BRAIN TUMOUR SEGMENTATION BASED ON LOCAL INDEPENDENT PROJECTION BASED CLASSIFICATION

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Abstract

Brain tumour detection and segmentation is most important and challenging task in early tumour diagnosis. There are various segmentation methods available but they are still challenging methods because of its complex characteristics such as ambiguous boundaries and high diversity. To overcome this problem we are going to implement automatic brain tumour detection and segmentation method by using local independent projection based classification. In this method we are going to consider tumour segmentation as a classification problem. In this paper locality is important in calculations of projections. Also local anchor embedding is used to solve linear projection weights. The softmax regression model is used to improve classification performance. In this study we used MRI images as training and testing data. Finally the brain tumour is classified into tumour and edema region. The area of tumour region is calculated in pixels.

Key Words: *Brain tumour detection & segmentation, local independent projection based classification, local anchor embedding and softmax regression.*

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1. INTRODUCTION

Brain tumor detection and segmentation is most challenging task in early tumor diagnosis. Now days, brain tumor detection and segmentation are done manually in clinic but this is time consuming process also difficult and depends on operator. Recently most people prefer MRI images for brain tumor detection and segmentation because it gives more information on tumor. The tumor area is divided into edema; contrast enhancing, non-enhancing and necrosis. In different MRI images these areas are different in size and shape. Fig 1 shows different areas in MRI image. The MRI images provide large data about tumor but still it is challenging because of different shapes and sizes of tumors. Brain tumor in different MRI image located at different locations so segmentation task becomes difficult. The noise present in MRI makes segmentation process difficult. Therefore semiautomatic or automatic method is needed for segmentation of brain tumor. There are various methods available for segmentation and detection of tumor but out of which we choose supervised and unsupervised learning method.

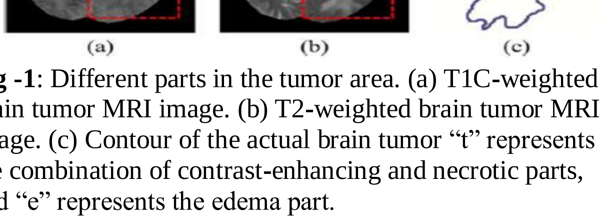

Fig -1: Different parts in the tumor area. (a) T1C-weighted brain tumor MRI image. (b) T2-weighted brain tumor MRI image. (c) Contour of the actual brain tumor “t” represents the combination of contrast-enhancing and necrotic parts, and “e” represents the edema part.

2. LITERATURE SURVEY

1. Meiyan Huang et.al discuss about problem of segmentation of brain tumors. For solving this several methods are available. In this Paper the aim of author is to solve the segmentation problem by using LIPC based method. Compared with other coding LAE method is more suitable in solving linear reconstruction weights under the locality constraint.
2. Dongjin Kwon et.al discusses about new method for deformable registration of post-operative and pre-operative brain MR scans of glioma patients. It matches intensities of healthy tissue as well as glioma to resection cavity. This method extracted pathological information on both scans using scan specific approaches and then registers scans by combining image based matching with pathological information.
3. Andac Hamamci et.al discuss about fast tool for segmentation of solid tumors with minimal user interaction. Segmentation algorithm for problem of tumor depiction which display varying tissue characteristics. The author discusses a tumor cut segmentation to divide the tumor tissue into its necrotic tumor and enhancing parts.
4. Stefan Bauer et.al discuss about a new method which makes use of sophisticated models of bio-physiomechnical tumor growth to adapt a general brain atlas to an individual tumor patient image. It can be applied for solid tumors and gliomas with distinct boundaries to capture important mass effect, while the less pronounced infiltration effect is not considered in this case.

3. OVERVIEW OF THE PROPOSED METHOD

The proposed method consists of four major steps, first step is preprocessing, second is feature extraction, third is tumor segmentation using the LIPC method, and last step is post processing. The multi-resolution framework is used to reduce computational costs in this proposed method. The block diagram and flowchart of the proposed method is illustrated in Fig. 2 and 3.

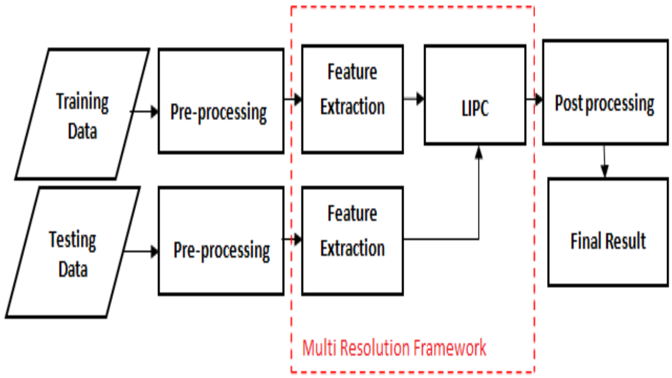

Fig -2: Block Diagram of the proposed method

Algorithm:

1. Create training dictionary.
2. Apply Local anchor embedding and save features.
3. Apply Local independent projection based classification and calculate reconstruction error (E).
4. Select testing sample and apply median filtering. Repeat step 2 and 3.
5. Detect patch whose intensity is greater than threshold value.
6. Divide patch into edema and tumour part.
7. Analyze tumour part.

Fig -3: Algorithm of the proposed method

3.1 Preprocessing: Image Filtering by using Median Filter

Median filtering and averaging filter are similar, In averaging filter each output pixel value is set to an average of the pixel values in the neighborhood of the corresponding input pixel and In median filtering, the value of an output pixel is determined by the median of the neighborhood pixels, rather than the mean. The major difference in between median and mean is median is less sensitive than the mean to extreme values. Therefore Median filtering is better to remove these outliers without reducing the sharpness of the image. The medfilt2 function is used to implement median filtering. Also PSNR, MSE, contrast and correlation values are calculated.

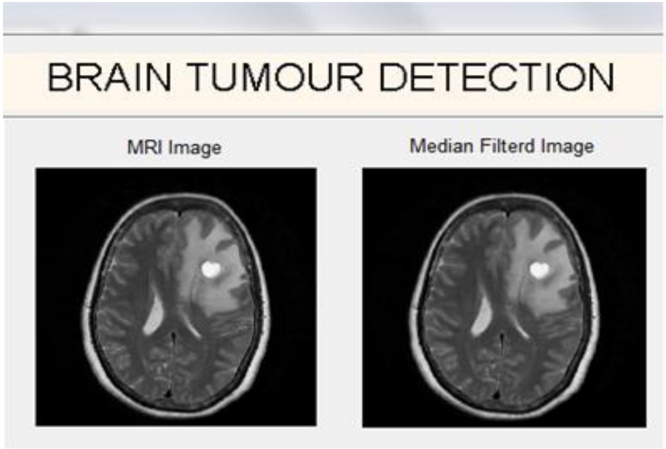

Fig -4: Filtered Image

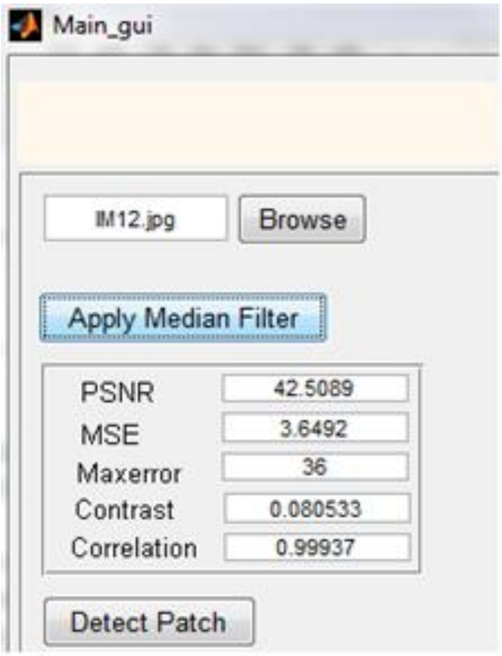

Fig -5: Results after median filtering

3.2 Feature Extraction

Image intensities in MRI images do not have a fixed meaning and widely vary within or between subjects so before extracting image features, intensity normalization and image inhomogeneity correction should be performed. In this project, we are using a patch-based technique for extracting the image feature. The intensity values in a patch around a voxel v were obtained and rearranged as a feature vector. The intensity values in patch are greater than threshold value. All intensity values in patch are plotted on graph.

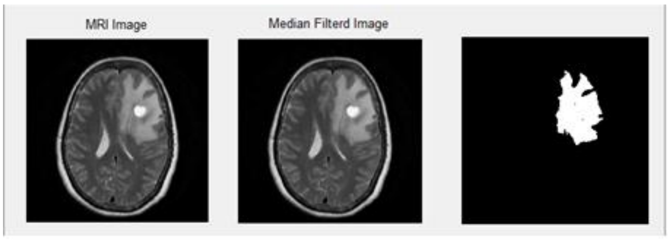

Fig -6: Patch Detection

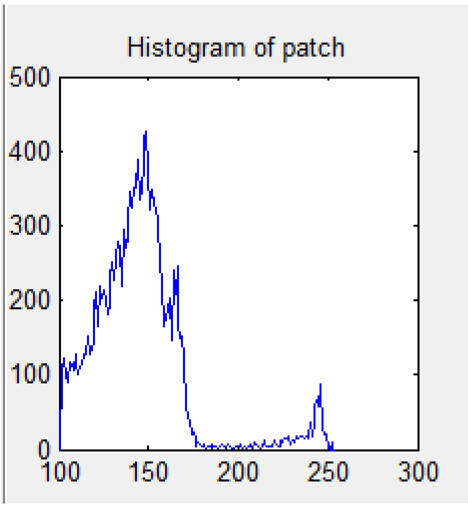

Fig -7: Histogram of patch

4. LOCAL INDEPENDENT PROJECTION BASED CLASSIFICATION

4.1 The basic principle of LIPC

The segmentation of brain tumor can be considered as a multiclass classification problem. To solve this problem, a one-versus-all (OvA) strategy can be used. In the One versus all strategy, a classifier is trained per class to distinguish a class from all other classes.

Therefore, N classifiers $f = \{f\}_{i=1}^{N}$

N real classification scores $y = {y_i}_{i=1}^{N}$ are computed using learned classifiers $f(x)$

For this proposed method, the following assumption was considered as the base for LIPC:

Assumption I: Each Sample is located on different non-linear sub manifolds according to their classes, and a sample can be approximately represented as a linear combination of several nearest neighbors from its corresponding sub manifold.

4.2 LIPC Implementation

4.2.1 Dictionary Construction

Dictionary is constructed by using manually labeled original samples in a training set. However, number of original training samples produces large D, which increases computational costs and memory. In the present study, more samples for each class are available for training but when we are going to implement this that time this process becomes impractical. For learning a compact representation of the original training samples, it is necessary to apply a dictionary learning method. The k-means method is used in this proposed method.

4.2.2 Locally Linear Representation

There are several methods are available for representation of sample which is linearly based on training sample. These methods are sparse coding, locally constrained linear coding and local anchor embedding. Sparse coding attempts to use the smallest number of training samples in reconstruction.LLC and LAE approaches focus on locality. To obtain solution for LAE, firstly select K nearest neighbors from dictionary. Here we can vary value of K from 5 to 100 and observe effect of this on reconstruction error.

Considering the concrete task in this paper, we formally re-formulize the cost function of LAE as

$$a^* = \arg\min\left(x - \sum_{j=1}^{N} a_j d_j\right)^2$$

s.t. $\forall d_j \nexists N_x(k), a_j = 0, \sum_j^N a_j = 1, a_j \geq 0$

Three steps were performed to obtain the solution of LAE.

1. Select k nearest neighbors of x from D and construct $N_x(k)$

2. For the samples that do not belong to $N_x(k)$,associated ajs were set to0

3. For samples that belong to $N_x(k)$,calculate $a_j s$

4.2.3 Classification Score Computation

Softmax regression model is used for computation. Softmax regression model uses Relation between Data distribution and reconstruction error. If distribution is uniform and noise is low then classification may be performed well. This model generalizes logistic regression to classification problems where the class label y can take on more than two possible values. Recall that in logistic regression, we had a training set of m labeled examples. With logistic regression, we were in the binary classification setting, so the labels were $y_{(i)} \in 0,1$

In the softmax regression setting, we are interested in multi-class classification (as opposed to only binary classification), and so the label y can take on k different values, rather than only two. Thus, in our training set $(x^1 y^1) \ldots \ldots.(x^m y^m)$; we now have that $y_i \in 1; 2; \ldots k$

Classification score

$$y_i = \frac{\exp(w_i^T \|\varepsilon\|_2)}{(\sum_{k=1}^{N} \exp(w_k^T \|\varepsilon\|_2)}$$

```
CF =

  178.8463

E =

   82.7316    0.1111    95.0036

final_Recontruction_Error =

   82.7316    0.1111    95.0036

No_of_Iteration =

     6

final_W =

   59.2821

final_CF =

  178.8463
```

Fig -8: Results after LIPC

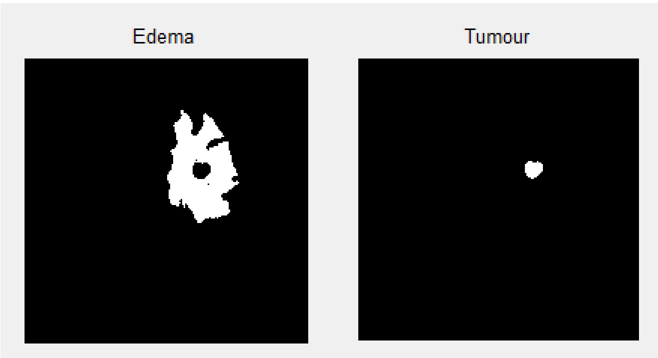

Fig -9: Classification into tumor and edema parts

5. POSTPROCESSING

In LIPC step we separated tumor and edema part. In post processing we analyze tumor part. Here we calculated area and perimeter of tumor in pixels. Also we can find in which lobe tumor is present and its stage.

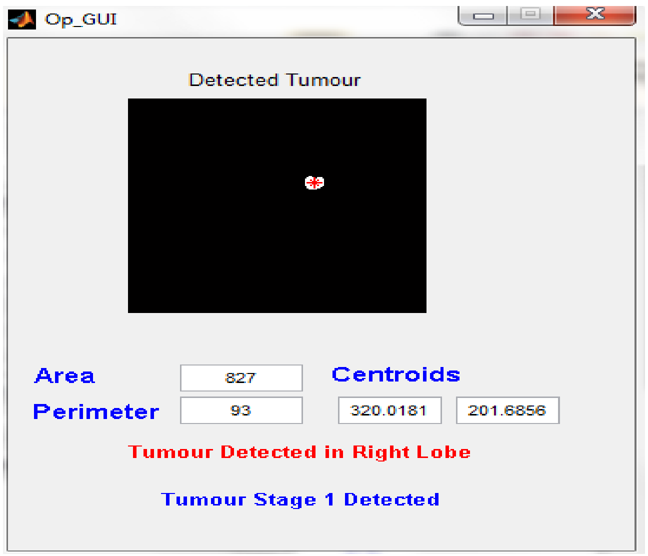

Fig -10: Tumor Analysis

6. CONCLUSIONS

This method is proposed to solve segmentation problem of brain tumor. Here we apply local independent projection based classification. Finally features are extracted by using threshold value and patch is detected which contain tumor and edema part. After analyzing tumor part we get area and perimeter of tumor region as well as we detected exactly in which lobe tumor is present and its stage.

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BIOGRAPHIES

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