



TUMOR DETECTION AND CLASSIFICATION MRI BRAIN IMAGE BY USING DWT AND CLUSTERING METHODS WITH SUPPORT VECTOR MACHINE

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Abstract: The accurate and effective algorithm for segmenting image is very useful in many fields, especially in medical image. In this paper we introduced a novel method that focus on segmenting the brain mr image that is important for neural diseases. Because of many noises embedded in the acquiring procedure, such as eddy currents, susceptibility artifacts, rigid body motion, and intensity in homogeneity, segmenting the brain mr image is a difficult work. In this algorithm, we overcame the in homogeneity shortage, by modifying the objective function with compensating its immediate neighborhood effect using Gaussian smooth method for decreasing the influence of the in homogeneity and increasing the segmenting accuracy. With simulate image and the clinical mri data, the experiments shown that our proposed algorithm is effective by using mat lab.

1. Introduction:

Brain tumor segmentation is one of the crucial procedures in surgical and treatment planning. However, at present, brain tumor segmentation in brain tumor images is mostly performed manually in clinical practice. Apart from being time consuming, manual brain tumor delineation is difficult and depends on the individual operator. MRI became the most preferred imaging technique in radiology because MRI enabled internal structures be visualized in some detail. With MRI, good contrast between different soft tissues of the body can be observed. This makes MRI suitable for providing better quality images for the brain, the muscles, the heart and cancerous tissues compared with other

medical imaging techniques, such as computed tomography (CT) or X-rays. Currently, multimodal MRI images are used simultaneously by radiologists in segmenting brain tumor images because multimodal MRI images can provide various data on tumors. Under certain conditions, brain cells grow and multiply uncontrollably because for some reasons, the mechanism that control normal cells is unable to regulate the growth of the brain cells. The abnormal mass of brain tissue is the brain tumor that occupies space in the skull and interrupts the normal functions of brain and creates an increasing pressure in the brain. Due to increased pressure on the brain, some brain tissues are shifted, pushed against the skull or are responsible for the damage of the nerves of the other healthy

brain tissues. Scientists have classified brain tumor according to the location. Segmentation is an important process in most medical image analysis and classification for radio logical evaluation or computer-aided diagnosis. basically, image segmentation methods can be classified into three categories:

- 1) edge-based methods,
- 2) region-based methods
- 3) pixel-based methods

k-means clustering is a key technique in pixel-based methods. Because pixel-based methods based on k-means clustering are simple and the computational complexity is relatively low compared with the region-based or edge-based methods, the application is more practicable. further more means clustering is suitable for biomedical image segmentation as the number of clusters is usually known for images of particular regions of the human anatomy.

2. Related Work

Topic :image segmentation via adaptive k-mean clustering and knowledge-based morphological operations

Image segmentation remains one of the major challenges in image analysis. In medical applications, skilled operators are usually employed to extract the desired regions that may be anatomically separate but statistically indistinguishable. Such manual processing is subject to operator errors and biases, is extremely time consuming, and has poor reproducibility. We propose a robust algorithm for the segmentation of three-dimensional (3-d) image data based on a novel combination

of adaptive k-mean clustering and knowledge-based morphological operations. The proposed adaptive k-mean clustering algorithm is capable of segmenting the regions of smoothly varying intensity distributions. Spatial constraints are incorporated in the clustering algorithm through the modeling of the regions by gibbs random fields. Knowledge-based morphological operations are then applied to the segmented regions to identify the desired regions according to the a priori anatomical knowledge of the region-of-interest. This proposed technique has been successfully applied to a sequence of cardiac ct volumetric images to generate the volumes of left ventricle chambers at 16 consecutive temporal frames. Our final segmentation results compare favorably with the results obtained using manual outlining. Extensions of this approach to other applications can be readily made when a priori knowledge of a given object is available.

3. Proposed system

3.1 Wavelets Method

The Wavelet change is a change of this sort. It gives the time-recurrence portrayal. (There are different changes which give this data as well, for example, brief time Fourier change, Wigner dispersions, and so on.)

As a rule a specific ghostly segment happening at any moment can be specifically compelling. In these cases it might be helpful to know the time interims these specific otherworldly segments happen. For instance, in EEGs, the idleness

of an occasion related potential is specifically compelling (Event-related potential is the reaction of the cerebrum to a particular improvement like blaze light, the inactivity of this reaction is the measure of time passed between the beginning of the upgrade and the reaction).

Wavelet change is equipped for giving the time and recurrence data at the same time, consequently giving a period recurrence portrayal of the picture. DWT utilizes two arrangements of capacities, called scaling capacities and wavelet capacities, which are related with low pass and high pass channels, separately. The disintegration of the picture into various recurrence groups is essentially gotten by progressive high pass and low pass sifting of the time space picture. The first picture $x[n]$ is first gone through a half band high pass channel $g[n]$ and a low pass channel $h[n]$. After the sifting, half of the examples can be dispensed with as per the Nyquist's standard, since the picture currently has a most noteworthy recurrence of $\pi/2$ radians rather than π . The picture can consequently be sub sampled by 2, basically by disposing of each other example. This comprises one degree of decay and can numerically be communicated as pursues:

$$y_{high}[k] = \sum_n x[n] \cdot g[2k - n]$$

$$y_{low}[k] = \sum_n x[n] \cdot h[2k - n]$$

where $y_{high}[k]$ and $y_{low}[k]$ are the yields of the high pass and low pass channels, individually, in the wake of sub sampling by 2.

The recreation for this situation is extremely simple since half band channels structure orthonormal bases. The above method is followed backward request for the remaking. The pictures at each level are up sampled by two, went through the combination channels $g'[n]$, and $h'[n]$ (high pass and low pass, individually), and after that additional.

3.2 K-mean algorithm

In the proposed method, we combine histogram statistics and k-means clustering to track the tumor objects in MR brain images. It's the on the techniques for the clustering concept in the data mining process and is very famous algorithm for the K-means clustering, because it is similar or simpler and easier in computation of an efficient K-means clustering algorithm it is the simplest unsupervised learning algorithms that solve the well known clustering problems. It's the K-means algorithm is an unsupervised clustering algorithm that classified in the input data points into multiple classes based on their intrinsic distance from other dataset points of his cluster The flowchart of our method is shown as fig.1.

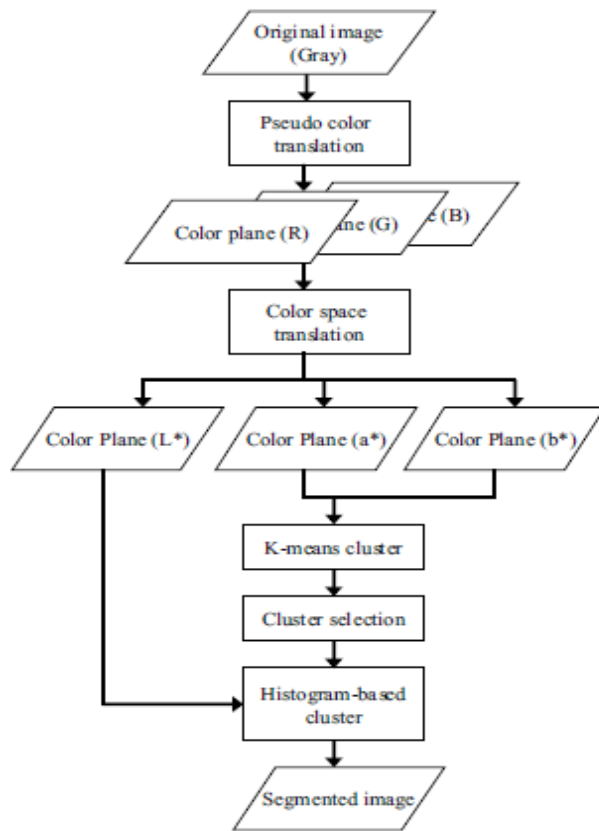


fig:1. Present algorithm for k-means

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 similar feature vectors into as in glecluster and for grouping data points with dissimilar feature vectors into different clusters. let the feature vectors derived from l clustered data set $\{x_{ji} | 1, 2, \dots, l\}$. The generalized algorithm initial task cluster centroids $c \square \{c_j | j=1, 2, \dots, k\}$ by randomly selecting k feature vectors from x . a pixel

can be classified into one or the two classes. An image $f(x,y)$ can be segmented into two classes using a gray value threshold t so that

$$g(x,y) = \begin{cases} 1 & \text{if } f(x,y) > T \\ 0 & \text{if } f(x,y) \leq T, \end{cases} \quad (1)$$

$$J_m = \sum_{i=1}^N \sum_{j=1}^C u_{ij}^m \|x_i - c_j\|^2, \quad 1 \leq m < \infty$$

Where m is any real number greater than 1, u_{ij} is the degree of membership of x_i in the cluster j , x_i is the i th of d -dimensional measured data, c_j is the d -dimension center of the cluster, and $\|*\|$ is any norm expressing the similarity between any measured data and the center.

4. SVM The classification

SVM The classification of hand gesture images is performed using the SVM classifier by employing one-against-all (OAA) approach. Support Vector Machine is a powerful machine learning technique for classification and regression. It is a supervised learning machine where its support vectors and kernels are employed for many learning tasks. By choosing the appropriate kernel functions, different tasks could be performed in various domains. A support vector machine constructs a separating hyper plane in a high dimensional space. SVM is used to classify the group of test data as one of the ten gestures, depending upon the feature values. In this research, classification is done for ten categories of gesture images. Therefore, ten

binary SVM models are created where each SVM model is trained to distinguish one class of images from the remaining nine classes. For example, the SVM classifier for class one data (number zero) is assigned +1 and the remaining nine classes (numbers one, two, three, four, five, six, seven, eight, nine) are assigned as -1. Other SVM classifiers are constructed on the same way. Ten SVMs are trained independently for classifying ten classes of hand gestures. When the test or query image is given, it is classified based on the trained SVM models This can be rewritten as: We can put this together to get the

$$\vec{w} \cdot \vec{x}_i + b \geq 1, \text{ if } y_i = 1$$

OR

$$\vec{w} \cdot \vec{x}_i + b \leq -1, \text{ if } y_i = -1.$$

To for "The and that solve this problem determine our classifier, An easy-to-see but important consequence of this geometric description is that max-margin hyper plane is completely determined by those which lie nearest to it. These are called support vectors.

5.Extraction Stage

Feature extraction is the process of getting useful information from the Image/character image. The information will be used to generate modules to train the classifier and to be used for classification purposes. In general there are two categories of features extracted, structural and statistical features. Choosing the right feature extraction method might be the most important step for achieving a high recognition rate . However, in some cases

the combination of several features extraction types could be a wise decision to enhance the overall recognition performance.

6.Result

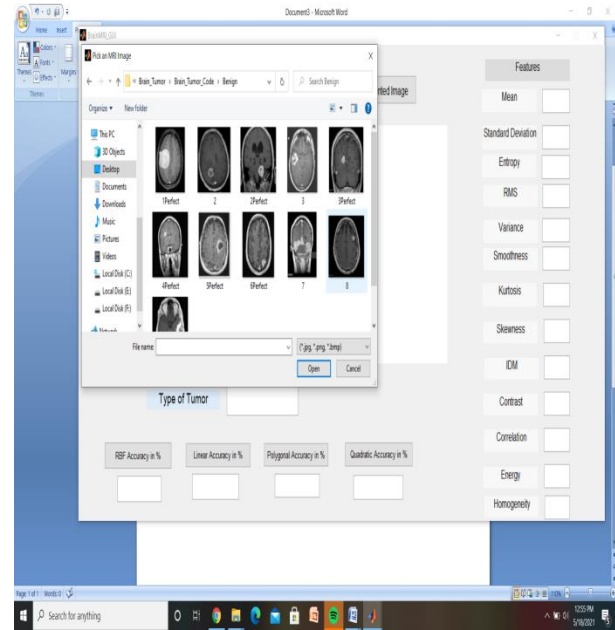


Fig: Selection Of Input Image

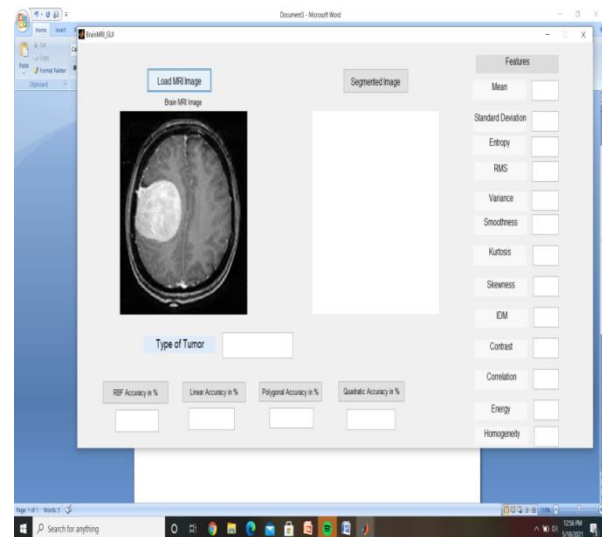


Fig: Input Image

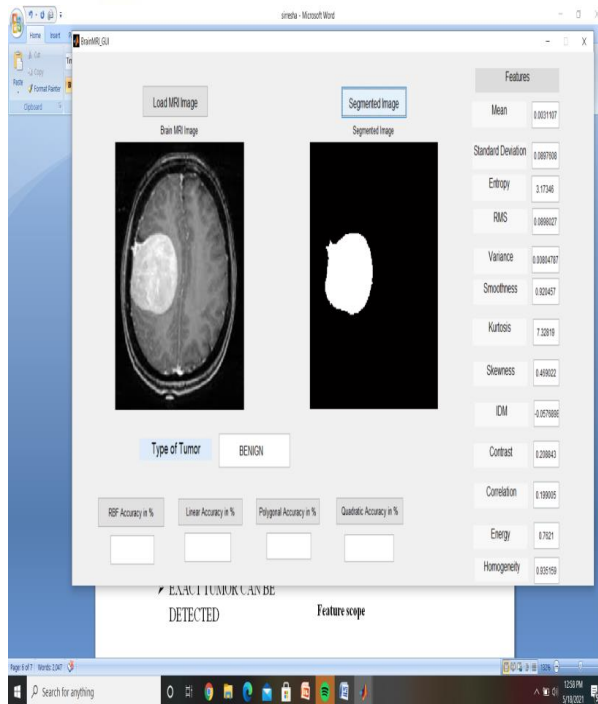


Fig: Segmented Image And Classification Image

APPLICATIONS

- BIO_-MEDICAL_IMAGE PROCESSING

ADVANTAES

- TUMOR AREA CAN BE REDUCE
- EXACT TUMOR CAN BE DETECTED
- EFFICIENCY CAN BE INCREASE

7.Conclusion

In this paper, we have described an unsupervised fuzzy segmentation method, based on new objective function, which seems well adapted and efficient for functional MRI data segmentation. The

proposed segmentation method is more robust than the FCM algorithm and k-means. When the real data are fuzzy, such as functional MRI brain data, the use of FCM segmentation is always more effective than the use of the other one. Further quantitative validation on more accuracy and stability of the method is still necessary, using realistic phantoms and a large number of clinical scans.

The results presented in this paper are preliminary and further clinical evaluation is required. There are also need new methods for preprocessing the original image, including denoising and enhancing to increase the SNR. How to combine segmenting with preprocessing procedure is our work in future.

Feature scope

As a future work, network performance can be analyzed with different bit mask and 'm' value along with different textural features.

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