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Epilepsy detection and classification based on the contour maps of brain MR images

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Epilepsy detection and classification based on the contour maps of brain MR images

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Abstract: A new method of epilepsy detection and classification of the degree of affliction is presented. The proposed method is based on the information generated by the filled contour maps of the brain MRI. The result is independent of the size and orientation of the target image. Distribution of multiple intensity levels in an MR image is generated by the proposed contour map segmentation technique. Disease afflicted regions are segmented using this technique. The epilepsy diagnosis is carried out by classifying MR images as healthy and diseased. The diseased ones are further classified into three sub-classes of affliction, namely, mild, medium and severe. The classification is based on the area of the top level segment relative to the total area of the non-skull region. In the proposed method, the classification error is found to be between 5% to 10%.

Keywords: contour map segmentation; skull-stripping; top level segment; area of non-skull region; filled contour map; contour level list.

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1 Introduction

Epilepsy is a neurological disease with associated social stigma. The disturbing characteristic of epilepsy is the sudden unexpected moderate to violent seizure, induced by the abnormal activity of neurons in the brain. Availability of relatively low cost MRI technology provides an early diagnostic capability to detect abnormalities in the brain tissue structure and composition. Brain MR images can be analysed using well-known image processing techniques based on spatial transformations (Mehrotra et al., 2020;

Bahadure et al., 2017; Babu and Sourirajan, 2017), feature extraction and neural networks (Demirhan et al., 2014; Shree and Kumar, 2018; Ouchtati et al., 2018), multilevel thresholding (Malviya, 2020), principal component analysis (Zhang and Wu, 2012) and segmentation (Datta and Chakraborty, 2011). These image processing methods, essentially, determine the characteristic features which can predict the presence of abnormalities in MRIs. In Mehrotra et al. (2019), the authors have given additional information on existing methods for MR image analysis for brain tumour detection and feature extraction.

Segmentation is the process of partitioning an image into different regions having certain common properties, such as intensity levels, colour-combinations, special-boundaries, etc. In this paper, the diseased regions of a brain MRI are detected using multi-level segmentation based on filled contour maps. The proposed method is designated as contour map-based epilepsy detection and classification (CM-EDC). In CM-EDC deals with those scenarios where the diseased region is made up of higher intensity level pixels compared to the surrounding healthy regions.

The remaining part of the paper is sectionalised as follows: Section 2 contains related work, Section 3 consists of the methodology and the algorithm, Section 4 gives experimental results and finally Section 5 carries the conclusion.

2 Related work

Several dedicated papers are available on MRI-based epilepsy detection and analysis (Cendes et al., 2016; Zhao et al., 2017; Rummel et al., 2017; Demerath et al., 2022; Bernasconi et al., 2019; Wagstyl et al., 2022). In Cendes et al. (2016), the authors have fully explored the details of neuroimaging of epilepsy. Here, it has been demonstrated that MR imaging for structural brain disorders can determine the aetiology of focal epilepsy. The authors have demonstrated the applications of MR images in detecting low-grade glial neoplasms, mesial temporal sclerosis, deficient cortical development and vascular anomalies in epileptic patients. Specific MRI protocols for efficient epilepsy detection have been recommended in this work. In Zhao et al. (2017), the authors have discussed several types of structural abnormalities in different regions of brain due to epilepsy. Detection of hippocampal sclerosis, which is the cause of temporal lobe epilepsy, has been demonstrated using T2FLAIR images. Additionally, the authors have shown the detection of extra-hippocampal lesions and atrophies at different locations of the brain. In Rummel et al. (2017), the importance of personalised MR image analysis in confirming the temporal lobe epilepsy has been highlighted. The authors have demonstrated that the automated identification of epileptogenic lesions and abnormalities based on MR image analysis is highly successful with reference to the associated expert-opinions. In Demerath et al. (2022), the authors have used MAP18, ‘morphometric analysis program’ to automatically detect focal cortical dysplasia (FCD). MAP18 is designed to demark and visualise epileptogenic pathologies. In Bernasconi et al. (2019), the International League Against Epilepsy has given suitable recommendations for the correct usage of MRI and the related basic epilepsy protocol. Additional instructions are provided for the proper evaluation of MR images for the optimal detection of epileptic lesions. The ‘harmonised neuroimaging of epilepsy structural sequences’ – HARNESS-MRI protocol is fully described in this document. In Wagstyl et al. (2022), MR image analysis for focal epilepsy due to FCD has been fully explored for a large

group of post-surgical patients. The authors have collected FCD lesion information and correlated with clinical and surgical factors and have created a prediction model for general usage.

Epilepsy and its severity can be detected using electroencephalogram (EEG) signals. EEG-based extensive research work on epilepsy is available in plenty (Hasan et al., 2021) and can augment the MRI-based solutions.

3 Methodology

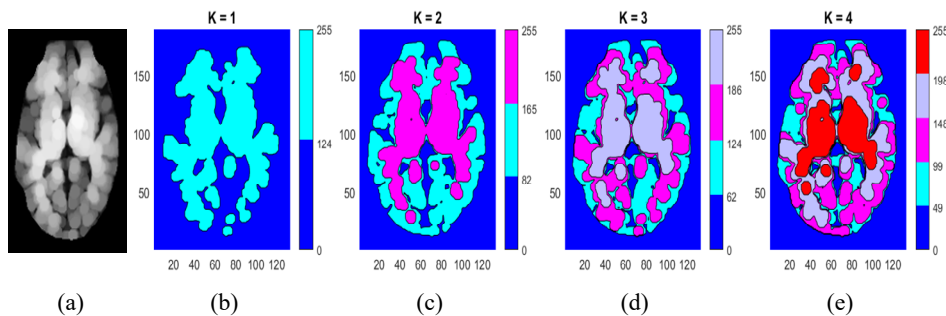
The proposed method CM-EDC uses filled contour maps of MR image sections for epilepsy detection and classification. Basically, the contour map (CM) (<https://in.mathworks.com/help/matlab/ref/contourf.html>) of a greyscale image separates the regions having the same intensity levels into the corresponding sub-regions. Then, these sub-regions are displayed in distinct pseudo-colours for easy recognition. The built in MATLAB function `contourf(A, K)` (<https://in.mathworks.com/help/matlab/ref/contourf.html>) to get the contour map information as:

$$[M, C] = \text{contourf}(A, K) \quad (1)$$

In (1), input parameter A is the image matrix and K is the number of desired foreground levels. The output parameter M is the contour matrix that gives the (x, y) coordinates of the pixels at successive levels and structure C holds the levels used in generating the CM and additional information (Bernasconi et al., 2019). To demonstrate the working of the function `contourf(A, K)`, an example of the CM of a brain MRI is given below.

Example 1: The image matrix A is obtained from a typical axial view of a skull-stripped MR Image as shown in Figure 1(a). Here, the CMs are obtained for $K = 1, 2, 3$ and 4 using equation (1). The resulting CMs and the associated colour bars are shown in Figures 1(b), 1(c), 1(d) and 1(e). From Figure 1, we see that CMs at different levels display the segments of the image differently, based on the corresponding intensity levels.

Figure 1 Filled contour maps for $K = 1, 2, 3$ and 4 , (a) grey image (b) CM: $K = 1$ (c) CM: $K = 2$ (d) CM: $K = 3$ (e) CM: $K = 4$ (see online version for colours)



In this paper, the diseased regions of a brain MRI are detected using multi-level segmentation based on filled contour maps. Here, we consider those cases where the

diseased region is made up of higher intensity level pixels compared to the surrounding healthy regions.

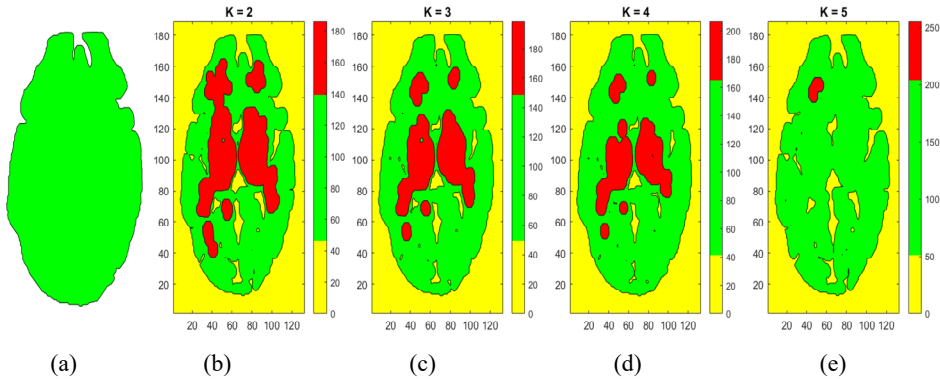
3.1 Top level segments

In a filled contour map display scheme, the range of intensity levels used for displaying different regions are marked in the respective colour bars accompanying the CMs and the actual contour regions are represented by the main CMs. From sFigure 1(b) to 1(e), it can be seen that the area of the top level segment (TLS) corresponding to the highest intensity range, gets reduced as K (number of levels used for CM) increases. Thus, by successively increasing K, the TLS generated represents the corresponding higher intensity ranges. Therefore, a suitable choice of K, leads to the TLS of desired highest intensity level range. The TLS plays the crucial role in the epilepsy brain disorder detection.

3.2 Area of top level segment

The TLS region for K = 2 to 5 is shown in red in Figure 2. The skull stripped brain section view is shown in green while the background is shown in yellow. Regions representing intermediate levels are merged to provide comfortable viewing.

Figure 2 Filled contour maps for K = 2, 3, 4 and 5, (a) non-skull region (b) CM: K = 2 (c) CM: K = 3 (d) CM: K = 4 (e) CM: K = 5 (see online version for colours)



The Area of the TLS is represented by TLSA. Continuing with Example 1, the areas (in red) represented by $TLSA\{K\}$ for $K = 2, 3, 4$ and 5 , are shown in Table 1. Areas are obtained by counting the pixels in the corresponding binary masks at specific intensity levels. Thus the areas in Table 1 are in pixels. In Figure 2, the area of non-skull region area (ANSR) is found to be 14,599.

Table 1 $TLSA\{K\}$ and $PTLSA\{K\}$'s for K = 2, 3, 4 and 5

K	2	3	4	5
Figure	Figure 2(b)	Figure 2(c)	Figure 2(d)	Figure 2(e)
$TLSA\{K\}$	4,352	3,230	2,653	188
$PTLSA\{K\}$	29.81%	22.12%	18.17%	01.28%

Since the areas depend on the scale of the image, to normalise the areas, they are represented relative to the area of non-skull region area (ANSR) of that image. Thus, the Percentage TLSA{K} represented by PTLA{K} is defined as,

$$PTLSA\{K\} = \frac{TLSA\{K\} * 100}{ANSR} \quad (2)$$

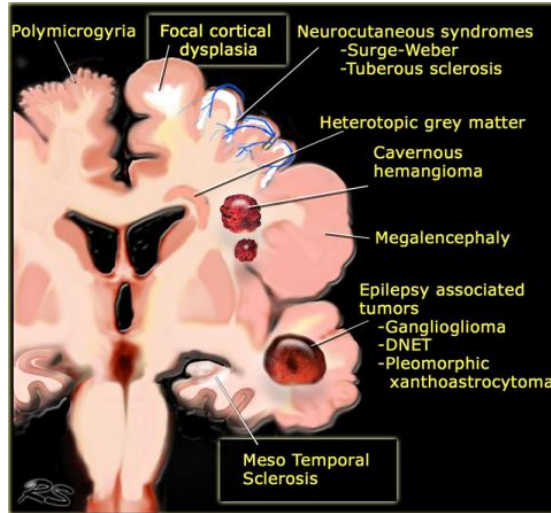
In Table 1, PTLA{K}s are shown below TLSA{K}s for each K. From Table 1, it can be seen that PTLA{K}s decrease progressively as K increases. Getting the top level segment and its relative area, corresponding to the highest intensity range, using contour maps, for a specific K, is designated as contour map segmentation.

3.3 Contour map segmentation

In contour map segmentation (CMS), the value of parameter K of equation (1) is appropriately selected to generate the TLS{K} as explained in Section 3.1. If K is too small, finer spatial variations in intensity levels are lost. On the other hand, a too large K highlights the noises and the CM gets cluttered by too many closely spaced contour maps.

In our proposed algorithm CM-EDC, K is selected as 5 and is found to give good results. Then the relative area PTLA{K} is determined for MR image sections of different candidates for the detection and classification of epilepsy based on the respective values of PTLA{K}s.

Figure 3 Abnormal features of epileptic MRI (see online version for colours)



3.4 Abnormal features of epileptic brain MR images

Epileptic brain MR images (EMRIs) exhibit several abnormalities (Cendes et al., 2016), some of which are shown in the axial view of Figure 3.

The most important feature of many of these abnormalities is the associated high pixel intensity spots which identify the abnormalities. Therefore, in an MRI, the presence of one or more unexpected high intensity spots implies the existence of epilepsy disease. Extending this implication further, we stipulate that bigger the size of the abnormal spot, higher is the severity of the disease. Therefore, the CMS technique can be used to detect the epilepsy disease and the value of $PTLSA\{K\}$ indicates the severity of the epilepsy disease of that image.

3.5 Three stages of epilepsy

For convenience in representing the possible outcomes of the analysis described in this paper, we have categorised the degree of epilepsy affliction into three stages.

- first stage: mild affliction, characterised by long gaps between non-violent seizures
- second stage: medium affliction, characterised by moderate gaps between seizures
- third stage: severe affliction, characterised by relatively shorter gaps between intense seizures.

3.6 Disease gravity ranges

The healthy stage and the remaining three stages and their $PTLSA\{K\}$ ranges selected are shown in Table 2 which can be called as the decision table (the values in Table 2 are obtained after a substantial discussion with professional radiologists familiar with MRI analysis).

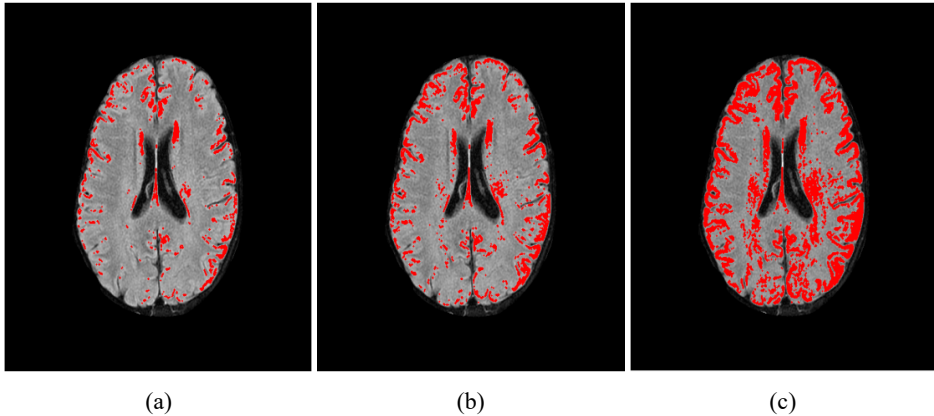
Table 2 Classification of epilepsy disease based on the $PTLS\{K\}$ values

$PTLSA\{K\}$ range for classification	$PTLSA\{K\}$ with $K = 5$			
	Healthy	Diseased		
		Mild (stage 1)	Medium (Stage 2)	Severe (stage 3)
		0 %	1 to 10 %	11 to 20 % Greater than 20 %

Thus, by knowing the $PTLSA\{K\}$ value of the MR Image, the status of the epilepsy disease is decided based on the classification criterion from Table 2. If $PTLSA\{K\} = 0\%$, the status is healthy, otherwise it is diseased. Then the degree of the disease is obtained by checking the range of the $PTLSA\{K\}$ and using the ranges of Table 2. The mathematical classification criterion, given in Table 2 is only for demonstrating the efficacy of our method CM-EDC. It may not be the final truth and is not recognised by any regulatory authority. The values of Table 2 are for academic purpose only. In Example 2, all the four cases are demonstrated.

Example 2: Here, the $PTLSA\{5\}$ s of epilepsy MR images representing the three stages, mild, medium and severe, are generated using the CMS technique and the result is shown in Figures 4(a), 4(b) and 4(c). As the degree of disease increases, the corresponding $PTLSA\{5\}$ (red colour) value also increases.

Figure 4 TLS{5} segments with mild, medium and severe degree of affliction, (a) mild affliction (PTLSA{5} = 7.43%) (b) medium affliction (PTLSA{5} = 13.31%) (c) severe affliction (PTLSA{5} = 28.45%) (see online version for colours)



3.7 Algorithm CM-EDC

Based on the theoretical background presented earlier, the CM_EDC algorithm is formulated as follows:

Algorithm CM-EDC

Input: The image matrix A of the MRI of the patient under investigation

Output: Decision $\rightarrow$ healthy or epileptic. If epileptic, its stage (*mild, medium, severe*)

- 1 Set $K = 5$ and get the $TSLA\{K\}$ of the given image matrix A using the contour maps.
 - 2 Get ANSR (area of the non-skull region).
 - 3 Get the corresponding $PTSLA\{K\}$ using (2).
 - 4 Using, $PTSLA\{K\}$, classify the disease stage based on Table 2.
 - 5 Over.
-

3.8 Discussion

In CM-EDC, K is set to 5. But in practice, depending on the features of target MR images, K can be set to other suitable values after proper experimental verification. If K is too small, fine grained details are lost. On the other hand, if K selected is too large, the TLS region gets broken into smaller sub-regions and some of the diseased region may be lost out. This loss depends on the nature of the dispersal (spread) of the diseased region in the concerned MR image. Hence, K selected should match the TLS distribution characteristics of the MR Image. Apart from MRI, the concerned radiologist can use the electroencephalogram (EEG) waveform analysis to aid in the diagnosis of epilepsy.

4 Performance evaluation

4.1 Classification error

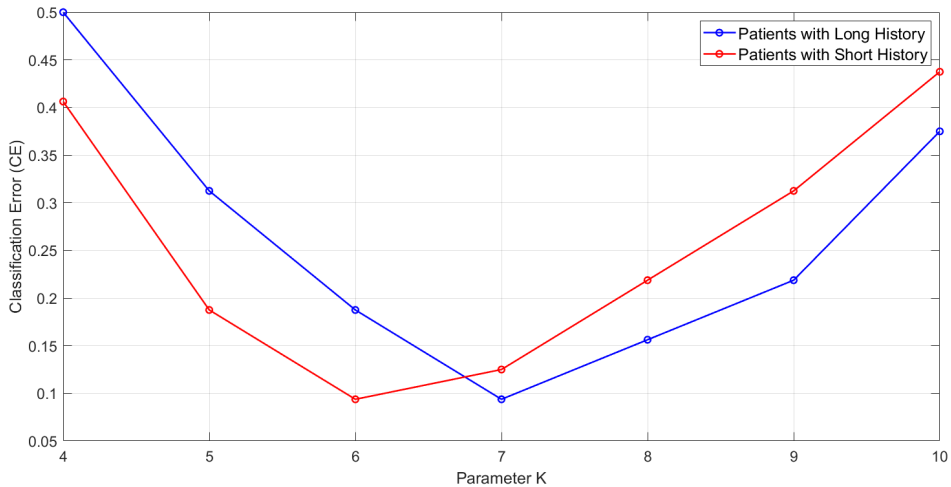
Classification error (CE) is the ratio of number of samples misclassified to the total number of aggregate samples. Here, we assume that the aggregate samples contain samples of different classes equally or almost equally. Thus CE is,

$$CE = \frac{\text{Number of misclassified samples}}{\text{Total number of samples}} \quad (3)$$

In practice, the value of CE will be higher whenever the parameter K of algorithm CM-EDC does not match correctly with the spread of the diseased regions of the target MR Image. Dependency of CE on parameter K is demonstrated in Example 3.

Example 3: Here, two categories of MR images namely, patients with ‘long history of epilepsy’ (more than 20 years) and those with ‘short history’ (less than 20 years) are taken as target images. Eight MR images in each class ‘healthy’, ‘mild epilepsy’, ‘medium epilepsy’ and ‘severe epilepsy’ and in each category are taken for contour mapping. Thus a total of 32 images are used in each category. CM-EDC algorithm is applied to determine the classification error CE’s when parameter K is varied from 4 to 10 with unit step. The result is shown in Figure 5. From Figure 5, it can be seen that the best values of K are 7 and 6 respectively for patients with ‘long history’ and ‘short history’.

Figure 5 Classification error versus K using CM-EDC (see online version for colours)

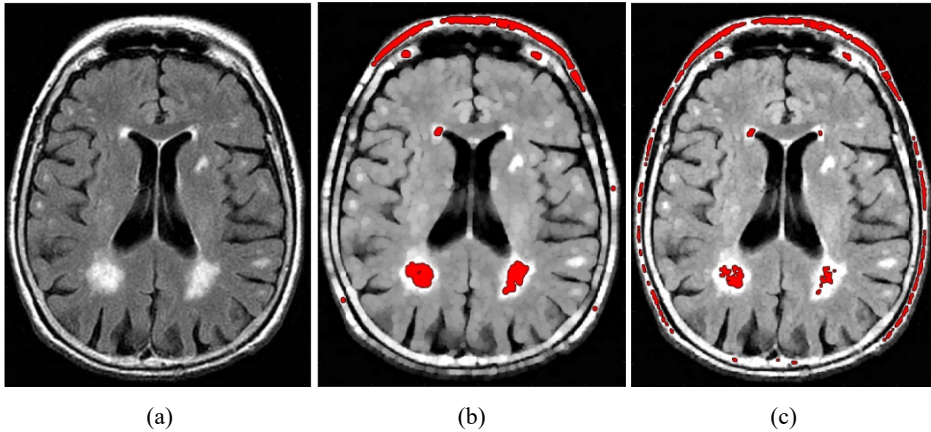


4.2 Comparison with DWT2 method

In this comparison, the DWT2 method proposed in Zhang and Wu (2012) is compared with our CM-EDC.

Example 4: The greyscale image is an axial view of a T1 MR image as shown in Figure 6(a). Contour map segmentation with $K = 6$ generates the $TLS\{6\}$ shown in Figure 6(b). A 4-level DWT2 is applied to get the segmented the high intensity regions and the result is, as shown in Figure 6(c). From Figures 6(b) and 6(c), it can be seen that the TLS region of Figure 6(c) has broken segments and its PTLSA is less than that of Figure 6(b). The PTLSA $\{K\}$ values calculated are 3.74% and 1.52% respectively for CM-EDC method and for the DWT2 method respectively.

Figure 6 Comparison of TLS detection in CM-EDC and using DWT2, (a) greyscale MRI (b) TLS using CM-EDC (c) TLS using DWT2 (see online version for colours)



Example 5: For the purpose of general comparison, four types of MR images namely, ‘healthy’, ‘mild epilepsy’ (MildE), ‘medium epilepsy’ (MediumE) and ‘severe epilepsy’ (SevereE) are segmented to get the TLS using CM-EDC and the DWT2 method. Each type has 4 MR images of that type whose ground truth is already known. Thus in total, we have 16 images with 4 in each type. Parameter K of CM-EDC is set to 6. After calculating PTLSA $\{K\}$, the images are classified based on Table 2. The result is shown in the Confusion Matrices of Figure 7. From Figures 7(a) and 7(b), we see that the classification errors are 3/16 and 7/16 for CM-EDC and the DWT2 method. Therefore, CM-EDC performs better than the DWT2 method.

Figure 7 Confusion matrices using (a) CM-EDC and (b) DWT2 (see online version for colours)



5 Conclusions

Even though several segmentation methods are available for detecting abnormal regions in MR images, contour map method provides a higher degree of granularity and hence better accuracy. By proper design of CM-EDC, an accuracy of 95 to 100% can be reached. CM-EDC can be dependably adopted for detection and classification of epilepsy without much pre-processing or post-processing. A major advantage of CM-EDC is the coloured visual display of MRI regions at different intensity levels which will help the pathologist to get a better appraisal of the greyscale MRI. CM-EDC can be extended to multi-planar analysis and volumetric processing using the appropriate 3D MR image slices.

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