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BRAIN TUMOR AND CLUSTERING TECHNIQUES REVIEW

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Abstract: A tremendous growth has been done in the last decade for brain tumor in the region of cerebral cancer diagnosis. Cerebral cancer has been noticed that is spreading over the world and many colleges and university medical research centers are focusing on the issue. It can be understand with an example in US, in which 3000 children are facing the brain related diagnosis and brain tumors. Half of the children are dying at the age of 5 years and leaving a fatal cancer in other children too. The problem is more associated with neurological disabilities psychological problems, retardation that is leading the cause and risk of death. The paper focus on the review of the problems related to brain tumor in medical image processing and different clustering techniques to segment the brain.

Keywords: Image segmentation, Digital Image Processing (DIP), Magnetic resonance imaging (MRI),

1. Introduction

The rapid evolution of advanced medical image modalities such as the modern MRI scanners and the large amount of data provided have brought about the need for more automatic processes in computer aided diagnosis. Clinicians need to examine large numbers of complex medical images to detect abnormalities; a difficult and time consuming task. Hence, there is a need for systems that will automatically detect organs and their possible abnormalities and provide useful metrics. In a survey of systems focusing on identifying pathologies in transplanted kidneys with most of those methods suffering from low accuracy, or the need for extended involvement of clinicians to identify organs and abnormalities was presented. In the field of transplant kidney rejection, and presented a related system based on dynamically enhancing the contrast of 2-D MRI images with achieve organ identification. The first part of their method is related to our own system and achieved an average accuracy of 92.31% (although our system focuses on tumor detection as well as generic abnormalities). Similarly, Breast cancer is a major health problem that affects the lives of millions. For the year 2012, it was estimated that 226,870 women in the United States will be diagnosed with breast cancer and that 39,510womenwill succumb to it .With these numbers, breast cancer is the leading cancer diagnosed in the US women and is second only to lung cancer in terms of total fatalities . It is generally recognized that much scientific advancements have been made in the area of breast cancer research, and it is because of these efforts that the chances of disease-free survival of breast cancer survivors have increased tremendously over the last few decades. However, this applies only if the breast cancer is diagnosed at an early stage and is limited to the primary organ. Once breast cancer metastasizes to other organs, the therapeutic options are very limited and the success rate of managing such patients in clinics is dismal.

Neuroendocrine tumors (NETs) are neoplasms derived from nerve and endocrine cells. NETs have the ability to produce hormones and have similarities with nerve cells, such as cytoplasmic granules and exocytotic machinery. NETs were called “carcinoid” 100 years ago and were considered benign neoplasms. Currently they are considered to be malignant, and the WHO histopathological classification eliminated the “carcinoid” label in 2000. In the WHO classification of 2010, NETs were defined as neuroendocrine neoplasms and were classified as NET G1, NET G2, NEC (large cell or small cell type), mixed adenoneuroendocrine carcinoma (MANEC), hyperplastic, and preneoplastic lesions, by theKi-67 index. NETs are increasing and are therefore attracting interest and attention. Generally, the majority of metastases occur in the liver, lungs, and bone. Other sites are rarer, and brain metastases are very rare. Here we present a case report of a probable primary brain NET. To our knowledge, this is the first reported case of a primary NET arising in that anatomical location. A 77-year-old man presented with headache and disturbance of skilled motor activities.The past medical history included hypertension, diabetes, and chronic idiopathic pericardial effusion. On physical examination, the Glasgow Coma Scale (GCS) score was 14 (E4V4M6), and finger agnosia and left-right disorientation were noted, like in the Gerstmann syndrome. Blood and CSF analyses were normal. Levels of tumor markers, including CEA, CA19-9, NSE, AFP, and IL- 2R, were normal. Head computed tomography (CT) showed a massive neoplastic lesion of 6.6 cm in diameter originating in the left temporal and parietal lobes that caused a mass edematous effect. Enhanced CT showed ring enhancement. The research in the field of medical imaging such as brain tumor and kidney stone will help both to the researcher, academician and mathematician to develop the algorithms with detection and removal of diseases in optimal time and industry will follow the same to produce its new medical instrument and provide latest disease solution.

Brain controls memory and learning, senses (hearing, sight, smell, taste, and touch), and emotion. It also controls other parts of the body, including muscles, organs, and blood vessels.

Brain tumors are diseases in which cancer (malignant) cells begin to grow in the tissues of the brain.Radiation oncologists, radiologists, and other medical experts spend a substantial portion of their time segmenting medical images. Segmentation is a tool that has been widely used in medical image processing and computer vision for a variety of reasons. Magnetic resonance [13] imaging (MRI) is an advanced medical imaging technique providing rich information about the human soft tissue anatomy. It has several advantages over other imaging techniques. The goal of magnetic resonance (MR) image segmentation is to accurately identify the principal tissue structures in these image volumes. In particular, the task of labeling brain tumors and edema in

MRI images are highly time consuming and there exists significant variation between the labels produced by different experts.[8] Further, in most cases the 2D image slices are labeled independently without taking into account the global 3D brain structure leading to potentially inaccurate segmentations. Subsequently, a large amount of research has been focused on semiautomatic and fully automatic methods for detecting and/or segmenting brain tumors from MRI scans.

2. Related Work

The review carried out on the following papers and discussed in brief

A.R Kavita et at.[1] In this paper, they propose an effective modified region growing technique for detection of brain tumour. Modified region growing includes an orientation constraint in addition to the normal intensity constrain. The performance of the proposed technique is systematically evaluated using the MRI brain images received from the public sources. For validating the effectiveness of the modified region growing, the quantity rate parameter has been considered. For the evaluation of the proposed technique of tumor detection, the sensitivity, specificity and accuracy values theyre used. Comparative analyses theyre made for the normal and the modified region growing using both the Feed Forward Neural Network (FFNN) and Radial Basis Function (RBF) neural network. The results show that the modified region growing achieved better results when compared to the normal technique. Region growing is an important application of image segmentation in medical research for detection of tumour. The MRI image dataset taken from the publicly available sources contains 40 brain MRI images in which 20 brain images with tumour and the other 20 brain images without tumour. The performance of proposed technique is evaluated by considering the region growing algorithm and the modified region growing algorithm in terms of the quality rate. The tumour detection is evaluated through performance metrics namely, sensitivity, specificity and accuracy. Comparative analyses were made considering the normal and the modified region growing using both the Feed Forward Neural Network (FFNN) and Radial Basis Function (RBF) neural network. From the results obtained, they could see that the modified region growing technique received a better quantity rate for all the input images. From the metrics obtained, it is seen that the proposed technique gives better results in terms of sensitivity, specificity and accuracy proving its effectiveness.

Ali Gholipouret at. [2]Functional localization is a concept which involves the application of a sequence of geometrical and statistical image processing operations in order to define the location of brain activity or to produce functional/parametric maps with respect to the brain structure or anatomy. Considering that functional brain images do not normally convey detailed structural information and, thus, do not present an anatomically specific localization of functional activity, various image registration techniques are introduced in the literature for the purpose of mapping functional activity into an anatomical image or a brain atlas. The problems addressed by these techniques differ depending on the application and the type of analysis, i.e., single-subject versus group analysis. Functional to anatomical brain image registration is the core part of functional localization in most applications and is accompanied by inter subject and subject-to-atlas registration for group analysis studies. Cortical surface registration and automatic brain labeling are some of the other tools towards establishing a fully automatic functional localization procedure. While several previous survey papers have reviewed and classified general-purpose medical image registration techniques, this paper provides an overview of brain functional localization along with a survey and classification of the image registration techniques related to this problem.

Jason J. Corso at at. [4] In the paper the authors have made three technical contributions. The main contribution is the mathematical formulation for bridging graph-based affinities and generative model-based techniques. Second, we extend the SWA algorithm to integrate model-based terms into the affinities during the coarsening. The model-aware affinities integrate classification without making premature hard, class assignments. Using model-specific affinity functions has clear advantages over conventional static affinity methods, both intuitively and justified in the experimental results. The third contribution is a mathematical formulation for learning the parameters of the model-specific affinity functions directly from training data. Furthermore, the algorithm is computationally efficient, running orders of magnitude faster than current state of the art methods. They apply these techniques to the difficult problem of segmenting and classifying GBM brain tumor in multichannel MR volumes. Our approach improves upon the current state-of-the-art in GBM brain tumor segmentation by incorporating information at multiple scales. The results show good segmentation and classification on a comparatively large dataset. We note that the technical contributions in this paper are general and can be applied to other problems with the proper application-specific models. They thoroughly analyze the failure modes of our algorithm. While the majority of the cases are segmented with accuracies near 70%, the failure modes will need to be addressed before the method is ready for the clinic, which is the goal. To that end, we have suggested possible solutions to fixing them, and we are developing a global context model of normal brain anatomy (cortical and subcortical structures) and brain tumor that will help disambiguate the complex phenomena exhibited in some of the more difficult cases. We are currently investigating stochastic methods to solve the extraction problem by treating the graph hierarchy as a set of model proposals as in Swendsen- Wang sampling.

K. S. Angel Vijiet at. [5]In this paper, after a manual segmentation procedure the tumor identification, the investigations has been made for the potential use of MRI data for improving brain tumor shape approximation and 2D & 3D visualization for surgical planning and assessing tumor. The results show that Watershed Segmentation is the best method to segment a tumor in MATLAB environment, provided the parameters are set properly. If the intensity level difference between the cancerous and non-cancerous regions is higher than the performance of Watershed Segmentation algorithm is better.

RachanaRanaet at. [5]In this paper, a computer-aided fully automatic brain tumour segmentation technique is proposed for Tl-weighted Coronal MRI data without any priori information. It provides lower missing rate and higher segmentation accuracy comparing to existing techniques. They have illustrated that some standard segmentation algorithms (such as level set method or normalized graph cut) can delineate exact tumour boundary if these algorithms are applied only within the bounding box. This region based approximate segmentation technique can enable effective MR database indexing system. Experimental results extract by method is very fast, efficient for indexing tumour images for both archival and retrieval purposes and it can be used as a vehicle for further clinical investigations.

Level Set method is better where the level of intensity difference between the tumours and nontumours regions is higher. Moreover, it can segment non-homogenous tumours provided the non-homogeneity is within the tumours region.

3. Image Clustering Techniques

The clustering techniques attempts to access the relationships among patterns of the data set by organizing the patterns into groups or clusters such that patterns within a cluster are more similar to each other than patterns belonging to different clusters.That is, clustering refers to the classification of objects into groups occurring to certain properties of same objects. In the clustering technique, an attempt is made to extract a vector from local areas of the image.A standard procedure for clustering is to assign each pixel to the class of the nearest cluster, mean. Clustering methods can be divided into two categories:

1. Hierarchaical clustering
2. Partitional clustering

Within each category, there exist many types of algorithms for finding cluster.

Hierarchical clustering:Hierarchical clustering techniques are based on the use of a proximity matrix indicating the similarity between every pair of data points to be clustered. The end result is a tree of clusters representing the nested group os patterns and similarity levels at which groupings changes. The resulting clusters are always produced as the internal nodes of the tree, while the root node is reserved for the entire dataset and leaf nodes are for individual data samples

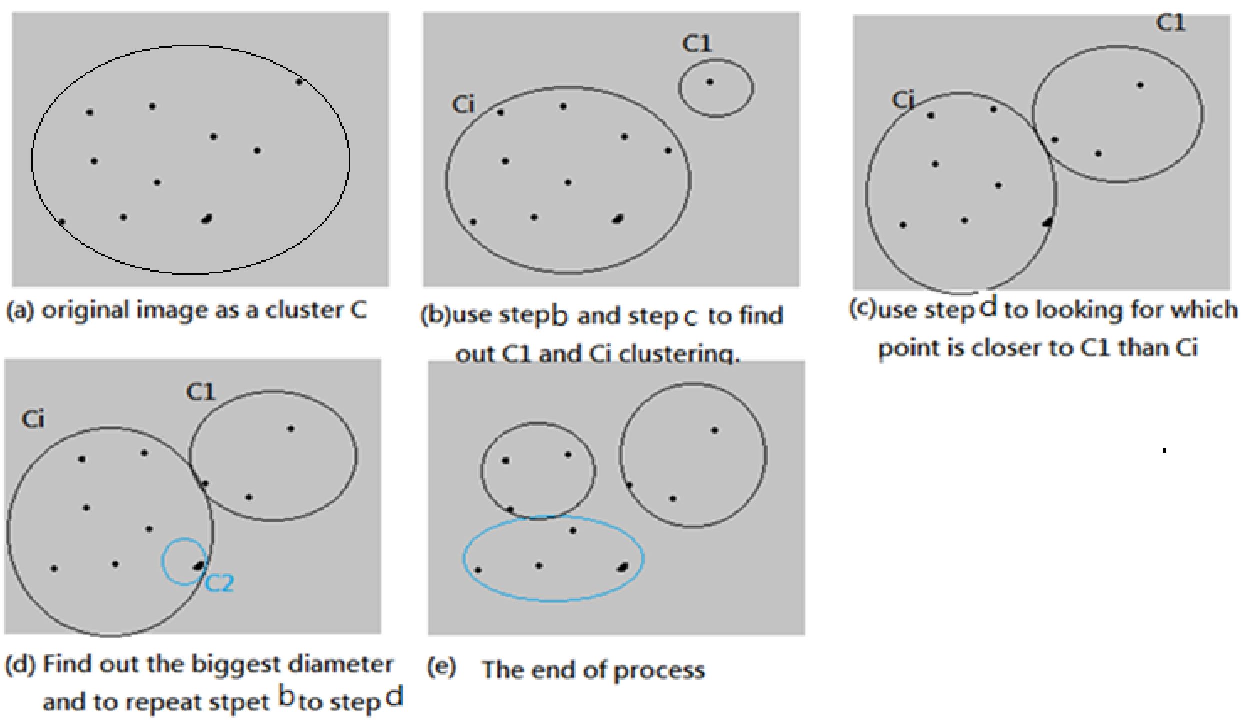

Fig 1 Hierarchical clutering

The clustering method differs in regard to the rules by which two small clusters are merged or a large cluster is split. The two main categories of algorithms used in the hierarchical clustering framework are agglomerative and divisive. Agglomerative algorithms seek to merge clusters to be larger and larger by starting with N single point clusters.The algorithm can be divided into three classes:

1. Single link algorithm
2. Complete link algorithm
3. Minimum variance algorithm

The single link algorithm merges two clusters according to the minimum distance between the data samples from two clusters. According, the algorithm allows for a tendency to produce clusters with elongated shapes. A complete link algorithm incorporates the maximum distance between data samples in clusters, but its application always results in compact clusters. The quality of hierarchical clustering depends upon how the dissimilarity measurement between two clusters is defined.The minimum variance algorithm combines two clusters in the sense of minimizing the cost function, namely, to form a new cluster with a minimum increase of the cost function. This algorithm has attracted considerable interest in vector quantization, where it is termed pair wise-nearest-neighborhood algorithm. Divisive clustering begins with the entire dataset in the same cluster, followed by iterative splitting of the dataset until the single-point clusters are attained on leaf nodes. It follows a reverse clustering strategy against agglomerative clustering. On each node, the divisive algorithm conducts a full search for all possible pairs of clusters for data samples on the node. Some of the hierarchical algorithms includes COBWEB, CURE and CHAMELEON.

Partition Clustering:Partition based clustering uses an iterative optimization procedure that aims at minimizing an objective function f, which measures the goodness of clustering. Partition based clustering are composed of two learning steps. The partitioning of each pattern to its closest clusters and the computation of the cluster centroid.A common feature of partition base clustering is that the clustering procedure starts from an initial solution with a known number of clusters.

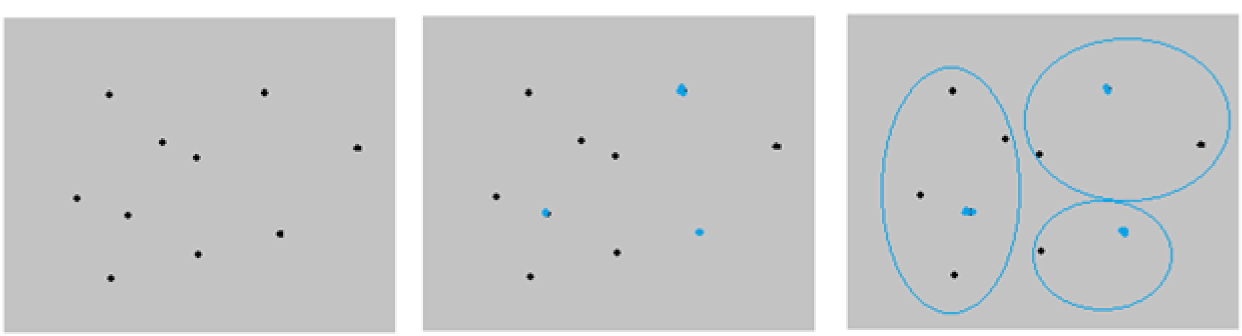

Fig. 2Partition clustering

The clusters centroids are usually computed based on the criterion such that the objective function is minimized.Partitionalgorithms are categorized into

1. Partitioning relocation algorithms
2. Density based partitioning

The Algorithms of the first type are further categorized into-

a. Probabilistic Clustering
b. K-medoids
c. K –means

The second type of partition algorithms, called density based partitioning; include algorithms such as DBSCAN, OPTICS DBC,DENCLUE.Partition clustering techniques such as K-means clustering and ISODATA have an advantage over hierarchical clustering techniques, where a partition of the data points

K - Mean Clustering:The K mean method is the simplest method in unsupervised classification. The clustering algorithms do not require any training data.K-means clustering is an iterative procedure. The K means clustering algorithms clusters data by iteratively computing a mean intensity for each class and segmenting the image by classifying each pixels in the class with the closet mean.The step involved in the k mean clustering algorithm is given below:

- Choose initial value of cluster.
- At kth iterative step, distribute the samples
- Compute the new cluster centers zj(k+1).
- If zj(k+1),j=1,2,3,…….k, the algorithm is terminated otherwise go to step 2.
- The drawback the K-means algorithm is that the number of clusters is fixed, once K is chosen and it always returns K cluster centers.

Fuzzy Clustering: Clustering methods can be classified as either hard or fuzzy depending on whether a patter data belong exclusively to a single cluster or to several clusters with different degrees. In hard clustering, a membership value of zero or one is assigned to each pattern data, whereas in fuzzy clustering, a value between zero and one is assigned to each pattern by a membership function.In general, fuzzy clustering methods can be considered to be superior to those of their hard counterparts since they can represent the relationship between the input pattern data and cluster more naturally.Fuzzy clustering seeks to minimize a heuristic global cost function by exploiting the fact that each pattern for multiple assignment of clusters.The fuzzy K mean algorithm iteratively updates the cluster centroid and estimates the class membership function by using the gradient descent approach.

4. Results & Discussion

To test the effectiveness of the proposed scheme, we have tested the density based morphological brain MR Image segmentation method Fig. 3 shows the MATLAB simulation carried out binary gradient mask, dilated mask, binary with filled holes, cleared border image and image segmentation applied as primary need for brain tumor detection techniques.

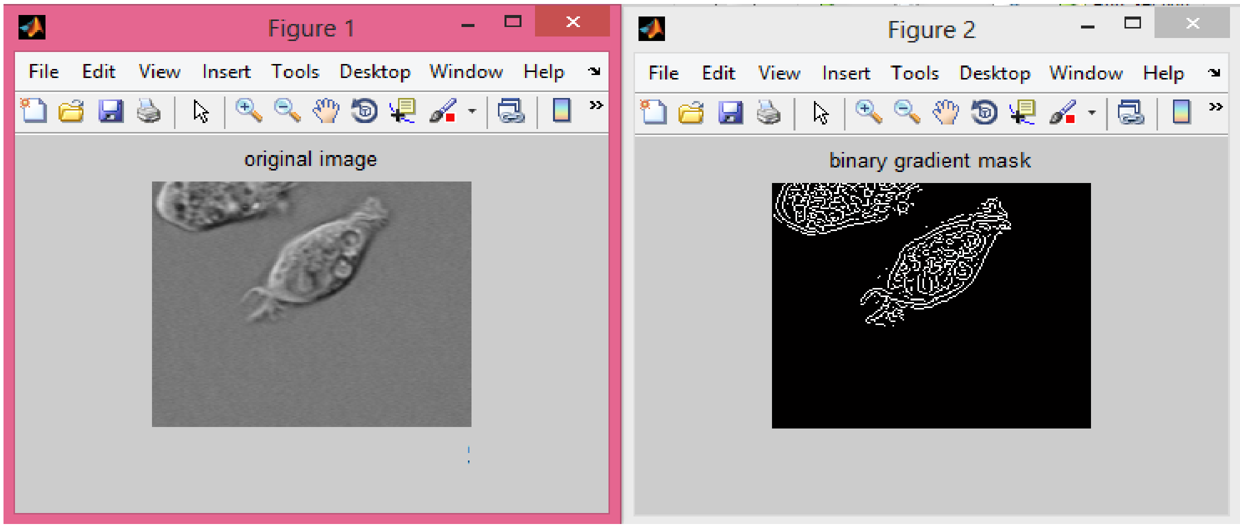

Fig. 3(a) original Image (b) Binary gradient mask

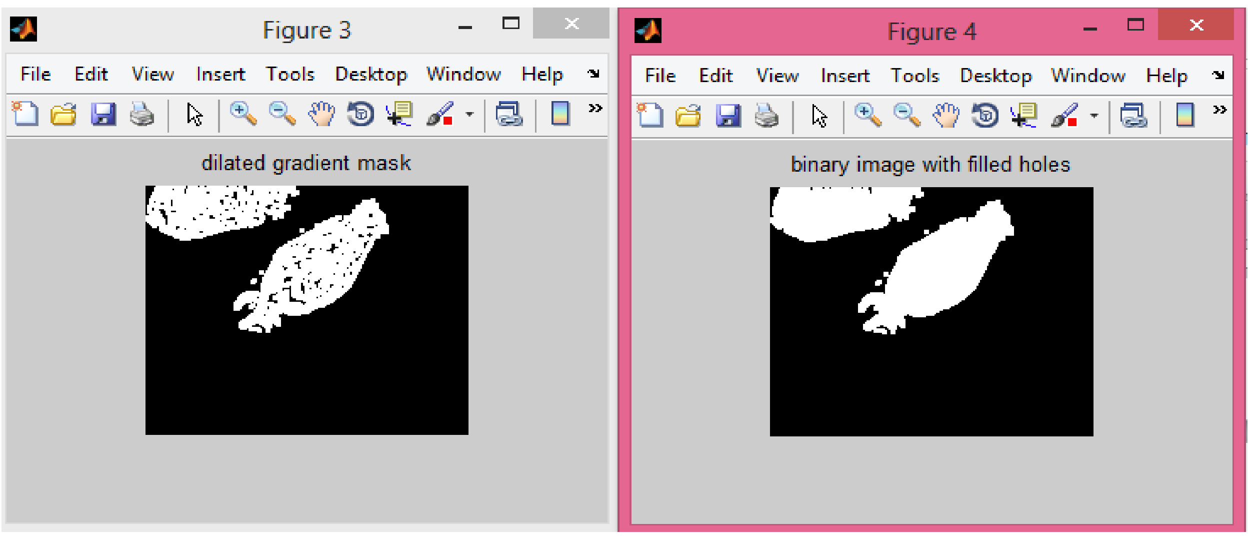

Fig. 3(c) Dilated gradient mask (d) Binary image with filled holes

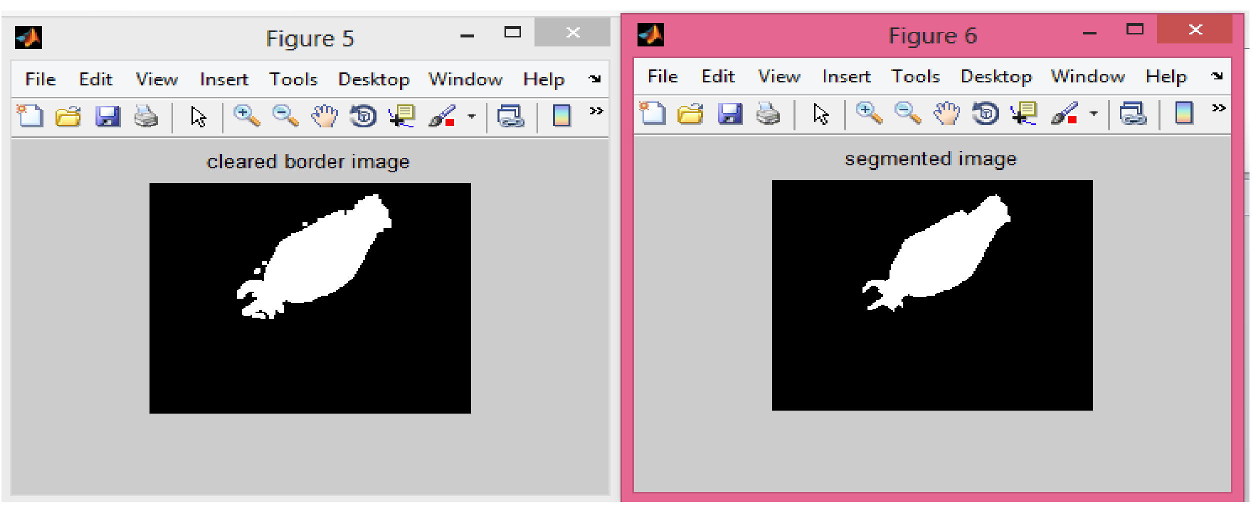

Fig. 3(e) Cleared border image (f) Segmented image

5. Conclusions

Brain MRI gives different information about those structures in the body which are otherwise observable with an X-ray, ultrasound, or computed tomography (CT) scan, but the advantage of MRI is the higher quality of its images and lack of side effects on the body tissues. MRI employs a magnetic field and pulses of radio wave energy to make pictures of organs and structures inside the body.The incidence of brain metastases for neuroendocrine tumor (NET) is reportedly 1.5∼5%, and the origin is usually pulmonary. The process of segmenting tumors in MR images as opposed to natural scenes is particularly challenging. The tumors vary greatly in size and position, have a variety of shape and appearance properties, have intensities overlapping with normal brain tissue, and often an expanding tumor can deflect and deform nearby structures in the brain giving an abnormal geometry also for healthy tissue. tivities. Brain tumor is a serious case and research should be carried out in the detection and extraction of brain tumor.

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