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Detection and Extraction of Brain Tumor from MRI Images Using K-Means Clustering and Watershed Algorithms

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ABSTRACT
Medical imaging is generally equated to radiology or "clinical imaging" and the medical practitioner responsible for interpreting (and sometimes acquiring) the image is a radiologist. Diagnostic radiography designates the technical aspects of medical imaging and in particular the acquisition of medical images. The radiographer or radiologic technologist is usually responsible for acquiring medical images of diagnostic quality, although some radiological interventions are performed by radiologists. Brain tumor is a disease, which is a common, chronic, systemic, autoimmune inflammatory disease in nature that mainly affects the human body; there are two main types of tumors: malignant or cancerous tumors and benign tumors. Cancerous tumors can be divided into primary tumors that started within the brain and those that spread from somewhere else known as brain metastasis tumors. This article deals mainly with tumors that start within the brain. All types of brain tumors may produce symptoms that vary depending on the part of the brain involved. These may include headaches, seizures, problem with vision, vomiting, and mental changes. The headache is classically worst in the morning and goes away with vomiting. More specific problems may include difficulty in walking, speaking and with sensation. As the disease progresses unconsciousness may occur. In this research work we have extracted and detected brain tumor using two different techniques. Simulation will be done on MALTAB from original brain tumor images from Clinical Laboratory.
Keywords:- Brain tumor, watershed, k-means clustering, MRI, MATLAB

I. INTRODUCTION

In medical image segmentation of images plays a vital role in stages which occur before implementing object recognition. Image segmentation helps in automated diagnosis of brain diseases and helps in qualitative and quantitative analysis of images such as measuring accurate size and volume of detected portion. Accurate measurements in brain diagnosis are quite difficult because of diverse shapes, sizes and appearances of tumors.

Tumors can grow abruptly causing defects in neighboring tissues also, which gives an overall abnormal structure for healthy tissues as well. In this paper, we will develop a technique of segmentation of a brain tumor by using segmentation in conjunction with different MATLAB techniques.

II. TUMOR

The word tumor is a synonym for a word neoplasm which is formed by an abnormal growth of cells Tumor is something totally different from cancer.

1) Types of Tumor:
There are three common types of tumor:
1)Benign;
2) Pre-Malignant
3)Malignant(cancer can only be malignant).

- ***a) Benign Tumor:*** A benign tumor is a tumor is the one that does not expand in an abrupt way; it doesn’t affect its neighboring healthy tissues and also does not expand to non-adjacent tissues. Moles are the common example of benign tumors.

b) ***Pre-Malignant Tumor:*** Premalignant Tumor is a precancerous stage, considered as a disease, if not properly treated it may lead to cancer.

c) ***Malignant Tumor***: Malignancy (mal- = "bad" and -ignis = "fire") is the type of tumor, that grows worse with the passage of time and ultimately results in the death of a person. Malignant is basically a medical term that describes a severe progressing disease. Malignant tumor is a term which is typically used for the description of cancer.

Magnetic Resonance Imaging (MRI)

MRI is basically used in the biomedical to detect and visualize finer details in the internal structure of the body. This technique is basically used to detect the differences in the tissues which have a far better technique as compared to computed tomography. So this makes this technique a very special one for the brain tumor detection and cancer imaging. CT uses ionizing radiation but MRI uses strong magnetic field to align the nuclear magnetization then radio frequencies changes the alignment of the magnetization which can be detected by the scanner. That signal can be further processed to create the extra information of the body. This research paper is divided in six parts, in the second part analysis and findings are discussed. In the third portion related work is explained, many researchers are currently working in this field. Many related research papers are properly explained in this region. Forth portion is proposed methodology, all the phases of our proposed system is explained in details. All the stages including preprocessing, processing and post processing are discussed there. In the next section all experimental results are shown with proper diagrams and figures. Then in the last section conclusion and future work is discussed.

Watershed Segmentation

In geography, a watershed is the ridge that divides areas drained by different river system. The watershed transform is a morphological gradient-based segmentation technique. The gradient map of the image is considered as a relief map in which different gradient values correspond to different heights. If we punch a hole in each local minimum and immerse the whole map in water, the water level will rise over the basins. When two different body of water meet, a dam is built between them. The progress continues until all the points in the map are immersed. Finally the whole image is segmented by the dams which are then called watersheds and the segmented regions are referred to as catchment basins. A catchment basin is the geographical area draining into a river or reservoir. The watershed algorithm applies these ideas to gray-scale image processing in a way that can be used to solve a variety of image segmentation problem. Watershed algorithm, a segmentation method in mathematics morphology, was firstly introduced to the image division area by Beucher and Meyer.

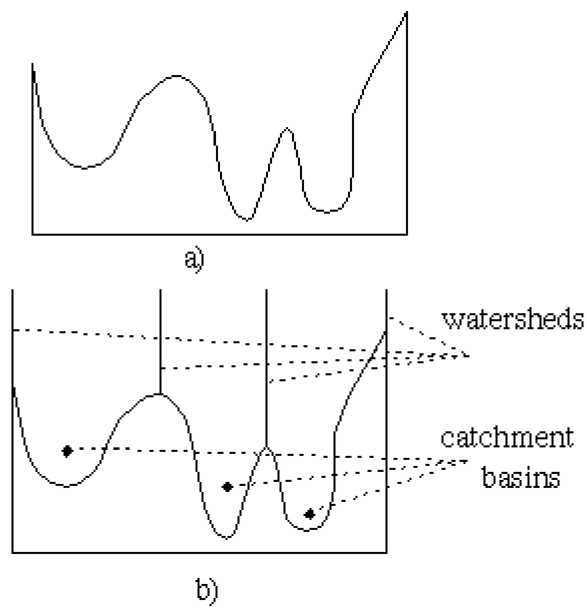


Figure 1 a) gray level profile of data.
b) Watershed segmentation

In the image, the gray level value of every pixel stands for the altitude of a certain spot and different areas of gray level value correspond to different geological features. The calculating process with this algorithm can be likened a submerging process by a flood. Firstly, the flood submerges the lowest point in the image and gradually the whole valley. When the water level reaches a certain height, it will overflow at a certain place where the dam can be built. Repeat the process until all the spots in the image. At this moment, the series of completed dams will be the watershed separating every basin. Direct application of the watershed algorithm to a gradient image usually leads to over segmentation due to noise and other local irregularities of the gradient. The resulting problems can be serious enough to render the result virtually useless. A practical solution to this problem is to limit the number of allowable regions by incorporating a preprocessing stage designed to bring additional knowledge into the segmentation procedure. An approach used to control over segmentation is based on the concept of controlled marker, which is proposed by Meyer and Beucher. This approach is based on the idea that a machine vision system knows from other sources the location of the objects to be segmented. Therefore, before segmentation we must indicate which objects are to be segmented and which one is the background.

k-means clustering

k-means clustering is a method of vector quantization, originally from signal processing, that is popular for cluster analysis in data mining. k-means clustering aims to partition n observations into ‘k’ clusters in which each observation belongs to the cluster with the nearest mean, serving as a prototype of the cluster. This results in a partitioning of the data space into Voronoi cells. The problem is computationally difficult (NP-hard); however, there are efficient heuristic algorithms that are commonly employed and converge quickly to a local optimum. These are usually similar to the expectation-maximization algorithm for mixtures of Gaussian distributions via an iterative refinement approach employed by both algorithms. Additionally, they both use cluster centers to model the data; however, k-means clustering tends to find clusters of comparable spatial extent, while the expectation-maximization mechanism allows clusters to have different shapes.

Background

The idea has been introduced in 1979 by S. Beucher and C. Lantuéjoul. It consists in placing a water source in each regional minimum, to flood the relief from sources, and build barriers when different sources are meeting. The resulting set of barriers constitutes a watershed by flooding. By taking this concept several works has been done in various research fields. The main idea behind this technique is to segmentation of images. We have tried to use this concept in a new dimension by detecting the human with MRI images. As an example we have chosen MRI images of human brains. Edge detection of human organs with MRI images is a major concerning problem in respect of the vision of the computer.

III. PROPOSED OBJECTIVES OF RESEARCH

Our main objective of research work is to extract and detect brain tumor in the MRI images using different methods, we used to calculate various parameters like

- Area, radius and perimeter of image
- Mean Square error
- Peak signal to noise ratio
- Execution time

Proposed methodology

As per our first approach, the marker controlled watershed transform is mainly for the problems where adjacent objects are there in an image and we have to separate them using image processing operations. This approach deals with catchment basins and watershed ridge lines in an image by assuming it as a surface where light pixels are low. In the initial step we have to convert a color image into gray scale and compute the gradient magnitude as the segmentation function where gradient is highest at the borders of the object and generally low inside the object. We will then use the internal marker to distinguish the foreground of adjacent objects. The background of the image will then be segregated from the foreground objects using

the external markers. Finally we will aggregate the computed result of the watershed transform and examine the final image. The detailed algorithm is the following:
STEP 1: Insert the original image as input.
STEP 2: Convert the image into gray scale.
STEP 3: Find out the gradient magnitude.
STEP 4: Mark the foreground objects.
STEP 5: Mark the background objects.
STEP 6: Estimate the watershed transform.

As per our second approach, k-means clustering is a method of vector quantization, originally from signal processing, that is popular for cluster analysis. k-means clustering aims to partition n observations into k clusters in which each observation belongs to the cluster with the nearest mean, serving as a prototype of the cluster.

STEP 1: Insert the original image as input.
STEP 2: Convert the image into gray scale.
STEP 3: Find out the ‘k’ in image by algorithm itself.
STEP 4: Get the clustered objects.
STEP 5: Estimate the k-means clustering algorithm.

IV. EXPERIMENTAL OUTCOMES AND RESULTS

The segmentation of image takes an important branch in the surgery navigation and tumor radiotherapy. However, due to medical imaging characteristics, the low contrast and fuzzy boundary is usually occurred in the images. In the experiment, the image data from clinical laboratory are included to test the proposed code. The output of watershed transformation algorithm is as shown below. Firstly the original MRI brain image is as shown in figure below is transformed to a proposed watershed algorithm is that a superimposed image of ridge lines and original binary image, note the over segmentation. The results for the k-means clustering algorithm are also shown below as labeled figures with details.

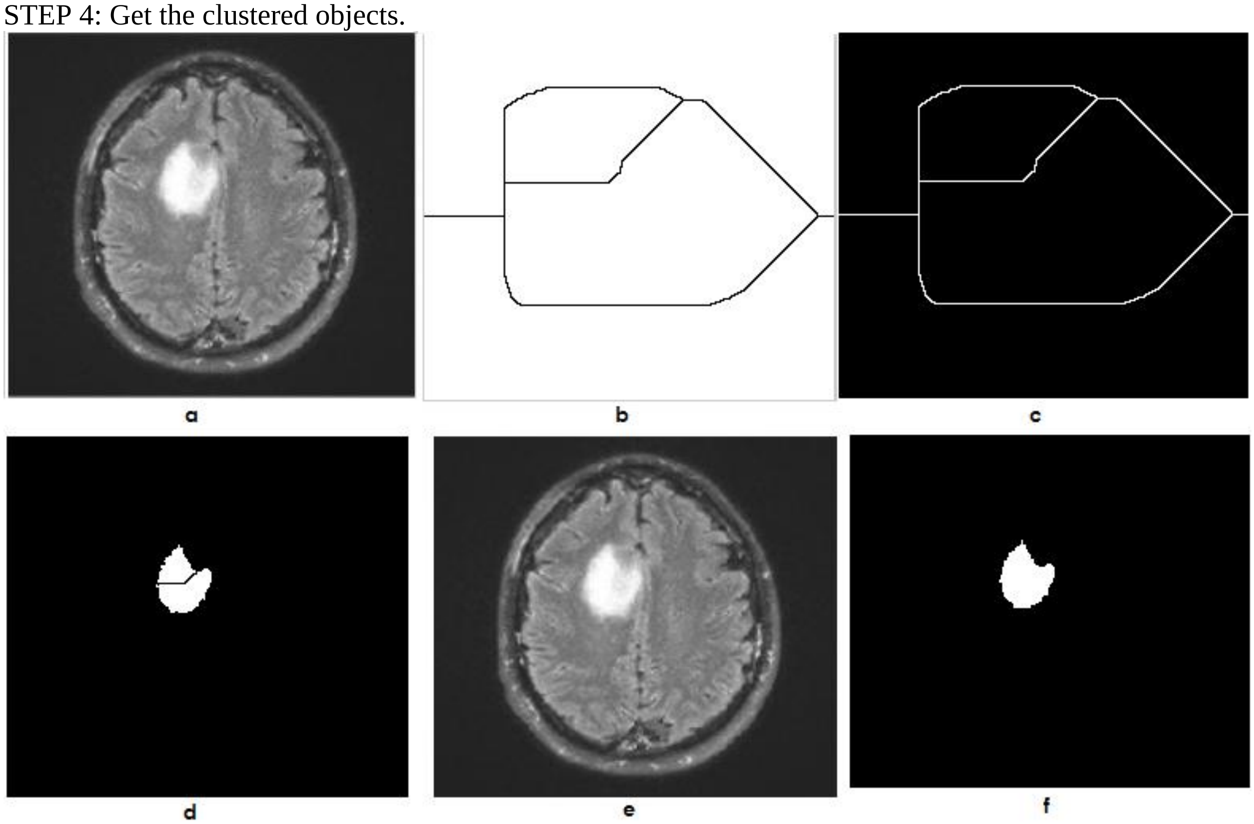
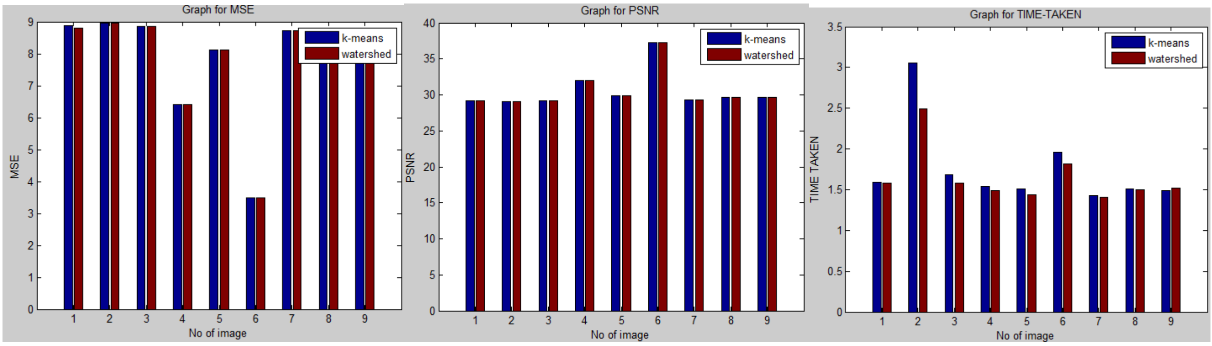


Figure 2. a) inout image for watershed segmentation, b) watershed mask, c) negative watershed mask, d) watershed output, e) input image for k-means clustering algorithm, f) k-means clustering output



a b c

Figure 3. a) Performance graph for Mean square error, b) performance graph for PSNR c) execution time graph.

Watershed Algorithm (Performance Table)

Sr. No.	Image	Area	radius	perimeter	MSE	PSNR	Execution Time
1	1.jpg	59856	138.31	867.27	8.88	29.15	5.42
2	2.jpg	182156	240.79	1512.95	8.96	29.08	3.56
3	3. jpg	74750	154.25	969.19	8.86	29.17	1.86
4	4. jpg	44128	118.51	744.66	6.42	31.97	1.59
5	5. jpg	45790	120.72	758.56	8.11	29.94	1.76
6	6.png	149768	218.34	1371.87	3.50	37.24	2.35
7	7.jpg	50235	126.45	794.52	8.73	29.30	1.52
8	8.jpg	39240	111.76	702.21	8.41	29.63	1.55
9	9.jpg	50388	126.64	795.73	8.43	29.60	1.54

k-means clustering algorithm (Performance Table)

Sr. No.	Image	Area	radius	perimeter	MSE	PSNR	Execution Time
1	1.jpg	57964	135.83	853.46	8.81	29.23	5.14
2	2.jpg	181076	240.07	1508.46	8.96	29.08	2.90
3	3. jpg	73377	152.82	960.25	8.86	29.17	2.65
4	4. jpg	42820	116.74	733.54	6.42	31.97	3.01
5	5. jpg	45361	120.16	754.99	8.11	29.94	2.41
6	6.png	148695	217.55	1366.95	3.50	37.24	2.75
7	7.jpg	49474	125.49	788.48	8.73	29.30	2.34
8	8.jpg	37749	109.61	688.74	8.43	29.60	2.29
9	9.jpg	50097	126.27	793.43	8.43	29.60	2.43

These tables show the results obtained by the proposed algorithms watershed algorithm and k-means clustering algorithm. These algorithms are implemented on different images taken from the laboratory for our research work. Calculation of area, radius, perimeter, mse, psnr and time taken is shown.

V. DISCUSSIONS

The need of the re-initialization is completely eliminated by the proposal of Chunming Li, for pure partial differential equation driven level set methods, the variational level set methods. It can be easily implemented by using simple finite difference method and is computationally more efficient than the traditional level set methods. But, in this algorithm, the edge indicator has little effect on the low contrast image. So it is hard to obtain a perfect result when the region has a fuzzy or discrete boundary. Mean while, the initial contour of evolution needs to be determined by manual, and it has the shortcomings of time consuming and user intervention. In this paper, we projected a new method to transform the algorithm. With the new edge indicator function, results of image segmentation showed that the improved algorithm can exactly extract the corresponding region of interest. Under the same computing proposal, the average time cost was lower. The iterative time of the k-means clustering algorithm is reduced as compared to watershed algorithm.

VI. CONCLUSIONS

In this paper, we proposed a new technique to replace the existing algorithm in the original space and then derived the alternative kernel-based k-means algorithm. The results of this paper confirmed that the methods we proposed could be used for the segmentation of low contrast images and medical images. The method has the advantages of calculating various parameters and reducing the time consumption. The validity of new algorithm was verified in the process of exacting details of images. In the future research, some better GUI design could be implemented and some new technique could also be offered.

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