Extraction of Brain Tumour from MRI Images using Marker-Based Watershed Transform

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Abstract:

A brain tumor is an abnormal tissue growth in the brain in which cells grow and multiply uncontrollably. The main aim of our task is to identify brain tumor from a particular MRI image and to extract the tumor region. The proposed method uses various digital image processing techniques such as noise removal, Otsu's thresholding, morphological operations etc. This paper focuses on the use of marker-based watershed transform for segmentation, to get near about accurate results.

Keywords: *Brain tumor, MRI, Marker-based watershed transform, Morphological operations, Otsu's Thresholding, Segmentation*

1. Introduction

Magnetic resonance imaging (MRI) is a type of scan that uses strong magnetic field and radio waves to generate detailed images of the inner parts of the body. Doctors identify brain tumour in patients by analyzing the MRI image of their respective brain scans. Segmentation is, in most cases, done manually by the radiologists and reports are generated thereafter based on texture, size and spread of the tumour region. However, computer aided methods for detection and extraction of brain tumour have been shown by researchers through past, to be promisingly accurate, robust and time saving. Substantial researches are still being carried out in recent times in the field of brain tumour extraction, detection and classification. Nowadays there are several methodologies for brain tumour extraction, namely region growing, K Mean, Fuzzy C Mean methods etc [1]. This paper aims to perform segmentation of brain MRI images of patients, thereby identifying and extracting the tumour region. This paper shows, how even a simple marker-based watershed transform along with morphological operations can yield surprisingly accurate results, when implemented correctly [2]. Image processing operations were mainly carried out using computer vision software libraries, namely, OpenCV, scikit-image and Python has been used as the main programming language, for the algorithms we have devised.

2. Methodology

Our proposed method can be divided into four distinct stages. First is preprocessing, then feature reduction, followed by some morphological operations and finally segmentation using marker-based watershed transform. We have considered 50 different samples of MRI images of patients with brain tumours. The sample images are of resolution 256x256 pixels. This will help us in maintaining consistency while finding the area of the tumour region, which we wish to address in our future works.

2.1 Preprocessing

First, the MRI image of resolution 256x256 pixels is converted to a grayscale image, as gray scale images are easier to work with. To remove salt-and-pepper noise from the image, we have applied a median filter [3]. Here, we have used the OpenCv function **cv2.medianBlur()**, which computes the median of all the pixels under the kernel window and the central pixel is replaced with this median value. We have taken aperture linear size to be 5 in our case, thus the function will smooth the image with a median filter of size 5x5.

2.2 Skull Stripping and Feature Reduction

This phase aims to isolate the brain from extra-cranial tissues and we wish to strip the skull completely, if possible, from the image. The algorithm we devised for this purpose is as follows:
Algorithm:
1.Otsu's binarization is used for thresholding the filtered MRI image [4].
2.Generating the connected components in the thresholded image and labelling them.
3.Getting the area consumed by each component.
4.Finding the label of the largest component by area.
5.Getting pixels corresponding to the brain, which is the largest component by area.
6. In a copy of the original image (the image obtained after applying the median filter),clearing those pixels that don't correspond to the brain.
7. Using morphological operators: **dilation** and **closing**, to fill the unwanted holes and spaces in the skull-stripped image which may have been formed while performing step 6 [5].This also aids in feature reduction of the skull-stripped MRI image. This is actually useful in segmentation where we wish to focus on our region of interest, i.e. the tumour region in the brain. It wouldn't matter much if the brain tissues surrounding the tumour region shrinks or dilates as long as we can keep the tumour region intact.
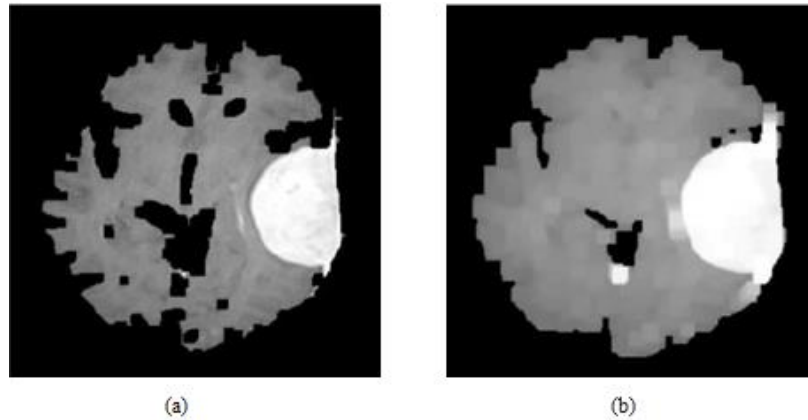
Fig.1 (a) Connected components, (b) Connected components after dilation and closing

2.3 Segmentation Using Marker-Based Watershed Transform

Watershed techniques can detect the continuous boundary of the region of interest, and it is suitable for those type of segmentations where precision is needed. Detection of tumor in the domain of biomedical research is an area where watershed segmentation can be applied effectively. Watershed is a gradient-based transform where different gradient values correspond to different heights. A hole is made in each regional minimum and immersed in water; the water will rise until regional maximums. When two bodies of water meet, a wall is built in between them. The water rises gradually until all points in the topographical map are immersed. The image gets segmented by the walls. The walls are known as watersheds and the segmented regions are known as catchments basins [6].

Mathematically the classical watershed transform can be seen as such [7,8,9,10], Let the set of coordinate points in the local minima be lm1, lm2…..lmz , of the image A(i, j) and C(lmi) refers to the points of catchment basins associated with local minima lmi . $X[n] = \{(x, y)\} \mid A(x, y) < n\}$

X[n] is the coordinate of points in A(i, j), lying below A(i, j) =n. If we visualize the image Topographically, stage of flooding varies from n=imax+1 to n = imin+1. MIN-VAL and MAXVAL, is the minimum and maximum gray value.

Therefore,

$Cn(lmi) = \cap\{ C(lmi), X[n]\}$ will be the set of points in the catchment basin associated with

lmi that are filled, at n.

And,

Cn(lmi) = 1, if (i,j) ϵ C(lmi) and (i,j) ϵ X[n]

And,

Cn(lmi) = 0 , otherwise.

Therefore , $C[n] = \bigcup_{m=1}^{z} Cn(lmi)$

Finally Cimax+1 is actually the union of all the catchment basins, given by,

$C_{imax+1} = \bigcup_{m=1}^{z} Cn(lmi)$

We initialize, C[imin+1] =X [imin+1]. Then the procedure follows recursively, keeping in mind

the assumption that at nth step C[n-1] has been generated.

Let Q be the set of connected components in X[n] then for each q ϵ Q[n],

i) q $\cap$ C[n-1] is empty,

ii) q $\cap$ C[n-1] contains one connected component of C[n-1],

iii) q $\cap$ C[n-1] contains more than one connected component of C[n-1].

However, the classical watershed transform suffers from oversegmentation due to noise or any other irregularities in the image, hence we have used marker-based watershed transform for segmenting the skull-stripped MRI image [11]. Our implementation uses a marker image, which is built from the region of low gradient inside the image. For that we have first, computed the local gradient of the skull-stripped image. In the gradient image, the areas of high values provide barriers that help to segment the image. Using markers on the lower gradient values will ensure that the segmented objects are found.

Markers are determined automatically, using the local minima of the gradient of the skullstripped image.We have used skimage.morphology.watershed() function for segmentation [12]. The image will be segmented into three parts-the tumour region(A), the unaffected brain tissues(B) and the background(C)
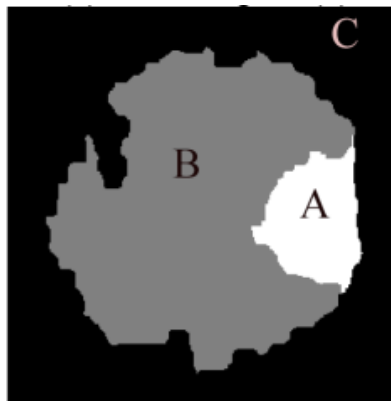

Fig.2 The three parts-(A)Tumour region,(B)Unaffected brain tissues(C)Background.

2.4 Extraction of the tumour region from the segmented image, thus obtained

We have observed that the tumour region is the smallest connected component by area, in the segmented image. So, by using connected component analysis, we have extracted only those pixels which correspond to the smallest connected component in the segmented image [13]. The summarization of the proposed method is shown below in a flowchart.
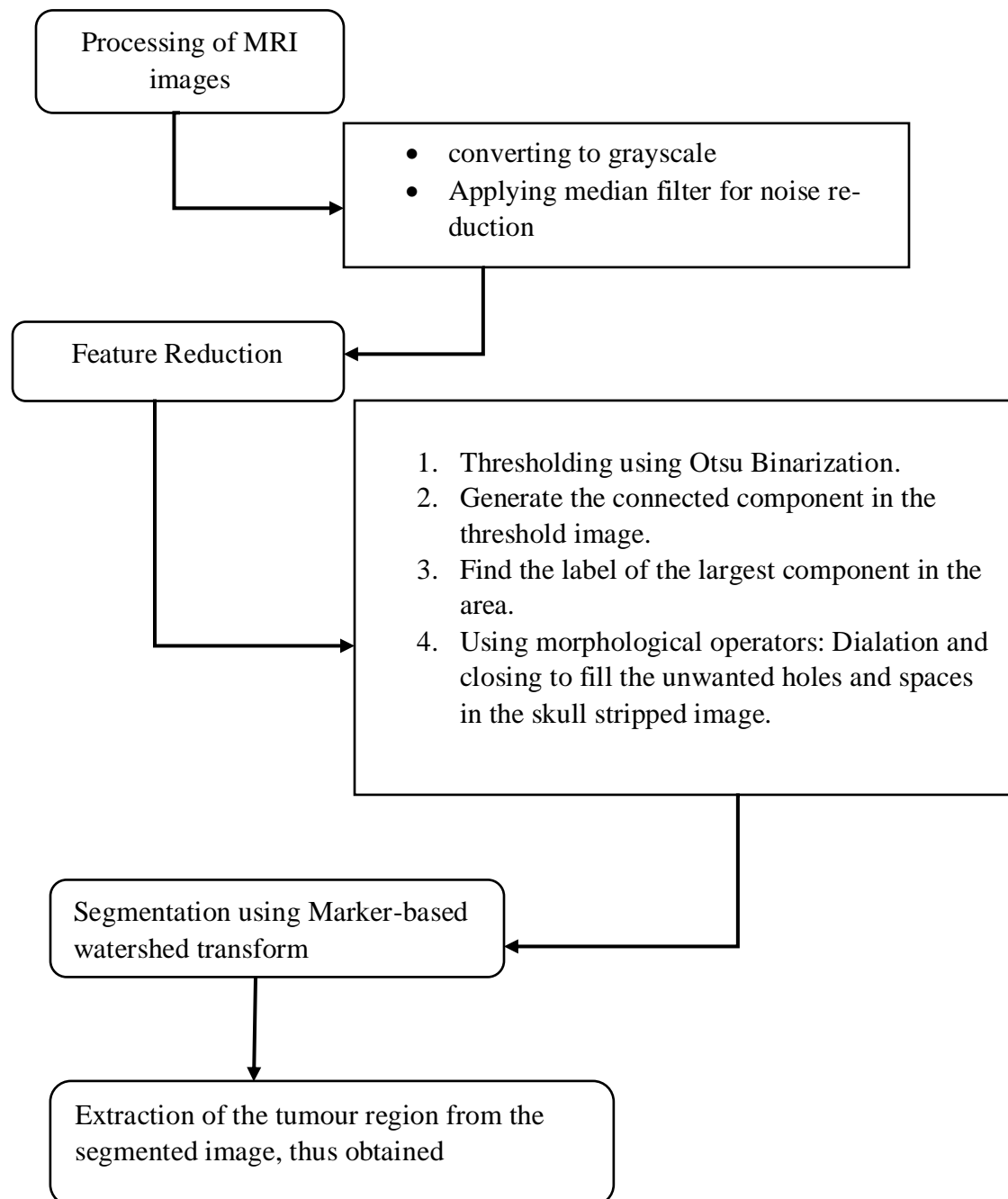

Fig.3 Flowchart, showing a summarized version of our methodology

3.Results

Our proposed algorithm was implemented on fifty MRI scans. The results that were obtained were accurate enough, considering the very basic segmentation method that has been used. Results obtained by using the proposed method, on one of the sample MRI images from the dataset that we acquired from Kaggle is shown below [14].
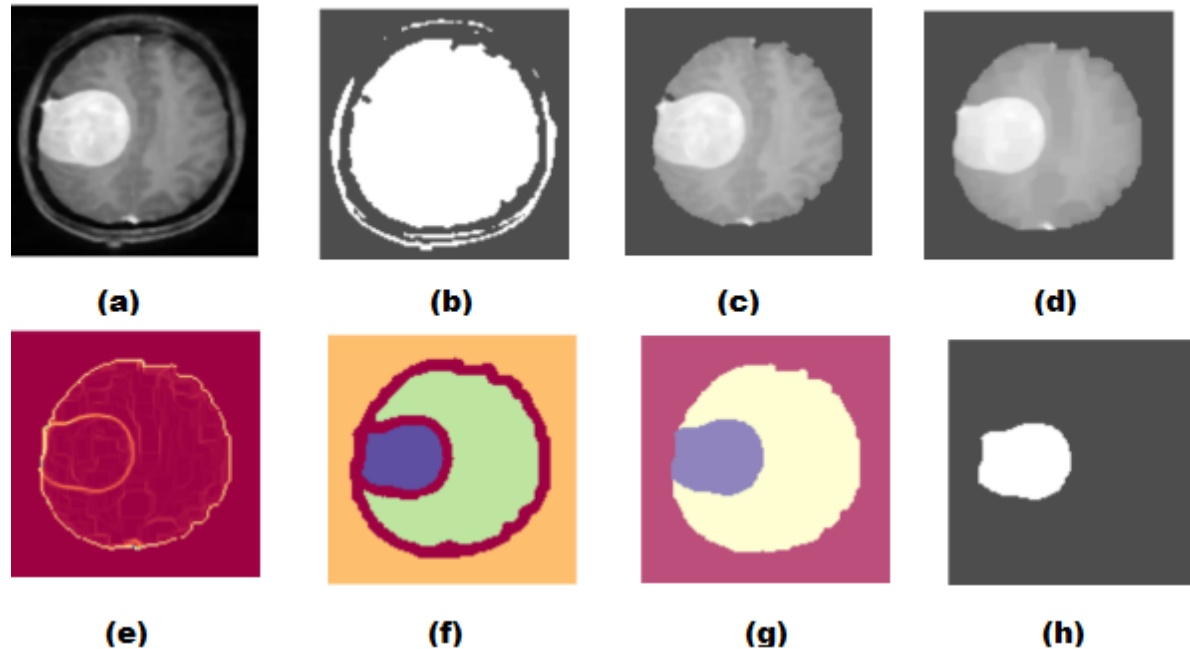

Fig 4 a) Original image b) Threshold image c) Feature reduced image d) Image after morphological operation e) Local gradient f) Markers g) Segmented image h) Extracted tumor region.

4. Conclusion

In this paper we have demonstrated how marker-based watershed transform can be used quite effectively to extract the tumour region from MRI images. In our implementation, we have selected the markers automatically from the local gradient of the image. In future we wish to acquire MRI images with ground truths, and apply this implementation of markerbased watershed transform and examine its accuracy.

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