Automatic clustering based approach for brain tumor extraction

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Abstract. The brain cancer is a deadly disease affecting almost 1.7% of world’s population with top mortality rate. The basic cause of brain cancer is the abnormal growth of brain tissues in the early stage. Further, these tissues are converted into tumors. Early detection and exact location of brain tumor can assist for further therapies of brain. In this paper a computer vision-based approach is developed for exacting an exact location of the brain tumors from the MRI images. The method starts from skull stripping for removal of the outer portion of brain and segregate the white matter. Further communication with local agent (CLA) clustering technique is applied followed by morphological post processing methods for extraction of tumor regions from white matter regions of the brain. The method is tested on a publicly available MRI dataset. Quantitative and qualitative measures show that the proposed method achieves an accuracy of 99.64% as compared to others.

Keywords: CLA Clustering, Brain tumor, Morphological operations

1. Introduction

Over the past decades it is observed that the brain tumor-based cancer is one of the fatal and dangerous diseases in human beings with a top mortality rate. The tumors are created because of abnormal growth of brain tissues which seriously affect the Central nervous system (CNS) [1].Originally brain tumors are categorized into two types, namely benign and malignant. Benign tumor is a non-cancerous which is originated from brain and grows slowly. This tumor is less aggressive. If these abnormal tissues are detected earlier, it can be removed easily. On the other hand, malignant tumors are cancerous and they spread in the body very rapidly. They can be either originated from brain and spread to other parts of the body, called as primary malignant or can be originated from other parts of body and spread towards the brain, are called as secondary malignants[2]. However, in this context, three different tumors namely Meningiomas, Gliomas, and Pituitary tumors have been discussed. Meningiomas come under benign tumors, which originate in a thin membrane surrounding the brain and spinal cord. The Gliomas are a collection of tumors that grow within the brain substance[3]. High-grade gliomas brain tumors are menacing and aggressive with a very low survival period of around two years.

In the recent era, different imaging modalities like computed tomography (CT), positron emission tomography (PET), ultrasound (US) and magnetic resonance imaging (MRI) have been used for the
detection of tumors by experts. Among these modalities, MRI is becoming popular because it gives clear, detailed features of tissue structures that other modalities cannot provide [4]. Brain MRIs are collected in four modalities: T1, T1c, T2, and FLAIR. In this paper, 3064 T1-weighted contrast-enhanced brain MRI slices are used for tumor extraction. Many Computer-aided diagnosis procedures have been developed to overcome uncertainty and improper manual detection. Recently in research, image processing using machine learning (both supervised and unsupervised) and deep learning algorithms are widely used for the detection and classification of brain tumors in medical images [5]. It has been observed that some brain tumors are homogeneous in structure whereas some are heterogeneous in terms of image texture, pixel intensity, shape, and size. For these reasons, it is a tough task to develop a universal segmentation method to segment all types of tumors accurately [6]. In this paper a universal skull stripping method known as morphological operation followed by Histogram based thresholding is used for removal of the skull and other unwanted matters from the brain. Later skull stripped image undergoes tumor segmentation by using clustering by communication with local agent. How the CLA clustering is dominant over other clustering techniques has been discussed by comparing the method with state-of-art methods in the same fields.

2. Related works
The computer vision methods developed for detecting brain tumors can be categorized as supervised and unsupervised methods. For supervised learning, a sizeable amount of dataset is required for training so it is time-consuming whereas in unsupervised learning training of the model is not required. One of the most used methods for supervised learning is clustering. Some state-of-art methods for brain tumor segmentation are discussed below. The authors in [7] proposed a content-based retrieval method for extracting brain tumors. The method used intensity, texture, and shape features for extracting tumor tissues along with the tissues surrounding the tumor. Method [8] demonstrated a tumor retrieval system using bag-of-visual-words model and domain knowledge of brain tumor imaging modality. The method used the transverse, coronal and sagittal views of brain images. The authors in [9] proposed a tumor extraction system by incorporating bag-of-visual-words with a partition learning approach. Similarly, [10] proposed a deep learning approach for tumor classification of three distinct types of tumors such as Glioma, Meningioma, and Pituitary tumors. But the approach is a supervised learning approach type that requires large image datasets increasing the complexity of the overall algorithm. Similarly [11] showed the usage of Capsule networks for tumor classification based on supervised classification of brain tumors. Continuing the trend of tumor extraction using tumor features, [12] proposed a retrieval system based on adaptive spatial pooling and feature vector representation. The approach uses local features for effective tumor extraction based on augmented region-of-interest used for informative contextual information. The feature-based approaches use either low level or high level or hand-crafted features for contextual information based on tumor extraction. So to address it, [13] proposed a deep convolutional neural network applying closed-form matrix learning for extraction of tumors.

By analyzing the literature, it is evident that the tumor extraction approaches developed so far are content-based which may be supervised or unsupervised in nature. The supervised approaches vary on large dataset training for contextual information extraction whereas unsupervised approaches do not require large training datasets. This makes the algorithm simpler as compared to supervised approaches. This paper introduces a clustering-based approach based on clustering by communication with local agents (CLA) [14]. The proposed method is simple in the context that no predefined contextual information is used rather the method utilizes the intensity clustering approach for effective identification of Meningioma and Glioma tumors from MRI images.

The remaining parts of the paper are organized as Section 3 provides a glimpse of dataset details. Section 4 discusses the proposed approach. Section 5 provides the result and discussion of the proposed method. Finally, the paper is concluded in section 6 with some future directions.
3. Data Collection
The dataset used in this paper was originally collected from Nanfang Hospital and General Hospital, Tianjing, China and was developed by Cheng in 2017. The dataset is now publicly available in Figshare brain tumor dataset[15]. The dataset has 3064 T1-weighted contrast-enhanced brain MRI slices were collected from 233 patients. All the images taken in the dataset are contrast-enhanced images with T1 modality. The images in the dataset are present in .mat extension format. Each .mat file contains the unique patient ID and the type of tumor. The total 3064 MRIs are in the form of three types of tumor named meningioma, glioma, and pituitary tumors (meningioma 708 slices, glioma 1426 slices, and 930 slices of pituitary tumors). The brain tumors present in the dataset are different in terms of their size, shape, and location. All the images present in this dataset are of size 512 x 512 and are present in all three views i.e. axial, coronal, and sagittal.

4. Proposed approach
The Proposed approach is divided in three parts i.e. (1) Preprocessing, (2) CLA Clustering and (3) Post processing for tumor extraction. The detailed architecture of proposed work is given in Figure.1

4.1. Preprocessing

4.1.1 Contrast enhancement using Histogram Equalization
The histogram of an image gives the intensity distribution of an input grayscale image which is used for contrast enhancement. Due to the intensity matching of tumors with the white matter present within the brain, the tumor intensities are not distinguishable. So, histogram equalization is performed for enhancing the tumors as compared to the white matter. This results in an enhanced gray image.

4.1.2 Thresholding
The enhanced gray image is thresholded using Otsu’s Threshold [16]. After thresholding, the gray image is converted into a binary image. In the present paper, the converted binary image has the value of 1(white) when the gray value exceeds a threshold value taken from the histogram and the binary image has a value of 0(black) as the gray image is less than the selected threshold.

The equation for Otsu’s Threshold is:

\[ bw = \begin{cases} 
0, & I(x, y) < Th \\
1, & I(x, y) \geq Th 
\end{cases} \]  

(1)

where, ‘bw’ is the binary image, I is the gray image and Th is the threshold taken from histogram in sub-section- 4.1.1. To remove the unwanted portions like skull regions from the binary image, the image is applied morphological erosion operation. The morphological erosion is expressed as

\[ bw \mathcal{O} S = \{ x | (s)_x \subseteq bw \} \]  

(2)

where ‘bw’ is the binary image which is eroded by the structuring element S. By this process skull stripped binary image is got leaving behind only gray and white matter along with the tumors present in the brain MRI image.
4.2. Clustering by Communication with Local agents (CLA)

Clustering approaches try to combine the similar intensity values of the image thereby providing an effective tool for image analysis. Several clustering approaches have been developed by various researchers for brain image analysis or tumor identification[17][18][19][20][21].

Communication with Local Agents (CLA) [14] is a recently developed clustering algorithm where the exact number of clusters is not pre-defined, unlike other clustering techniques. According to the intensity values present in the image, the number of clusters is automatically decided. The cluster with a large number of identical intensity values is selected as a tumor mask.

Figure 1. Architecture of proposed method
The CLA clustering is inspired by Newton’s theory of gravitation, reflecting a relationship between pixels and its local neighbor pixels. As per Newton’s law of gravitation, the force of attraction between two point masses can be determined as follows:

$$\vec{F}_{12} = G \frac{m_1 m_2}{R_{12}^2} \hat{a}_{R_{12}}$$  \hspace{1cm} (3)$$

where, $\vec{F}_{12}$ denotes the force between two point masses $m_1$ and $m_2$. The distance between masses $m_1$ and $m_2$ is $R_{12}$. The term $\hat{a}_{R_{12}}$, represents the unit vector specifying the direction of line joining the two masses and $G$ represents the gravitational constant.

For each pixel, associated with a mass, the distance between current pixel and its connected neighbors do not vary significantly. So, $R_{12} \approx 1$. Hence equation (3) becomes

$$\vec{F}_{12} = G m_1 m_2 \hat{a}_{R_{12}}$$  \hspace{1cm} (4)$$

Applying principle of superposition, the resultant force on pixel $p$ due to its K-nearest neighbors can be calculated as

$$\vec{F}_p = \sum_{q=1}^{K} \vec{F}_{pq} = G m_p \sum_{q=1}^{K} m_q \hat{a}_{R_{pq}}$$  \hspace{1cm} (5)$$

where unit vector $\hat{a}_{R_{pq}}$ gives the direction between pixel $p$ and its neighbors and the set of $m_q$ pixels play a crucial role in composing forces in neighborhood. Based on the above interpretation, the pixels with larger mass provide more influence to its neighbors.

The local resultant force (LRF) is motivated by equation (5), paves the path for clustering. The LRF is given by

$$\vec{F}_p = \frac{1}{m_p} \sum_{q=1}^{K} \vec{a}_{R_{pq}}$$  \hspace{1cm} (6)$$

Where the mass $m_p$ of pixel $x_p$ is defined as

$$m_p = \frac{1}{\sum_{q=1}^{K} R_{pq}}$$  \hspace{1cm} (7)$$

In higher intensity regions, the pixels will attain shorter distances from their neighbor pixels as per equation (7) while, in the lower intensity regions, the distances become smaller. Similar analysis can be applied to the LRF expression in equation (6). At higher intensity regions, a pixel is surrounded by neighbor pixels in a more uniform way, resulting in smaller magnitude for $\sum_{q=1}^{K} R_{pq}$ and a larger $m_p$.

In lower intensity areas, particularly at the border of the clusters, a pixel is usually surrounded by neighbor pixels in less uniform way, which results in an unbalanced resultant force. The magnitude of $\sum_{q=1}^{K} \hat{a}_{R_{pq}}$ in lower intensity areas is usually larger and $m_p$ is smaller. According to equation (6) the resultant force $\vec{F}_p$ will have a larger magnitude and a more distinct direction towards the center of clusters. The centrality (CE) of the pixel $x_p$ is defined as

$$CE_p = \frac{\sum_{q=1}^{K} \cos(\vec{F}_q, \vec{R}_{qp}) / K}{K}$$  \hspace{1cm} (8)$$
where, $\mathbf{R}_{qp}$ refers to the displacement vector from $q^{th}$ neighbor of pixel $x_p$ to it and $K$ is the number of neighbor pixels. A pixel with $CE_p > 0$ indicates that most of LRFs of its neighbors are pointed towards it. Since $-1 \leq \cos(\mathbf{F}_q, \mathbf{R}_{qp}) \leq 1$ and $-K \leq \sum_{q=1}^{K} \cos(\mathbf{F}_q, \mathbf{R}_{qp}) \leq K$. Considering the property of CE from equation $(8)$ $-1 \leq CE_p \leq 1$. The coordination of the pixel $x_p$ is defined as

$$CO_p = \sum_{q=1}^{K} (\mathbf{F}_p \cdot \mathbf{F}_q)$$

where, $\mathbf{F}_p$ refers to the LRF of pixel $x_p$ and $\mathbf{F}_q$ is the force associated with its neighbors. The CO refers to the compatibility of a particular pixel with its neighbor pixels. A pixel with $CO_p > 0$ indicates that its LRF has roughly same direction as its neighbor pixels and it may probably be at border.

The Clustering using CLA is performed using two steps

(i) CLA calculates the LRF and CE values for all the pixels in an image.
(ii) Each pixel tries its best to find a local agent and each local agent communicates with each other to form the clusters.

In CLA, local agents are considered as the pixel values with higher CE values than that of neighbor pixels. In this clustering, each pixel intensity value is regarded as one vector. Each vector tries its best to find the local agents to its neighbor pixels. Local agents are decided as per their higher CE values and lower LRF magnitude.

The criteria are given by

$$CE_p < CE_q$$

$$\|\mathbf{F}_p\| > \|\mathbf{F}_q\|$$

$$\mathbf{F}_p \cdot \mathbf{D}_{pq} > 0$$

Where $\mathbf{F}_p$ represents LRF of $p^{th}$ pixel $\mathbf{D}_{pq}$ refers to displacement from pixel p to pixel q and $\|\mathbf{F}\|$ represents the magnitude of LRF. Let $x_q$ is the local agent of $x_p$ ’s neighborhood. In following stages the local agents are selected in a CLA clustering.

- For each pixel $x_p$, it tries to find the first pixel in its K-nearest neighbors that satisfies equations (10-12)
- If such a point $x_q$ exists then $x_p$, labels $x_q$ as its local agent

This can be further elaborated in Algorithm 1 and Algorithm 2

**Algorithm 1** (for finding local agents)

**Inputs:**
Input image X
LRF’s and CE’s of each pixel in image X

**For** each pixel $x_p$
If \( x_q \) satisfies equations (10-12) in its K-nearest neighbors

label \( x_q \) as the agent \( x_p \)

end if

end for

For each pixel \( x_p \)

If \( x_p \) does not have agent and \( x_q \) is the first pixel which satisfies equation (10) and equation (11) in its k-nearest neighbors.

label \( q \) as the agent of pixel \( p \)

end if

end for

For each pixel \( x_p \)

If \( x_p \) does not have agent and \( x_q \) is the first pixel which satisfies equation (10) in its k-nearest neighbors.

Then label \( q \) as the agent of pixel \( p \)

end if

end for

Algorithm 2 (communication between set of local agents)

Inputs:
Input image X
CE’s of each pixel in image X
\( A \) as local agent in the index set

Initialize \( C=\emptyset \) at cluster number \( c=0 \)

For each agent \( A_p \)

If \( A_p \) is clustered, continue with next \( A_p \)

end if

Increment of cluster number: \( c = c+1; \ C = C + C_c; \ C_c = C_c + \{A_p\} \)

Communicate with the nearest agent, which is not clustered
If communicate with \( A_q \)

\( C_c = C_c + \{A_q\} \)

Let \( A_q \) performs the same task as \( A_p \)

else
continue with next $A_p$

end if

end for

where, $\emptyset$ is a null set, $C_c = $ Cluster set of cluster number c, $A_p = $ local agent of $p^{th}$ pixel, $A_q = $ local agent of $q^{th}$ pixel.

4.3. Post Processing

After clustering of skull stripped images, the tumor mass of most of the images is extracted. But some regions are extracted where some unwanted masses are found along with tumor mass. So, after the process of clustering, the tumor is present in those images with the biggest area, hence the tumor mass is extracted using $N_8$-connectivity keeping 8 adjacent pixels of a particular pixel. This results in the biggest blob extraction process from the clustered image.

After biggest blob extraction, the blob contains some unwanted noisy spikes at the boundary. To remove these spikes, first, the perimeter of the blob is found and at the perimeter, the spikes are removed by the median filter. The filtered perimeter undergoes region filling operation to get the actual segmented tumor mask is found and later the tumor is extracted from the segmented mask.

Once the final segmented mask is extracted, is compared with the original brain MRI images to extract the intensity images containing the tumors only out of entire brain MRI image.

5. Result and Discussion

The experimentation is done in MATLAB 2017a environment using a PC with Intel Corei3 1.99GHz processor with 4GB RAM. The proposed method is tested on brain image data set(14) containing 3064 T1-weighted contrast enhanced MRI images.

To demonstrate the effectiveness of the proposed method the performance parameters like Accuracy (Acc), Sensitivity (SN), Specificity (SP), Dice Coefficient (DC), Jaccard index (J) and Precision (PREC) are calculated from True Positive (TP), True Negative (TN), False Positive (FP) and False negative (FN) values. Further, the proposed method is compared with other existing methods. The performance parameters are given in equations (16-21)

$$Acc = \frac{(TP + TN)}{(TP + TN) + (FP + FN)}$$  \hspace{1cm} (16)

$$SN = \frac{(TP)}{(TP + FN)}$$  \hspace{1cm} (17)

$$SP = \frac{(TN)}{(TN + FP)}$$  \hspace{1cm} (18)

$$DC = \frac{2(TP)}{(TP + FP) + (TP + FP)}$$  \hspace{1cm} (19)

$$J = \frac{(TP)}{(TP + FP + FN)}$$  \hspace{1cm} (20)

$$PREC = \frac{(TP)}{(TP + FP)}$$  \hspace{1cm} (21)
where, TP is the indication that the tumor exists and is located correctly whereas TN is the indication that tumor does not exist and it is not located. FP indicates that tumor does not exist but shows as it is located. Similarly, FN indicates that tumor exists, but it is not located.

The quantitative performances of the proposed method as compared to existing approaches are given in Table 1. In the proposed work accuracy is calculated as 99.64%, Sensitivity (SN) of 91.19%, Specificity(SP) of 99.77%, Dice Coefficient(DC) of 86.65%, Jaccard index(J) of 80.15% and Precision(PREC) is calculated as 93.88%.

**Table 1** Comparison of different performance measures of various approaches with the proposed method.

| Methods                                           | Performance measures |
|---------------------------------------------------|----------------------|
| Tumor margin information and learned distance      | Acc 99.64%           |
| metric[7]                                          | DC 86.65%            |
| bag-of-visual-words model[8]                       | SN 91.19%            |
| Rank Error-based Metric Learning (REML)[9]         | SP 99.77%            |
| CNN model[10]                                      | PREC 93.88%          |
| CapsNets Deep Neural Network [11]                  | J 80.15%             |
| Adaptive Spatial Pooling and Fisher Vector         |                      |
| Representation [12]                                |                      |
| VGG19 deep neural network[13]                      |                      |
| Proposed Method                                    |                      |

The quantitative performance of the proposed method can be visualized from Fig.2. The Fig.2 shows 4 distinct MRI images with their original image along with the extracted tumor output. The Fig. 2(a) shows the original brain MRI image from the dataset. The Fig. 2(b) shows their corresponding ground truths provided in the dataset. The Fig. 2(c) represents the segmented mask got by using proposed approach. The Fig. 2(d) shows the extracted tumor regions from their corresponding original brain MRI images.

For better analysis of the proposed approach, consider the image set given in Fig.2 i.e. 5th row of Figure.2. This may be taken as a special case given in Fig.3. In Figure.3(a) the original brain MRI image is taken. The red encircled region, marked as ‘A’ in the figure, indicates the actual position of the tumor. A magnified version of Figure.3 (a) is shown in Figure. 3(b) where the previous encircled red region ‘A’ is segregated into two different regions ‘B’ and ‘C’. For better identification in Fig.3 (b) one region corresponding to the larger section of tumor mask is encircled in red, identified as region B. The smaller section encircled in blue is marked as the tumor section lying close to the skull area. But it can be well remarked from Fig.3(c) which is ground truth manually annotated in the dataset that the smaller tumor regions i.e. ‘C’ in Fig 3(b) is missing.
The proposed approach identifies both the region ‘B’ and ‘C’ in the segmented mask. This indicates that the proposed approach can better extract the tumor region, even if it is closely associated near the skull regions. This can be proved from the extracted tumor mass shown in Fig. 3(e).

The Table.1 and Fig. 2 show that the proposed method provides better results both quantitatively and qualitatively. After comparing the parameters with previous works, it is depicted that our method has given a better result with an average accuracy of 99.64% for Glioma and Meningioma tumors.

Figure 2. Tumor extraction results of the proposed method: (a) Original MRI image, (b) Ground truth, (c) Segmentation mask obtained from proposed method, (d) Extracted tumor via segmentation masks given in (c).
Figure 3. Segregated output for Row-5 of Fig.2: (a) Original Image, (b) Magnified version i.e., red encircled region A of (a), (c) ground truth from the dataset, (d) Segmentation mask obtained by the proposed method, (e) extracted tumor via (d).

6. Conclusion
This paper discusses Communication with Local Agents (CLA) clustering where the exact number of clusters is not pre-defined unlike other clustering techniques and according to the intensity values of the image, the number of clusters is found. The cluster with a large number of identical intensity values automatically results as a tumor mask. The present work provides an efficient method for brain tumor extraction using the CLA Clustering approach. To achieve better results, all the image slices undergo Skull stripping using a histogram-based approach with the morphological operation. For validation of the study, originally three types of tumors are considered namely Meningiomas, Gliomas and Pituitary tumor from publicly available brain tumor dataset. It is observed that the algorithm works better in Meningiomas as compared to the other two types of tumors. The method can extract tumors even it is located near the skull regions, which proves the effectiveness of the proposed method as compared to others.

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