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Various clustering algorithms that implemented on the brain tumor identification

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Abstract:

Image segmentation technology has always been one of key technologies in image processing, in recent years, many algorithms are applied in the field of image segmentation. Image segmentation technology divides the image into several areas, and needed information is extracted. General segmentation technology are based on threshold segmentation method, based on region segmentation method, the segmentation method based on edge, and the segmentation method based on the specific theory. In this paper study the different clustering methods in image segmentation. In view of the traditional clustering image segmentation algorithm for image segmentation accuracy is low problem, put forward a kind of fuzzy control based on C-means clustering image segmentation method. Methods firstly in clustering image segmentation algorithm based on fast, using fuzzy C-means clustering algorithm for image segmentation. The experimental results show that the algorithm in clustering, to optimize the performance of the same premise, image segmentation edge clear, segmentation better than traditional clustering algorithm for image segmentation.

Keywords: Image segmentation, fuzzy c-means clustering algorithm and optimization.

Introduction

MRI is an advanced medical imaging technique providing rich information about the human soft-tissue anatomy. It is mostly used in radiology in order to visualize the structure and function of the human body. It produces the very detailed images of the body in any direction. Particularly, MRI is useful in neurological (brain), musculoskeletal, and oncological (cancer) imaging because it offers much greater contrast between the diverse soft tissues of the body than the computer tomography (CT). MRI is different from CT, it does not use ionizing radiation, but uses an effective magnetic field to line up the nuclear magnetization of hydrogen atoms in water in the body.

Most research in developed countries has exposed that the death rate of people affected by brain tumor has increased over the past three decades. Today, one of the major causes for the increase in fatality among children and adults is brain tumor. A tumour is a mass of tissue that grows out of control of the normal forces that regulates growth [panos kotsas (2005)]. Tumours can directly destroy all healthy brain cells. It can also indirectly damage healthy cells by crowding other parts of the brain and causing inflammation, brain swelling and pressure within the skull. Brain tumours are of different sizes, locations and positions. They also have overlapping intensities with normal tissues.

Tumour can be benign or malignant can occur in different parts of the brain and may or may not be primary tumours. The most common primary brain tumours are Gliomas, Meningiomas, Pituitary adenomas and Nerve sheath tumours. Identification and segmentation of brain tumour in magnetic resonance images is very crucial in medical diagnosis because its accurate segmentation is very important for detecting tumours, edema and necrotic tissues.

Brain tumor is one of the most dangerous diseases occurring commonly among human beings, so study of brain tumor is very crucial. The proposed image segmentation technique to identify the tumor from the brain magnetic resonance imaging (MRI). Several existing thresholding techniques have produced different result in each image. Thus, to produce a satisfactory result on brain tumor images, they have proposed a technique, where the detection of tumor was done uniquely. As well, another author Badran have proposed a computer-based technique for identifying the tumor region accurately in the brain via MRI images. Here, the classification has been performed on a brain tumor image for identifying whether the tumor is a benign or malignant one. The steps involved in the proposed algorithm were preprocessing, image segmentation, feature extraction and image classification via neural network techniques. Finally, using the region of interest technique, the tumor area has been located.

The presented a cohesion based self merging (CSM) algorithm for the segmentation of brain MRI in order to find the exact region of brain tumor is utilized. CSM has drawn much attention because it gives a satisfactory result when compared to other merging processes. Here, the effect of noise has been reduced greatly and found that the chance of obtaining the exact region of tumor was more and the computation time was very less. Their algorithm was much simpler and computationally less complex.

Particle Swarm Optimization (PSO) based clustering algorithmis used here. The proposed algorithm has identified the centroids of number of clusters, where each cluster has grouped together the brain tumor patterns, obtained from MR Images. The results obtained for three performance measures have been compared with those obtained from Support Vector Machine (SVM) and Ada Boost. The performance analysis has shown that the qualitative results of proposed model are analogous with those obtained by SVM. Moreover, the different values of PSO control parameters have been selected in order to acquire better results from the algorithm.

The robust system for brain tumor diagnosis as well as for braintumor region extraction which has been Initially, the proposed system has diagnosed the tumor from the brain MR images by naive bayes classification. After the diagnosis, the K-means clustering and boundary detection techniques have been applied to extract the exact brain tumor region. Here, above 99% accuracy has been achieved for diagnosis. Experimental results have shown that the proposed system has extracted accurate tumor region.

Hassan Khotanlou et al. (2009) have proposed a technique for segmenting the brain tumors in 3D magnetic resonance images. Their technique was suitable to different kinds of tumors. Initially, the brain has been segmented using the proposed approach. Then, the suspicious areas have been selected with respect to the approximate brain symmetry plane and fuzzy classification for tumor detection. Here, in the segmentation stage, the tumor has been segmented successfully using the combination of a deformable model and spatial relations.The efficient system, where the Brain Tumor has been diagnosed with higher accuracy using artificial neural network. After the extraction of features from MRI data by means of the wavelet packets, an artificial neural network has been employed to find out the normal and abnormal spectra. Normally, the benefit of wavelet packets is to give richest analysis when compared with the wavelet transforms and thus adding more advantages to the performance of their proposed system.

Medical image segmentation technique, which combines watershed segmentation and Competitive Hopfield clustering network (CHCN) algorithm to minimize undesirable over-segmentation is used. A region merging method is presented, which is based on employing the region adjacency graph (RAG) to improve the quality of watershed segmentation. The performance of the proposed technique is evaluated through quantitative and qualitative validation experiments on benchmark images.

A new unsupervised MRI segmentation method based on self-organizing feature map and algorithm included extra spatial information about a pixel region by using a Markov Random Field (MRF) model. The MRF term improved the segmentation results without extra data samples in the training set. The cooperation of MRF into SOFM has shown its great potentials as MRF term models the smoothness of the segmented regions. It verified that the neighbouring pixels should have similar segmentation assignment unless they are on the boundary of two distinct regions.

In the early research of medical tumor detection, the algorithms have directly used the classic methods of image processing (Such as edge detection and region growing) based on gray intensities of images. In recent years, the classification of human brain in MRI images is possible via supervised techniques such as k-nearest neighbour, Artificial neural networks and support vector machine(SVM) and unsupervised classification techniques such as self organization map(SOM) and fuzzy C-means algorithm have also been used to classify the normal or pathological T2 weighted MRI images.

Clustering techniques

A Clustering is one of the most useful techniques in MRI Segmentation, where it classifies pixels into classes, without knowing previous information or training. It classifies pixels with highest probability into the same class. Clustering technique training is done by using pixel features with properties of each class [Wang *et al*. (2008)].

K-means

K-means clustering algorithm is the simplest unsupervised learning algorithm that can solve clustering problem. The procedure followed to classify a given set of data through a certain number of clusters is very simple. In K-means 'K' centres are defined, one for each cluster. These clusters must be placed far away from each other. The next step is to take a point belonging to a given data set and associate it to the nearest centre. When no point is pending, the first step is completed and early grouping is done. The second step is to recalculate

'k' new centroids as barycentre of the clusters resulting from the previous step. After having 'K' new centroids a new binding has to be done between the same data set points and the nearest new centre. A loop has been generated. As a result of this loop, the k centres change their location step by step until centres do not move any more. Finally this algorithm aims at minimizing an objective function known as squared error function given by,

$$J(V) = \sum_{i=1}^{c} \sum_{j=1}^{c_i} \left\| x_i - v_j \right\|^2$$

Where,

$\left| x_i - v_j \right|$ is the Euclidean distance between xi and vj

'Ci' is the number of data points in ith cluster.

'C' is the number of cluster centres.

Algorithmic steps for K-means clustering:

Let X = {x1, x2, x3, ...xn}be the set of data points and V = { v1, v2, v3, ...vc }be the set of centres.

Step1: Randomly select 'c' cluster centres

Step2: Calculate the distance between each data point and cluster centres.

Step3: Assign the data point to the cluster centre whose distance from the cluster centre is minimum of all the cluster centres.

Step4: Recalculate the new cluster centre using

$$v_i = \left(\frac{1}{c_i}\right)\sum_{j=1}^{c_i} x_i$$

Where 'Ci' represents the number of data points in ith cluster.

Step5: Recalculate the distance between each data point and newly obtained cluster centres.

Step6: If no data point was reassigned then stop, otherwise repeat from step 3.

K-means algorithm is fast, robust and easier to understand. It also gives better result when data set are well separated from each other. But, if there are 2 highly overlapping data then k-means will not be able to resolve that there are 2 clusters.

Fuzzy C-means (FCM)

FCM clustering is an unsupervised method for the data analysis. This algorithm assigns membership to each data point corresponding to each cluster centre on the basis of distance between the cluster centre and the data point. The data point near to the cluster centre has more membership towards the particular centre. Generally, the summation of membership of each data point should be equal to one. After each iteration, the membership and cluster centres are updated according to the formula.

$$V_j = \frac{\left(\sum_{i=1}^{n}(\mu_{ij})^m x_i\right)}{\left(\sum_{i=1}^{n}(\mu_{ij})^m\right)}, \forall_j = 1,2.....c$$

$$\mu_{ij} = \frac{1}{\sum_{k=1}^{c}\left(\frac{d_{ij}}{d_{ik}}\right)^{\left(\frac{2}{m-1}\right)}}$$

Where,

'n' is the number of data points

'V_j' represents the j_{th} cluster centre

'm' is the fuzziness index m €[1,∞]

'c' represents the number of cluster centre

'μ_{ij}' represents the membership of i_{th} data to j_{th} cluster centre.

'd_{ij}'represents the Euclidean distance between i_{th} data and j_{th} cluster centre.

'xi' is the i_{th} of d-dimensional measured data

'cj' is the d-dimension centre of the cluster

$\|*\|$ is any norm expressing the similarity between any measured data and the centre.

$d_{ij} = \| x_i - c_j \|$, $d_{ik} = \| x_i - c_k \|$

The main objective of fuzzy c-means algorithm is to minimize

$$J(U,V) = \sum_{i=1}^{n}\sum_{j=1}^{c}(\mu_{ij})^m \left\| x_i - v_j \right\|^2 \quad 1 \le m < \infty$$

Where, $\left\| x_i - v_j \right\|$ is the Euclidean distance between i_{th} data and j_{th} cluster centre

1) Algorithmic steps for fuzzy C-means clustering:

Let X = {x_1, x_2, x_3, ...x_n}be the set of data points and V = { v_1, v_2, v_3, ...v_c }be the set of cluster centres.

Step1: Randomly select 'c' cluster centres

Step2: Calculate the fuzzy membership 'μ_{ij}'using the equation

$$\mu_{ij} = \frac{1}{\sum_{k=1}^{c}\left(\frac{d_{ij}}{d_{ik}}\right)^{\left(\frac{2}{m-1}\right)}}$$

Step3: Compute the fuzzy centres 'v_j'using

$$V_j = \frac{\left(\sum_{i=1}^{n}(\mu_{ij})^m x_i\right)}{\left(\sum_{i=1}^{n}(\mu_{ij})^m\right)}, \forall_j = 1,2.....c$$

Step4: Repeat step2 and step3 until the minimum 'J' value is achieved or $\| U_{(k+1)} - U_{(k)} \| < \beta$

Where, 'k' is the iteration step

'β' is the termination criterion between [0,1]

'U=$(\mu_{ij})_{n□c}$' is the fuzzy membership matrix

'J' is the objective function

The first loop of the algorithm calculates membership values for the data points in clusters and the second loop recalculates the cluster centres using these membership values. When the cluster centre stabilizes the algorithm ends.

The FCM algorithm gives best result for overlapped data set and also gives better result than k-means algorithm. Here, the data point can belong to more than one cluster centre. The main drawback of FCM is 1) the sum of embership value of a data point xi in all the clusters must be one but the outlier points has more membership value. So, the algorithm has difficulty in handling outlier points. 2) Due to the influence of all the data members, the cluster centres tend to move towards the centre of all the data points [Cox (2005)]. It only considers image intensity thereby producing unsatisfactory results in noisy images. A bunch of algorithms are proposed to make FCM robust against noise and in homogeneity but it's still not perfect [Zhang and Chen (2004)].

Modified fuzzy c-means

Many approaches have been made to modify the existing standard FCM algorithm to improve its performance. Each of the modified FCM algorithms proposes a new membership function for calculating the membership of data points in clusters.

A. FCM with modified distance function

A new distance function based on dot product instead of the conventional Euclidean distance [Frank and Annette]. The introduced new membership function is given in below equation

$$\mu_{ik} = \frac{1}{\sum_{j=1}^{c}\left(\frac{d^{2}(v_i, x_k)}{d^{2}(v_j, x_k)}\right)^{\left(\frac{1}{m-1}\right)}}$$

B. Modified c-means for MRI segmentation

A new approach for segmentation of MRI images that have been corrupted by intensity inhomogeneities and noise is also proposed. The algorithm is formulated by modifying the objective function of the standard fuzzy C-means method to compensate for intensity inhomogeneities. Here the membership function is given

$$\mu_{jk} = \frac{1}{\sum_{l=1}^{c}\left(\frac{\delta_{jk} + \gamma_k}{\delta_{jl} + \gamma_l}\right)^{\left(\frac{1}{m-1}\right)}}$$

Here, 'δ' is the distance and 'γ' denotes the influence on a pixel by the neighbouring membership values. In the proposed IFCM algorithm of shan shen *et al*. (2005) during clustering, each pixel attempts to attract its neighbouring pixels towards its own cluster. Here the attraction depends up on the intensity of the pixel. In MRI brain images, the presence of noise will alter the pixel intensity. Due to this the segmentation may be affected so, instead of modifying the objective function, the measurement of similarity was extended by considering neighbourhood attraction.

C. Adaptive fuzzy clustering

The adaptive fuzzy clustering algorithm [Cox (2005)] is a modified version of standard FCM. The membership values in this method are calculated using

$$\mu_{ij} = \frac{n * \left(\frac{1}{d_{ji}}\right)^{\frac{1}{m-1}}}{\sum_{k=1}^{p}\sum_{z=1}^{n}\left(\frac{1}{d_{kz}}\right)^{\frac{1}{m-1}}}$$

This algorithm is efficient in handling data with outlier points. In comparison with FCM algorithm it gives very low membership for outlier points [Cox (2005)].

Experiment and Analysis

In order to test the performance of the algorithm, this paper adopts brain MRI images of the Montreal neurological institute for simulation. Traditional clustering image segmentation result is shown in Fig.1, the noise elimination of image using the median filter is shown in fig 2. The tradition approach for the detection of tumor is implemented using K means Clustering is shown in fig 3. Final tumor detection using K-means Clustering is shown in fig 4. Traditional FCM image segmentation result is shown in Fig.5, and image segmentation result of proposed algorithm of section 2. The proposed fast image segmentation is superior to the traditional algorithm, the edge details is clear, this algorithm can ensure clustering optimization performance unchanged, reduce the cost of operation, and obviously improves the segmentation efficiency.

Conclusion

Many image segmentation methods have been developed in the past several decades for segmenting MRI brain images, but still it remains a challenging task. A segmentation method may perform well for one MRI brain image but not for the other images of same type. Thus it is very hard to achieve a generic segmentation method that can be commonly used for all MRI brain images. In this work, the merits and demerits of various automated techniques for brain tumour identification is analyzed in detail. Finally simulation is carried out for the two clustering techniques i.e K-means and Fuzzy C means. The Fuzzy techniques gives the good performance for detection of tumor in MRI images.

References

[1] Abdullah, N., Ngah, U.K., Aziz, S.A (2011): "Image Classification of brain MRI using Support Vector Machine," Imaging systems and Techniques (IST), 2011. IEEE International conference on 17-18 May 2011.

[2] Ahmed, M.N., Yamany, S.M., Mohamed, N., Farag, A.A., Moriarty, T (2002): "A modified fuzzy c-means algorithm for bias field estimation and segmentation of MRI data," IEEE transaction medical imaging, Vol.21, No.3, pp.193-199.

[3] Anam., Mustaqeem., Ali Javed.,Tehseen Fatima (2012): "An Efficient brain tumour detection algorithm using watershed and thresholding based segmentation," International journal of image, Graphics and Signal processing(IJIGSP), Vol.4, No.10, pp. 34-39.

[4] Bezdek, J.C (1981): "Pattern Recognition with Fuzzy objective function algorithms" New York.

[5] Chou, T., Chen, C., Lin, W (1993): "Segmentation of dual-echo MR images using neural networks", Proceeding SPIE, medical imaging, vol , pp.220-227.

[6] Chowdhury, M.H., W.D.Little., (1995) "Image thresholding techniques" IEEE pacific Rim conference on communications, computers and signal processing, proceedings 17-19 may 1995, pp.585-589.

[7] Clarke, L. P., Velthuizen, R. P., Phuphanich, S., Schellenberg, J. D., Arrington, J. A. Silbiger, M (1993): "MRI: Stability of Three Supervised Segmentation Techniques", Magnetic Resonance Imaging, 11: pp. 95-106, 1993.

[8] Clarke, L.P. (1991): "MR image segmentation using MLM and artificial Neural Network," Medical physics, Vol.18, No.3, pp.673.

[9] Cox, E.,(2005): " Fuzzy Modeling and Genetic Algorithms for Data mining and Exploration," Elsevier, 2005.

[10] Dave, R.N (1991): "Characterization and detection of noise in clustering," Pattern Recogn Lett 12(11):657–664

[11] Deeplai Kelkar and Surendra Gupta (2008): "Improved Quadtree method for split merge image segmentation", Emerging Trends in Engineering and Technology, 2008 ICETET.

[12] Deorah, S., Charles, L., Zita, A., Timothy, R(2006): "Trends in brain cancer incidence and survival in the United States: Surveillance", Epidemiology and End results program. Neurosurgery Focus 2006; 20:1-7.

[13] Diamantaras. K.I., Kung. S.Y., (1996): "Principal Component Neural Networks: Theory and Applications", Wiley.

[14] Dzung L.Pharm, Chenyang Xu, Jerry L.Prince (1998): “A Survey of Current Methods in Medical Image Segmentation,” Technical Report JHU / ECE 99-01, Department of Electrical and Computer Engineering.

[15] Gonzalez, Rafael C., Richard E.Woods (2007): “Digital Image Processing”, Pearson Education., 3rd Edition.