Identification of Seizures in MRI Brain Images Based On Bivariate Gaussian Mixture Model

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***Abstract*— Brain MRI images are mostly used in order to identify the diseases related to brain. Of late many models are presented by utilizing the MRI medical imaging technology. However most of the models failed to identify the inhomoginities in the brain accurately. Among the various inhomoginities, seizures are responsible for alzimers diseases which cause brain deaths. Hence this paper addresses a mechanism for the early identification of seizures by reducing the dimensionality of the images using PCA. The database from UCI is considered for experimentation and the performance is evaluated using benchmark metrics like image fidelity, mean square error, peak signal noise ratio (PSNR).**

***Index Terms*— Brain images, Alzimers disease, seizures, performance evaluation, PCA, Quality Metrics.**

I. INTRODUCTION

Brain imaging is a mainly focused area at the present hour due to the increase in mortality rate due to the brain related diseases. Many models are proposed by the researches to identify the diseases related to brain. Among the various diseases in brain, multiple Seizures, lesions, Selorisis and inhomoginities corrections are mainly focused areas. The brain image consists of three vital tissues namely White Matter (WM), Grey Matter (GM) and cerebrospinal fluid (CSF). The MS Seizures is mainly witnessed in young adults and it affects the white matter. MS lesions affect the grey matter part and seizures are the outer layers in any brain images. In order to have a complete study of the brain and identify the related diseases, it is customary to extract the images accurately and the inhomoginities in the intensity of the pixels lead to the mis-interpretations. Hence, affective mechanisms are to be developed for the identification of these diseases. This article in particular highlights the contribution made in the identification of seizures. In any brain MRI images, t1 and t2 weighted images are mostly witnessed. The high intensity levels inside these images reflect the white matter (WM), the medium intensity levels reflect the grey matter (GM) and the lesser intensity levels help towards the identification of cerebrospinal fluids (CSF). Any intensity levels which differs the above levels are formulated as the outer layers or the abnormal pixel intensity inside the medical image regions are coined as seizures. Many models have been proposed by the researchers to witness the seizures. An identification failure of the seizures accurately leads to abnormalities in brain or leads towards specific diseases like alzimers. Hence it is customary to identify the diseases more accurately. The global threshold of the medical brain image is extracted and all the pixels above this global threshold are generally categorised as seizures. Good amount of research is projected to identify the seizures based on intensity levels using gaussian mixture models (GMM). However, if the image is not pre-processed and contains noisy data, it is difficult to sensitize the noisy part and the abnormal intensity value which is supposed to be the seizure pixel. Hence the shape and density of the pixel should be considered along with the intensity. Therefore this article utilizes these features and proposes a model based on bivariate gaussian mixture model. The dimensionality reduction technology of Principal Component Analysis (PCA) is considered for reducing the dimensionality and extraction of the feature vectors. The rest of the paper is organized as follows. Sections 2 of the paper deals with bivariate gaussian mixture model (GMM), the features considered are presented in section 3. The dimensionality reduction using PCA is proposed in section 4. Section 5 of the paper highlights the experimentation together with the results obtained. Section 6 of the paper highlights the performance of the proposed model and section 7 of the paper summarizes the paper.

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II. BIVARIATE GAUSSIAN MIXTURE MODEL

In order to have an effective recognition rate, in identifying a tumour, one need to consider a bivariate approach since it can handle the characteristics of the tumours more effectively. Any tumour processes a bivariate approach rather than a univariate approach.
The probability density function of the bivariate gaussian mixture model is given by

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

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. FEATURE EXTRACTION

In order to demonstrate the proposed methodology, a database is extracted from UCI brain imaging which contains the information pertaining to various brain images with diseases. The image pixels are categorized into four groups, where the outer group consists of the pixels having very high intensity values or abnormal pixels. The next intensity levels

are assumed to be the white matter (WM), grey matter (GM) and cerebrospinal fluid (CSF) respectively. Each pixel in the brain image under consideration are extracted and given as input to the bivariate gaussian mixture model (GMM) discussed in the section 2 of the paper. The features are the pixel intensity levels and the Eigen values obtained after using PCA.

IV. PRINCIPAL COMPONENT ANALYSIS (PCA)

PCA is utilized in this paper to reduce the dimensionality of the image and identify the principal components called the Eigen values. Here each image is considered are categorised into four regions namely region of cerebrospinal fluid (CSF), grey matter (GM), white matter (WM) and outer layer. This region separation is highlighted by plotting the histogram of the image or from the frequency cure of the image. Each image consists of a mixture of sub images each exhibiting a particular distribution. Hence the whole image is assumed to be a mixture of distribution. The PCA is applied to each of these regions and the Eigen values along with the intensity values are given as input to the bivariate model given in the section 2.

V. METHODOLOGY

In order to evaluate the proposed method, the images from the UCI dataset are extracted and are normalised to a size of 100 by 100. Each image is pre-processed for identifying the missing data and eliminating the noise. These processed images are extracted to identify the regions. On each of these regions, along with the pixel intensities of the region, the probability density function of the bivariate gaussian mixture model is generated. Any pixel is categorised basing on the likelihood estimates. If the maximum likelihood of a pixel satisfies a region, the pixel belongs to that region. This mechanism highlights the seizures more accurately because we are considering the likelihood of each pixel against each region more abruptly. The intensities of the voxel pixels are the outer layers can be easily identified by this method.

A. SEGMENTATION ALGORITHM

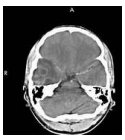
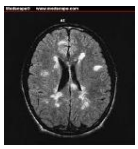
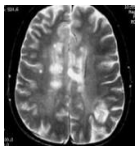
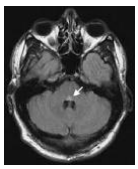
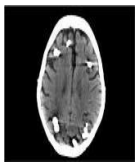
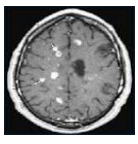
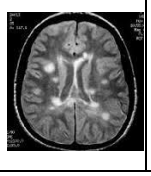
After estimating the initial parameters, the first step is assigning the pixels to the segments. The procedure is carried out by the segmentation algorithm, consisting of the following steps.

Step 1: Acquire the pixel intensities of the image. Denote them by x_{ij}.
Step 2: Find initial basing on the intensity values.
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 .In this paper a methodology for Seizures identification is conducted basing on 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 Seizures. 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. Quality Measures

Image	Quality Metric	GMM	Bivariate GMM with K-Means	Standard Limits	Standard Criteria
	Average Difference Maximum Distance Image Fidelity	0.719 0.489 0.37	0.81 0.88 0.78	-1 to 1 -1 to 1 0 to 1	Closer to 1 Closer to 1 Closer to 1
	Average Difference Maximum Distance Image Fidelity	0.47 0. 19 1. 0.3534	0.90 0.81 0.87	-1 to 1 -1 to 1 0 to 1	Closer to 1 Closer to 1 Closer to 1
	Average Difference Maximum Distance Image Fidelity	0.58 0.47 0.53	0.83 0.85 0.87	-1 to 1 -1 to 1 0 to 1	Closer to 1 Closer to 1 Closer to 1
	Average Difference Maximum Distance Image Fidelity	0.39 0. 33 0.37	0.51 0.93 0.81	-1 to 1 -1 to 1 0 to 1	Closer to 1 Closer to 1 Closer to 1
	Average Difference Maximum Distance Image Fidelity	0.34 0.29 0.48	0.73 0.89 0.87	-1 to 1 -1 to 1 0 to 1	Closer to 1 Closer to 1 Closer to 1
	Average Difference Maximum Distance Image Fidelity	0.29 0.24 0.19	0.41 0.78 0.79	-1 to 1 -1 to 1 0 to 1	Closer to 1 Closer to 1 Closer to 1
	Average Difference Maximum Distance Image Fidelity	0.36 0.17 0.29	0.48 0.34 0.92	-1 to 1 -1 to 1 0 to 1	Closer to 1 Closer 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. PERFORMANCE EVALUATION

In order to evaluate the above model, quality metrics like image fidelity, peak signal noise ratio, mean squared error, average distance are used. The formulae for calculation of these metrics are given as follows

Quality Metrics	Formulae to Evaluate
Average Difference	$\sum_{j=1}^{M}\sum_{k=1}^{N}\left[F(j,k)-\hat{F}(j,k)\right]/MN$ Where M,N are image matrix rows and columns
Maximum Distance	$max\left[\left\|F(j,k)-\hat{F}(j,k)\right\|\right]$
Image Fidelity	$1-\left[\sum_{j=1}^{M}\sum_{k=1}^{N}\left[F(j,k)-\hat{F}(j,k)\right]/\sum_{j=1}^{M}\sum_{k=1}^{N}\left[F(j,k)\right]2\right]$

VIII. SUMMARY

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 SEIZURES accurately there by helping in proper diagnosis and preventing disabilities.

REFERENCES

[1] Ross, B.D., Moffat, B.A., Lawrence, T.S., Mukherji, S.K., Gebarski, S.S., Quint, D.J., Johnson, T.D., Junck, L. and Robertson, P.L., Muraszko K.M., Dong Q., Meyer C.R., Bland P.H., McConville P., Geng H., Rehemtulla A., Chenevert T.L., "Evaluation of cancer therapy using diffusion magnetic resonance imaging", Molecular Cancer Therapeutics 2(6), 581-587 (2003).

[2] Chenevert, T.L., Stegman, L.D., Taylor, J.M., Robertson, P.L., Greenberg, H.S., Rehemtulla, A. and Ross, B.D., "Diffusion magnetic resonance imaging: an early surrogate marker of therapeutic efficacy in brain tumors", Journal of the National Cancer Institute 92(24), 2029-36 (2000).

[3] Moffat, B.A., Chenevert, T.L., Meyer, C.R., Mckeever, P.E., Hall, D.E., Hoff, B.A., Johnson, T.D., Rehemtulla, A.and Ross, B.D., "The Functional Diffusion Map: An Imaging Biomarker for the Early Prediction of Cancer Treatment Outcome", Neoplasia 8(4), 259–267 (2006).

[4] Huo, J., Pope, W.B., Okada, K., Brown, M.S., Kim, H.J., Alger, J.R., Wang, Y and Goldin, J.G., "Early Detection of Treatment Response for GBM Brain Tumor using ADC Map of DW-MRI", Proc MICCAI 2008 workshop on Computational Diffusion MRI, 183-190 (2008).

[5] Pope, W.B., Kim, H.J., Huo, J, Alger, J.R., Brown, M.S., Gjertson, D., Sai, V., Lai, A., Nghiemphu, P., Cloughesy,T. and Goldin, J.G., "ADC histogram analysis predicts response to bevacizumab treatment in GBM patients". Accepted to Radiology on Jan 12th (2009).

[6]lexander Wong, Jacob Scharcanski and Paul Fieguth, Automatic Skin Lesion Segmentation via Iterative Stochastic Region Merging‖, IEEE Trans. on Information Technology in Biomedicine, Vol.15, No.6,pp.929-936, 2011.

[7]Wei Ren Tan, Chee Seng Chan ,Pratheepan Yogarajah, and Joan Condell , A Fusion Approach for Efficient Human Skin Detection , IEEE Transactions on Industrial Informatics, Vol.8, No.1,pp.138-147., 2012

[8] Ki-Won Byun and Ki -Gon Nam,Skin Region Detection Using a Mean Shift Algorithm Based on the Histogram Approximation Vol.13,No.1,pp.10-15,2012

[9]B. Thamaraichelvi and G. Y. Yamuna, "A novel efficient kernelized fuzzy C-means with additive bias field for brain image segmentation," in Proceedings of the International Conference on Communication and Signal Processing, pp. 68–72, Melmaruvathur, India, April 2013. View at Publisher · View at Google Scholar

[10]A. Biniaz, A. Abbassi, M. Shamsi, et al., "Fuzzy c-means clustering based on Gaussian spatial information for brain MR image segmentation," in Proceedings of the 19th Iranian Conference on Biomedical Engineering (ICBME '12), pp. 154–158, Tehran, Iran, December 2012.

[11]S. Xie and H. Nie, "Retinal vascular image segmentation using genetic algorithm Plus FCM clustering," in Proceedings of the 3rd International Conference on Intelligent System Design and Engineering Applications Date, pp. 1225–1228, January 2013.

[12] M.Vamsi Krishna, et. al. "A Bivariate Gaussian Mixture Model for Tumour Detection" in Global Journal of Computer Science and Information Technology (GJCSIT), Vol – 1 (1), 2014, 38 – 42.