index Terms*— Bivariate Gaussian Mixture Models (BGMM), sclerosis, Segmentation, MRI images, evaluation metrics**

I. INTRODUCTION

Multiple sclerosis is a wide spread neurological syndrome occurring among young adults. It is a proactive disease and lays the basis for both axonal loss and development of mass called lesions inside the central nervous system. Many imaging techniques are utilised for better understanding of the disease, assess the prognosis and evaluate the best suited drugs to counter attack the disease. The disease is estimated generally, by correlating the clinical findings along with the volume of mass accumulated in the brain away from the major tissues. The main disadvantage with the existing methodologies is that, a precise relationship between the MRI measured lesions and pathological findings are still vague[1],[2]. Therefore it is necessary to develop an effective segmentation algorithm which can segment the healthy tissues and the unhealthy tissues separately and efficiently. In most of the cases, the seizure that gets traced is concentrated in the grey matter (GM) part[3],[4]. Hence it is necessary to have a precise distinction between grey matter (GM) and unhealthy tissues called sclerosis. The greatest challenge in the identification of sclerosis is that they cannot be identified accurately due to the factors such as noise and tissue regions. The lesions regions may be rough, uneven and violating the anatomical structures thereby making it difficult for the analysis. Also, the geometric shape of the damaged tissue is difficult to model and another most shortcoming in the identification process is that the inconsistency of the tissue geometry that changes from person to person, along with intensity overlapping and thereby making the process next to impossible. Thus, to have an effective identification of the sclerosis, in this paper we present a model based on Bivariate Gaussian mixture model (BGMM). For effective discrimination of the SCLEROSIS, unique features may not be effective [5],[6],[7]. Therefore, in this paper, Bivariate features; intensity and the shape are considered. The intensity of the damaged tissue is considered as a global parameter and the whole brain tissue is categorized into three main groups apart from the global parameter. K-means algorithm is considered with k = 3 to cluster the data into three partitions namely white matter (WM), grey matter (GM) and cerebrospinal fluid (CSF). The abnormal pixel which does not fit into these three groups is considered as outlier and is categorised as sclerosis. In order to experiment the data, we have considered a standard dataset from UCI database. The performance evaluation is carried out using quality metrics. The rest of the paper is organized as follows. Section 2 of the paper presents the Bivariate Gaussian Mixture Model (BGMM) framework; Sclerosis Detection and Feature Extraction are presented in section 3 and 4 respectively. The algorithm validation on benchmark brain images are showcased in section 5. Discussions along with the conclusions are highlighted in section 6.

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II. BIVARIATE GAUSSIAN MIXTURE MODEL

In order to have an effective recognition rate, in identifying a deformity among brain images, one need to consider a bivariate approach since it can handle the characteristics of the brain tissues more effectively.
The probability density function of the bivariate gaussian mixture model is given by

$$f(x1,x2,\rho) = \left[2\pi\sqrt{(1-p2)} - 1\ e\ \left(\frac{-1}{2(1-p2)}\right)(x12 - 2\mu x1x2 + x22)\right]$$

Where x1, x2 are the parameters of the tumours, μ is the mean of the MRI image under consideration, ρ is the shape parameter. For a particular value of $\rho = 0$, it assumes the circular normal distribution and for $\rho = 0$, and $\sigma 1 \neq \sigma 2$, it formulates an elliptical normal distribution.

III. SCLEROSIS DETECTION BASED ON BIVARIATE GAUSSIAN MIXTURE MODEL

In order to have an appropriate and efficient experimentation, features play an effective role. Hence in this paper, we have considered two features namely the intensity and the size. The existing models in the literature fail to identify the sclerosis effectively, for the reason being, the consideration of unique features i.e., intensity, colour, size or texture. In this paper, we have considered the first two features. In order to have an effective analysis, the intensity values obtained from each of the brain images are categorised into white matter (WM), grey

matter (GM) and cerebrospinal fluid (CSF) respectively and the abnormal intensity ranges of the pixels in each of the regions are categorised as outliers i.e. sclerosis. The k – means algorithm is experimented with the initial value of k as 3 and we have considered different threshold values for white matter (WM), grey matter (GM) and cerebrospinal fluid (CSF) values. The mean of the pixels in each of these regions are computed and the global mean is also computed. A pixel considered from the image is categorised basing on the mean values. Each pixel from the image region is given as input to the BGMM presented in section 2 of the paper. The probability density functions of each of the image regions are identified. In general, to have a precise classification, T1, T2, photon density based images are considered to segment white matter (WM), grey matter (GM) and cerebrospinal fluid (CSF). Basing on the probability density functions, the estimates are evaluated and are categorised into the groups.

IV. K-MEANS ALGORITHM AND FEATURE SET EXTRACTION: K- MEANS CLUSTERING ALGORITHM

In order to have an effectual segmentation, one needs to recognize the pixels which are damaged and non-damaged thereby helping to recognize the different groups to which the pixels belong, i.e., WM,GM and CSF.

k- Means Algorithm:

1. Place K points into the space represented by the pixels that are being clustered. These points represent initial group centroids.
2. Assign each pixel to the group that has the closest centroid.
3. When all pixels have been assigned, recalculate the positions of the K centroids.
4. Repeat Steps 2 and 3 until the centroids no longer move. This produces a separation of the objects into groups from which the metric to be minimized can be calculated.

V. METHODOLOGY

In order to exhibit the proposed methodology, a medical MRI images obtained from UCI medical imaging database is considered. For testing the method, we have considered 40 images and for training purpose we have considered 10 images. Every image is pre-processed to minimize the noise. The histogram of the images is obtained and basing on the peaks, the various intensity levels of the pixels are identified, and likelihood pixels are grouped together, thereby the initial outliers can be estimated. In order to have an effective analysis, each pixel is assigned to Bivariate Gaussian mixture model presented in section 2 and generated PDF matrices. For testing purpose, each the PDF of the image under consideration, are calculated and basing on its maximum likelihood estimate, the outliers or SCLEROSIS are estimated.

A. SEGMENTATION ALGORITHM

After estimating the initial parameters, the first step is assigning the pixels to the segments. The procedure is carried out by the segmentation algorithm, consisting of the following steps.

Step 1: Acquire the pixel intensities of the image. Denote them by x_{ij}.

Step 2: Find initial clusters using K-Means algorithm and partition the image into regions.

Step 3: For each region obtain the initial estimates for mean μ_i and variance σ_i.

Step 4: Implement the segmentation algorithm by reconstruct the image by assigning the images based on maximum Likelihood estimate.

Step 5: Estimate the image quality by using metrics from the reconstructed image using the step 4.

VI. EXPERIMENTAL RESULTS AND PERFORMANCE EVALUATION

After developing the segmentation algorithm, the algorithm is applied to T1-weighted brain medical images obtained from the UCI database of dimensions 150x174 and 163x199 respectively. The initial parameters obtained are used for the reconstruction by assigning each pixel in the PDF of the image and the outputs obtained are presented below in Figure 1.

VI. DISCUSSION AND CONCLUSION:

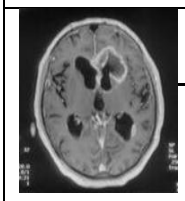
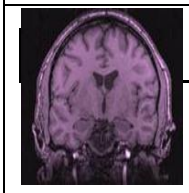
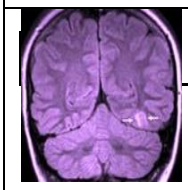
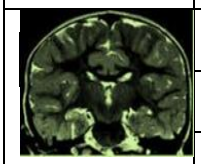
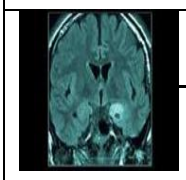
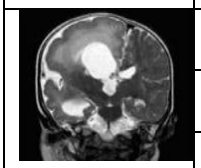
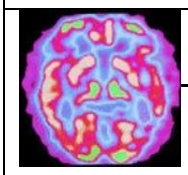
In this paper a methodology for sclerosis identification is conducted basing on bivariate gaussian mixture models (BGMM). The brain image is classified into three major regions white matter (WM), grey matter (GM) and cerebrospinal fluid (CSF) and the likelihood estimates of each of these regions are estimated. Each pixel is compared against the region and if it does not satisfy the likelihood estimates, they are classified as a sclerosis. This process is repeated for all the images. In order to evaluate the performance of the reconstructed image, image quality metrics are used and the metrics utilized for this purpose are presented below.

Table 1 Formulae for Evaluating Quality Metrics Used

Quality metric	Formula to Evaluate
Average Difference	$\sum_{j=1}^{M}\sum_{k=1}^{N}\left[F(j,k)-\hat{F}(j,k)\right]\Big/MN$ Where M,N are image matrix rows and columns
Maximum Distance	$\underset{\text{Max}}{\left[\left\lvert F(j,k)-\hat{F}(j,k)\right\rvert\right]}$
Image Fidelity	$1-\left[\sum_{j=1}^{M}\sum_{k=1}^{N}\left[F(j,k)-\hat{F}(j,k)\right]\Big/\sum_{j=1}^{M}\sum_{k=1}^{N}\left[F(j,k)\right]^2\right]$ Where M,N are image matrix rows and columns

Using above metrics, the performance evaluation is carried out and the comparison is done with respect to the model proposed using Bivariate Gaussian distribution [15] and the results are presented below in Table 2

Table 2. Quality Measures

Image	Quality Metric	GMM	Bivariate GMM with K-Means	Standard Limits	Standard Criteria
	Average Difference	0.679	0.802	-1 to 1	Closer to 1
	Maximum Distance	0.41	0.892	-1 to 1	Closer to 1
	Image Fidelity	0.398	0.796	0 to 1	Closer to 1
	Average Difference	0.41	0.89	-1 to 1	Closer to 1
	Maximum Distance	0. 25	0.91	-1 to 1	Closer to 1
	Image Fidelity	0.35	0.85	0 to 1	Closer to 1
	Average Difference	0.59	0.73	-1 to 1	Closer to 1
	Maximum Distance	0.42	0.85	-1 to 1	Closer to 1
	Image Fidelity	0.54	0.89	0 to 1	Closer to 1
	Average Difference	0.35	0.48	-1 to 1	Closer to 1
	Maximum Distance	0. 37	0.95	-1 to 1	Closer to 1
	Image Fidelity	0.33	0.84	0 to 1	Closer to 1
	Average Difference	0.36	0.78	-1 to 1	Closer to 1
	Maximum Distance	0.37	0.83	-1 to 1	Closer to 1
	Image Fidelity	0.43	0.85	0 to 1	Closer to 1
	Average Difference	0.29	0.38	-1 to 1	Closer to 1
	Maximum Distance	0.25	0.89	-1 to 1	Closer to 1
	Image Fidelity	0.27	0.79	0 to 1	Closer to 1
	Average Difference	0.37	0.41	-1 to 1	Closer to 1
	Maximum Distance	0.17	0.27	-1 to 1	Closer to 1
	Image Fidelity	0.25	0.89	0 to 1	Closer to 1

From the above Table 2, it can be clearly seen that the model developed by using K-Means clustering shows better results with respect to the quality metrics. The model is compared the existing models based on Gaussian Mixture Model

VII. CONCLUSION

A medical image segmentation technique based on Bivariate Gaussian distribution model with K-Means clustering is developed and evaluated. The results obtained by this algorithm outperform the existing method of GMM. This method can be mainly suited in particular cases of medical pathology for the identification of SCLEROSIS accurately there by helping in proper diagnosis and preventing disabilities.

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