Journal of Computer Applications (JCA)
ISSN: 0974-1925, Volume IV, Issue 1, 2011

A Study on Detection of Focal Cortical Dysplasia Using MRI Brain Images

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Abstract— **Focal Cortical Dysplasia (FCD) is the most frequent malformation of cortical development in patients with medically intractable epilepsy. In this paper, following brief introduction to the FCD, the chronology of its detection method is comprehensively surveyed. Next, the various techniques for detection of FCD are studied separately and their important factor and parameters are summarized in comparative table. It is the purpose of this paper to present an overview of previous and present conditions of the detection of FCD as well as its challenges. Accordingly, the importance, characteristics and the different approaches are discussed and analyses of these methods are evaluated.**

***Index Terms*— Focal Cortical Dysplasia (FCD), MRI, Gray-White Matter, Texture Analysis, Morphological operations.**

I. INTRODUCTION

Focal Cortical Dysplasia, a malformation caused by abnormalities of cortical development has been increasingly recognized as an important cause of medically intractable focal epilepsy. FCD was described as a pathologic entity first in 1971 by Taylor et al. FCD lesions are characterized on T1 weighted MRI by cortical thickening, blurring of GM/WM interface, and hyper intensity signal with respect to the rest of the cortex. Small FCD lesions are difficult to distinguish from non-lesional cortex and remain overlooked on radiological MRI inspection. Magnetic Resonance Imaging (MRI) plays a pivotal role in the presurgical evaluation of patients. MRI is currently the noninvasive method of choice for the in vivo diagnosis of FCD. Although MRI has allowed the detection of FCD in an increased number of patients, standard radiological evaluation fails to identify lesions in a large number of cases due to their small lesions and complexity of the cortex convolution [1].

Detecting the FCD, as epileptogenic lesion and consequently the decision about epilepsy surgery can never rely on one diagnostic tool alone. However, with respect only to brain imaging, MRI seems to be very important. In many patients, lesions of FCD are characterized by minor structural abnormalities that go unrecognized or are too subtle to be detected by standard radiological analysis. Using Quantitative methods, only few studies have been dedicated to the automatic detection of FCD and to the evaluation of structural

changes too subtle can be detected by visual inspection. Niels K.Focke et al [2] presented a novel technique that uses standard clinical T_2 FLAIR scans to automatically detect FCDs. Leonardo Bonilha et al [3]; their work suggests that VBM (Voxel-Based Morphometry) can detect GMC excess in patients with FCD. The detection of FCD consists of several steps namely: preprocessing, enhancement, segmentation, feature extraction, and detection. After the detailed study of the previous research works on MRI brain images to detect the FCD, the various steps referred in the following figure Fig1, have to be proposed.

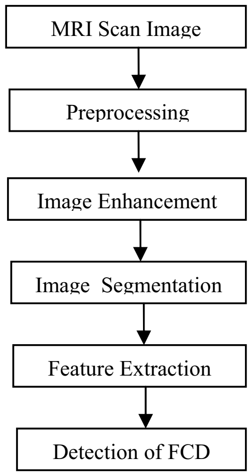

Figure.1 Proposed FCD detection

The rest of this paper is organized as follows: In section2, the overview of methodologies and technical details of previous work is described (i) Preprocessing: morphological operations are used; tissue classification is done. (ii) Image Enhancement: calculated the gray level intensity, smoothing and noise removal is done, and the threshold value is used to identify the lesion. (iii) Image Segmentation: segmenting the cortical tissues: WM, GM, and CSF. (iv) Feature extraction: calculating the color, texture, shape, and spatial relationship within the segmented model. DWT (Discrete Wavelet Transform) is used. (v) Detection of FCD: Automated classifier is used to identify FCD; MRI Characteristics of FCD are used to differentiate lesions from normal tissues. Finally, the conclusions are given in section3.

Manuscript received March 14, 2011.

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II. METHODOLOGY

A. PREPROCESSING

The aim of preprocessing is to process the images in raw form and obtain images suitable for detection of FCD. All 3D MRI images are corrected for identifying non-uniformity, intensity standardization, automatic registration, automatic tissue classification, and Brain Extraction. Morphological operations such as dilation, erosion are used for removing the scalp and lipid layers. Cerebellum was also removed.

In 2002, Jan Kassubek, Hans-Jurgen Huppertz, et al.,[4] in their work based on using the SPM segmentation algorithm the gray matter was automatically segmented and the resulting gray matter was smoothed by using the fixed Gaussian kernel . Finally they represented the gray-matter density maps.

In 2005, Andy Khai Siang Eow [5] have proposed the different input modalities were considered for a particular patient and the tissue classification is done by considering the isotropic patient- specific head model.

In 2006, O. Colliot, T. Mansi et al [6] they used the Brain Extraction Tool (BET, Smith, 2002) for intensity non-uniformity and intensity standardization, automatic registration into a common stereotaxic space. For classifying the brain tissue in GM, WM and CSF the histogram method is used.

In 2009, Jeny Rajan, K.Kannan et al., [7] their work was based on the median voxel-wise intensity were normalized and morphological operations such as dilation, erosion and connected component analysis were used for removing the scalp and lipid layers from brain MR images. Reducing the false positives cerebellum was removed. The intensity threshold between gray and white matter was automatically determined by using the Gaussian curves. The white matter and CSF was removed from the segmented image.

In 2009, Rajeshwaran Logeswaran [8] has proposed to eliminate the background and artifacts by using the low-field MRI brain images in various regions. For identifying the WM, GM, ventricle, skull, etc., the Selection and Segmentation process were used and finally the MRI brain abnormalities were detected and labeled.

In 2009, April Khademi, Anastasios Venetsanopoulos, Alan Moody [9] have discussed to extract the entire brain region from FLAIR images various algorithms were required i.e. Global thresholding, Otsu thresholding, k-means clustering, active contours without edges and the BET tool were all unsuccessful. Firstly they applied a threshold value and then the absolute value was taken. Secondly, by applying a nonlinear mapping function they separated the intensity value (WML) from the outer head tissues. A k-means clustering is used to classify the regions and connected component analysis is used to find the largest region, which is the brain with WML included.

B. IMAGE ENHANCEMENT

The image enhancement is to improve the interoperability or perception of information in images for human viewers, or to provide 'better' input for other automated image processing techniques. Various noise and contrast with different percentages are generated. Noise level acquisition parameters have to be segmented. Threshold value is used to correctly identify the lesions.

In 2002, Jun Yang and Sung-Cheng Huang et al [10], work based on evaluation of different MRI segmentation approaches, the noise level of MR images varies with acquisition parameters including slice thickness, pixel size, field of view etc., An adaptive Gaussian noise distribution is assumed. Various noises with different percentages of signal power are generated using a Gaussian distribution random number generator and added to the simulated MR images.

In 2003, Andrea Bernasconi et al [11], their work proposed on advanced MRI for detection of FCD, to model the blurring of GM/WM transition, we calculated the absolute gradient of gray level intensities, a first-order texture feature. To model the hyper intense signal within the FCD on T1-weighted images, we developed and calculated the absolute difference between the intensity of a given voxel and the intensity at the boundary between GM and WM, defined using a histogram. To maximize the visibility of FCD lesions, a ratio map was generated.

In 2008, Pierre Besson, Olivier Colliot, Alan Evans et al [12], their work based on the automatic detection of FCD using surface-based features, the blurred WM/GM interface was modeled by applying a gradient operator on the MR image. The gradient magnitude was then interpolated at each vertex of the inner cortical surface to obtain the gradient surface map. The lesional probability maps obtained from the classifier were binarized by thresholding them at the best trade-off between detection rate and amount of false positives (FP). Using this threshold, the classifier correctly identified the lesion in 17/19 (89%) patients.

In 2008, Shan Shen, Andre J. Szameitat, and Annette Sterr [13], their work proposed on detection of infarct lesions from single MRI modality, the fuzzy memberships for each cluster are smoothed with a Gaussian kernel of 4mm to increase connectivity among neighboring voxels. Next, the inconsistency between the fuzzy memberships and the sampled and smoothed prior probability maps are calculated.

In 2009, Jeny Rajan, K.Kannan et al., [7] in their work based on FCD lesion analysis with Complex Diffusion Approach, the reason for selecting non-linear complex diffusion is that intra region smoothing will occur before inter region smoothing. So FCD and non-FCD areas in gray matter will defuse separately. The contrast between FCD areas and non-FCD areas will increase in the real plane after complex diffusion. The imaginary part of complex diffusion is almost equal to Laplacian of Gaussian (LOG), in which the borders will be highlighted. When the real part of the complex diffusion is divided with imaginary part, all the smooth areas in the gray matter will also get enhanced.

C. IMAGE SEGMENTATION

Image segmentation plays a crucial role in many medical imaging applications by automating or facilitating the delineation of anatomical structures and other regions of interest. Segmenting the structures or objects in an image is of great importance in a variety of applications including medical image processing, computer vision and pattern recognition. Different methods are applied to cortical tissues: WM, GM, and CSF.

In 1995, Simon Warfield, Joachim Dengler, Joachim Zaers, Charles R.G. Guttmann et al [14], they proposed the Automatic Identification of Grey Matter Structures from MRI to improve the Segmentation of White Matter Lesions, they developed a new algorithm for the development of the cortex. They have developed a segmentation method that uses the positive features of both statistical classification and elastic matching methods to overcome the limitations. Elastic matching provides robust and accurate localization of these structures. This allows for improved segmentation of white matter lesions. A parzen window classifier is used to segment the volume into brain and non-brain classes. Intensity-based statistical classification and intensity in homogeneity correction are calculated simultaneously using the Expectation-Maximization (EM) segmentation algorithm.

In 2004, Faguo Yang, Tianzi Jiang, Wanlin Zhu, and Frithjof Kruggel [15], on their work based on developed novel and effective white matter lesion segmentation algorithm from volumetric MR images, their method is based on T1 and T2 image volumes. Firstly, we analyze those T1 slices, which have corresponding T2 slices. The segmented lesions in these slices provide location, shape and intensity statistical information for processing other neighboring T1 slices without corresponding T2 slices. This prior information is used to initialize a discrete contour model in the segmentation of the remaining T1-weighted slices.

In 2005, Jing Yang, Hemant D. Tagare, Lawrence H. Staib, James S. Duncan et al [16]., they proposed a level set based deformable model for the segmentation of multiple objects from 3D medical images using shape prior constraints. Their approach to multiple objects segmentation is based on a MAP estimation framework using level set based prior information of the objects in the image. We evaluate this level set distribution model by comparing it with the traditional point distribution model [4] using the Chi-square test. For our experiments, the mean distances show improvement in all these cases comparing with/without the level set based prior: average left and right ventricles, sub-cortical structures, amygdala and hippocampus.

In 2006, O. Colliot, PhD; T. Mansi, MSc; N. Bernasconi, MD, PhD et al [6], this paper presents a method for segmenting FCD lesions on T1-weighted MRI, based on two successive deformable models. The first deformable model is driven by feature maps representing known characteristics of FCD and aims at separating lesions from healthy tissues. The second evolution step expands the result of the first stage towards the underlying and overlying cortical boundaries, throughout the whole cortical section, in order to better cover the full extent of the lesion.

In 2007, Elsa D. Angelini, Ting Song, Brett D.Mensh, and Andrew F. Laine [17] presents Brain MRI Segmentation with Multiphase Minimal Partitioning: A Comparative study, the four segmentation methods that were applied to ten brains T1-weighted MRI for segmentation of cortical tissues: white matter (WM), gray matter (GM), and cerebrospinal fluid (CSF). Segmentation errors are reported with comparison to manual labeling. The segmentation methods are intensity thresholding, fuzzy connectedness, Hidden Markov random field-expectation Maximization, and Multiphase three-dimensional level set. Addressing the in homogeneity issue, all four segmentation methods tested and perform a partitioning of the volumetric data into three tissue classes and a background relying on a strong assumption of tissue homogeneity for WM, GM, and CSF. Comparison to three other segmentation methods was performed with individual assessment of segmentation performance, statistical comparison of the performance, and evaluation of the statistical difference between the methods.

In 2008, Jacobus F. A. Jansen, PhD, Marielle C. G. Vlooswijk, MD et al[18], proposed on White Matter Lesions with Localization-Related Epilepsy, the performance of an automated WML detection algorithm, based on intensity thresholding, , a WML volume is calculated by collecting the hyper intense voxels after counting the number of voxels exceeding a predefined threshold of intensity, and K-Nearest Neighbor classification to segment GM, CSF, and WM, artificial neural networks, and fuzzy connected algorithms. WML were segmented from normal tissue by defining a global cut-off threshold on the images. These methods use only a single global intensity threshold to segment the WML for the whole brain or for each slice of the brain images.

D. Feature Extraction

When the input data to an algorithm is too large to be processed and it is suspected to be notoriously redundant (much data, but not much information) then the input data will be transformed into a reduced representation set of features (also named features vector). Transforming the input data into the set of features is called *feature extraction.* To detect the lesion, GM, WM, and hyperintensity signal were extracted from MR images. The recent research works based on combination of different feature extraction and classification tools.

In 2003, Mohammad-Reza Siadat, Hamid Soltanian-Zadeh et al [19] presents the development of a human brain multi-modality database for surgical candidacy determination in temporal lobe epilepsy. The focus of the paper is on content-based image management, navigation and retrieval. The visual feature extraction module includes a set of applications each of which calculates a visual feature (e.g., color, texture, shape, and spatial relationship) within the segmented model and in a proper image modality. There are a variety of features such as volume, surface area, intensity mean-value and standard deviation, length, width, and principal vectors that are often of interest. These features are calculated once the segmented model is built. Using the extracted features, the classification module decides if the image set is going to be retrieved (on-line procedure). The result of classification is sent to the query module for further analysis and display to user. The clustering module performs the procedure of unsupervised indexing based on a portion of the extracted features.

In 2003, Marius George Linguraru, Miguel Ángel González Ballester, Nicholas Ayache [20] they presented a method of feature extraction for brain morphological studies. Using phase congruency, the detection results are not sensitive to image intensity and overcome common difficulties in brain imaging, such as the presence of a bias field. The method outperforms thresholding and gradient-based segmentation approaches and provides a good localization of features. Future applications of the method will focus on the detection of evolving tumors and multiple sclerosis lesions from temporal sequences of MR images. Sulci will be detected as structures with minimal temporal variations, in order to remove false positives.

In 2003, R. Tetzlaf, C. Niederhofer, P. Fischer [21], proposed the bioelectrical activity of a human brain in epilepsy would be analyzed using a Cellular Neural Network - Universal Machine (CNN-UM) proposed by Roska. Therefore a feature extraction method based on binary input-output patterns and Boolean CNN with linear weight functions called pattern detection algorithm is used. The treatment is focused on two types of pattern occurrence that are defined as follows: **1.** A binary pattem occurs only once before a seizure and never occurs in any other recording. ***2.*** A binary pattern occurs frequently in all recordings of brain electrical activity never exceeding a maximum distance of ***N*** data segments between two occurrences. This distance is much smaller than the distance between the last occurrence of the pattern and the seizure onset.

In 2008, Madhubanti Maitra, Amitava Chatterjee, and Fumitoshi Matsuno [22] their present work proposed a method that uses an improved version of orthogonal discrete wavelet transform (DWT) for feature extraction, called Slantlet Transform, which can especially be useful to provide superior time localization with simultaneous achievement of shorter supports for the filters. The feature extraction from MR brain images can be carried out utilizing several popular signal/image analysis methods already available, e.g. independent component analysis, Fourier transform based techniques, wavelet transform based techniques etc. The discrete wavelet transform (DWT) is particularly useful for signal/image processing in the fields of de-noising, compression, estimation etc. An excellent classification ratio of 100% could be achieved for a set of benchmark MR brain images, which is significantly better than the results reported in a recent research work employing combination of different feature extraction and classification tools e.g. Wavelet Transform, Neural Networks and SVM.

In 2008, *Felipe P.G. Bergo, Alexandre X. Falcao* et al [23] have proposed the FCD segmentation using texture asymmetry of MR-T1 images of the brain. Their method works on volumetric MR-T1 images interpolated to an isotropic voxel size of 1.0*mm*3, and comprises the feature extraction, for each voxel p within the brain; we extract a 16×16 planar texture patch T_1 (p) tangent to the brain's curvature (as computed by the CR) and centered at p. The gradient vector of the CR distance transform at the voxel's location provides the surface normal. We also extract a symmetric patch T_2 (p), located at the reflection of T_1 (p) by the MSP. The patch size was chosen experimentally. Smaller patch sizes did not provide good classification results, while larger patch sizes led to similar results with higher computational cost. For each patch we compute 6 features: sharpness (h), entropy, homogeneity, contrast, intensity mean (μ) and intensity standard deviation (σ). All features are scaled to fit within the [0, 1] interval.

E. DETECTION OF FCD

FCD detection, a challenging and clinically valuable task that has not been addressed previously. We have to include the features from morphometric characteristics to the small lesions. While many techniques are being developed to detect FCD lesions from MR images. In most of the methods thickness map along with gradient techniques are used to compute FCD areas. The proposed method discusses the present conditions of the detection of FCD.

In 2002, Montenegro M.A, Li LM, Guerreiro MM, Guerreiro CA, Cendes F. [24], their work is based on FCD: Improving Diagnosis and Localization with Magnetic Resonance Imaging Multiplanar and Curvilinear Reconstruction, The diagnosis of FCD was based on the neuroimaging findings after a three step evaluation, always in the same order: (a) plain MRI films, (b) MPR, and (c) CR. For data analysis, we first assessed the contribution of the additional findings of MPR analysis compared with the results of the evaluation using only plain. MRI films, as is usually done in routine practice. Second, we assessed the contribution of CR to the findings of plain.

In 2003, S. B. Antel1, N. Bernasconi, L. D. Collins et al [25], their work is based on an automated classifier to identify focal cortical dysplasia in patients with epilepsy was developed. The classifier was trained on 3D maps of first-order statistical and morphological models based on MRI characteristics of focal cortical dysplasia and 3D second-order maps constructed from second order texture analysis. A Bayesian classifier was trained on the maps of the first-order statistical and morphological models and three second order texture features to classify voxels within a T1 volume as CSF, GM, WM, GM/WM interface, GM/CSF interface, or lesional. The results of the classifier were compared to standard visual evaluation of presurgical MRI. Finally, they conclude strength of the classifier is its consideration of first- and second-order information from the T1-weighted MRI volume.

In 2006, O. Colliot_, T. Mansi, N. Bernasconi, V. Naessens et al [6], their work is based on a level set driven by MR features of focal cortical dysplasia for lesion segmentation. A method to segment FCD lesions on T1-weighted MRI, based on a 3D deformable model, implemented using the level set framework. Three MRI features drive the deformable model: cortical thickness, relative intensity and gradient. These features correspond to the visual characteristics of FCD and allow differentiating lesions from normal tissues. The proposed method was tested on 18 patients with FCD and its performance was quantitatively evaluated by comparison with the manual tracings of two trained raters. The validation showed that the similarity between the level set segmentation and the manual labels is similar to the agreement between the two human raters. This new approach may become a useful tool for the presurgical evaluation of patients with intractable epilepsy.

In 2006, Olivier Colliot, Samson B. Antel, Veronique B. Naessens et al [26], have proposed FCD on high-resolution MRI with computational models, On MRI, focal cortical dysplasia (FCD) is characterized by a combination of increased cortical thickness, hyper intense signal within the dysplastic lesion, and blurred transition between gray and white matter (GM–WM). Their methods are a set of voxel-wise operators was applied to high resolution 3D T1-weighted MRI in 23 patients with histological proven FCD and 39 healthy controls, creating maps of GM thickness, maps of relative intensity highlighting areas with hyper intense signal, and maps of gradient magnitude modeling the GM–WM transition Moreover, in all patients, the FCD lesion had at least two of these three characteristics.

In 2008, Christian Loyek, Friedrich G. Woermann and Tim W. Nattkemper [27], their work based on detection of FCD lesions in MRI using textural features, Focal Cortical Dysplasia is a frequent cause of medically refractory partial epilepsy. The visual identification of FCD lesions on magnetic resonance images (MRI) is a challenging task in standard radiological analysis. Quantitative image analysis, which tries to assist in the diagnosis of FCD lesions, is an active field of research. In this work we investigate the potential of different texture features, in order to explore to what extent they are suitable for detecting lesional tissue. The results can show first promising results based on segmentation and texture classification.

III. COMPARISIONS AND DISCUSSIONS

In 1999, Yun Jang applied Gaussian distribution random number generator method for segmenting the MRI brain images and resulted with the detection rate of 77%. In 2003, Andrea Bernasconi proposed the MRI analysis methods for detection of FCD using the absolute gradient of gray level intensity based enhancement produces 87.5% detection rate. In 2006, O. Calliot got 75% detection rate by presented a method of preprocessing for intensity non-uniformity, intensity standardization and feature-based deformable model is used for segmentation of FCD lesions on MRI using level set evolution. In the same year, they proposed the Brain Extraction Tool for classifying the brain tissue by using histogram method, feature-based deformable model for segmenting the brain tissue, measuring the MRI image cortical thickness and relative intensity gradient value and finally, they got 70% detection rate. Again the same year, T.Mansi proposed preprocessing methods for intensity non-uniformity, intensity standardization and Gradient Vector Flow, automated histogram based segmentation methods which produced 75% accuracy. In 2007, Elsa D. Angelini proposed brain MRI segmentation with multiphase minimal partitioning: A comparative study. They got 86.7% detection rate by applying the segmentation methods are intensity threshold, fuzzy connectedness, Hidden Markov random field-expectation Maximization, and Multiphase three-dimensional level set. In 2008, Madhubanti Maitra proposed an improved version of orthogonal discrete wavelet transform (DWT) for feature extraction and results reported as 97% detection rate. In the same year, Felipe P.G. Bergo proposed the methods are intensity standard deviation, intensity mean, and gradient vector for detecting the FCD in MRI brain images which produced 94% detection rate. In 2009, Rajeshwaran Logeswaran got 80% by applied the dynamic histogram analysis for preprocessing and identified the brain tissue for segmentation.

IV. CONCLUSION

In this paper, the various techniques for detection of FCD is studied and presented. Also, a table is presented to summarize the previous research methods and their results studied. Using 3D MRI brain images for the detection of FCD, the maximum detection rate is 98%. In this case the FCD was identified by applying Surface-Based segmentation and blurred WM/GM segmentation using threshold classifier. Next 97% of detection rate was obtained by applying Fourier transform based feature extraction techniques, wavelet transform based feature extraction technique. For 3D MRI brain images the FCD detection rate is increased by combining both texture and morphological analysis.

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