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Automated Brain Image Classification Using Gustafson–Kessel (G-K) Fuzzy Clustering Algorithm

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ABSTRACT

.Medical imaging has becoming as a transpire discipline in diversified medical diagnosis. It has been plays a vital role in automatic detection, which bestows information about abnormalities for further treatment. The traditional approach of detecting MRI has been based on manual inspection, which has become inappropriate for vast volume of data. Automated tumor detection has gaining importance that conserves the time of radiologist. In this paper, brain tumor image has been segmented using Enhanced Fuzzy C-Means (EFCM) and classified using Gustafson-Kessel (G-K) fuzzy clustering algorithm. In order to exhibit the supremacy of proposed algorithm it has been compared with Support Vector Machine (SVM) algorithm. The proposed method reports promising results in terms of accuracy rate, specificity and sensitivity.

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INTRODUCTION

Medical imaging techniques like X-ray, CT scan and MRI are the source of medical image data which is used in medical diagnosis. Magnetic field excitation and RF coil pulses produces MRI image (Koley, S., A. Majumder, 2011). On comparing with CT scan MRI seems to be powerful for diagnosis since it doesn't utilize radiation. MRI images present a unique perception that determines whether brain tumor is present or not (Chandra, S., *et al*., 2009). Manual examination of MRI image is a time consuming job, prone to error while manipulating huge scale of data.

Koley, S. and Majumder, A. (2011) have presented a cohesion based self merging (CSM) algorithm for the segmentation of brain MRI in order to find the exact region of brain tumor. 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. More than a few, an optimization, intelligent techniques are also (Chandra, S *et al*. (2009), Qurat-ul Ain *et al*. 2010) proposed in the medical image processing. Wen-Feng Kuo *et al*. (2008) have proposed a robust medical image segmentation technique, which combines watershed segmentation and Competitive Hopfield clustering network (CHCN) algorithm to minimize undesirable over-segmentation.

However, due to the uncertainty and complexity of images encountered in actual applications, it is one of the most difficult tasks that affect directly the results of subsequent tasks such as feature extraction and pattern recognition. Since fuzzy logic is an effective way of researching and processing fuzziness and uncertainty, it used to be a powerful tool to deal with the ambiguity images. Different aspects of fuzzy logic theory have been successfully used in image processing problems. For example, fuzzy c-means (FCM) algorithm is a famous method that can obtain segmentation results by fuzzy classification Ganapathi Padmavathi, *et al*., (2010) However, fuzzy logic methods usually do not generate satisfactory results when they are applied to the images with higher degree of uncertainty.

In this paper, the segmentation of brain MR image has been carried out using EFCM and the G-K fuzzy is exploited for MRI image classification to detect whether the image is normal or abnormal. The feature extraction from MRI Images is done by GLCM.

In order to analyze large volume of MRI, automation is inevitable which results in economic analyzer. High accuracy of tumor detection is required, because human being is involved. The most significant procedure in the automated process is brain tumor classification. A few ordinary classifiers are accessible for classification yet

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the vast majority of the prior works rely on Artificial Intelligence (AI) systems which yield exceptionally precise results over the traditional classifiersThe foremost objective of this work is to provide an excellent outcome of MRI brain cancer classification.

Segmentation Using Enhanced FCM (EFCM):

An Enhanced FCM (EFCM) of MRI brain image segmentation is proposed and results are compared with conventional watershed segmentation and FCM. The performances of the segmentation methods were compared to highlight the proposed method. Flow chart representation of EFCM algorithm is presented in Figure 1.

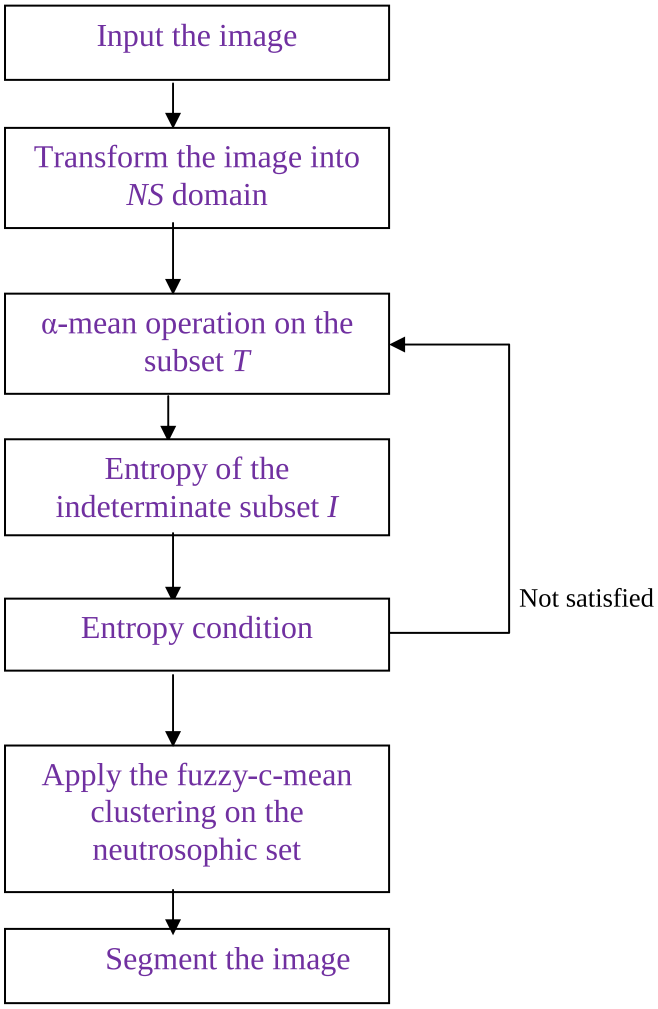

Fig. 1: Flow chart of EFCM segmentation algorithm

In this paper, the proposed segmentation method is applied to a brain tumor of real images, and compared with a fuzzy C-means segmentation algorithm and watershed segmentation technique. The segmentation methods have been tested for more than 50 images (a combination of normal and abnormal images). In this paper, for simplicity one image is taken common for analysis. The segmented outputs using watershed algorithm, FCM and EFCM are presented in Figure 2,3 and 4 respectively.

Watershed segmentation results:

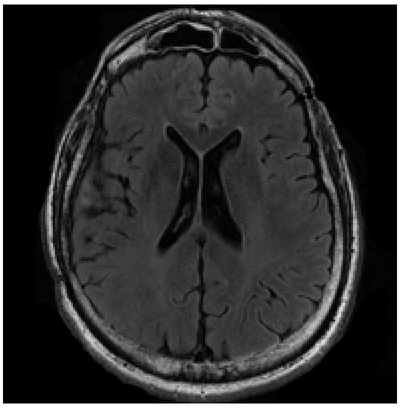

Fig. 2:a RGB image

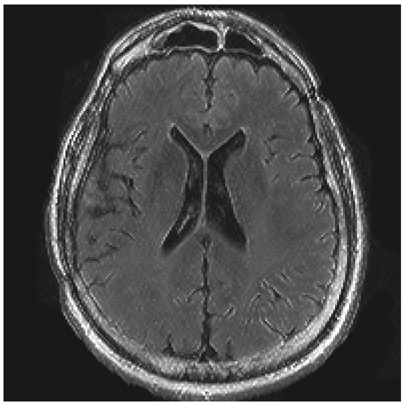

Fig. 2:b High pass filtered image

Fig. 2:c Threshold image

Fig. 2:d Watershed segmented image

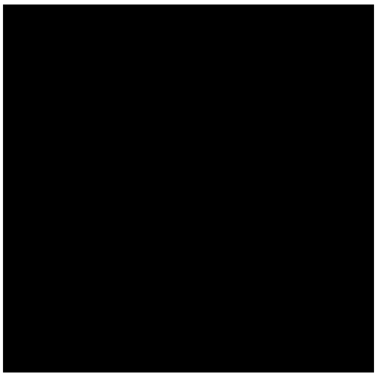

Fig. 2:e Morphological output

FCM segmentation results:

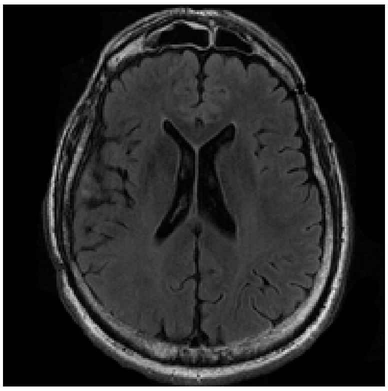

Fig. 3:a RGB MRI image

Fig. 3:b Threshold image

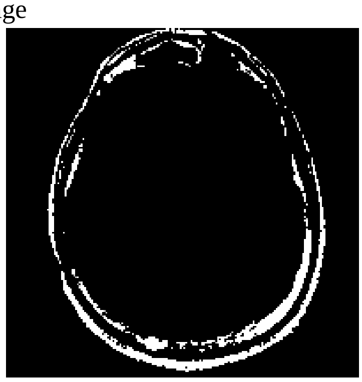

Fig. 3:c FCM segmented image

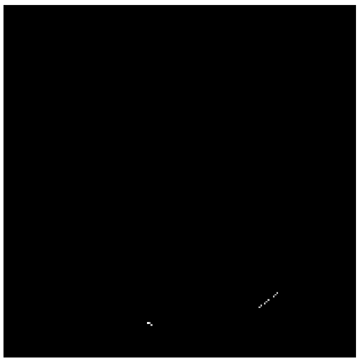

Fig. 3:d Morphological output

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EFCM segmentation results:

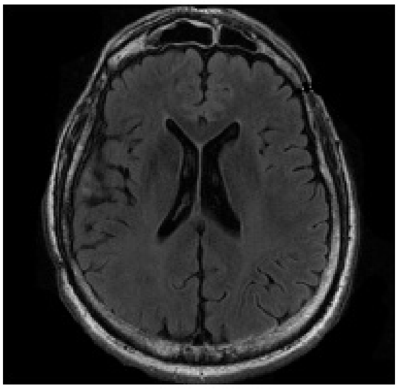

Fig. 4:a Original

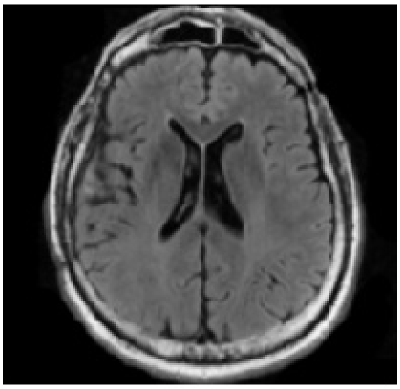

Fig. 4:b T-domain

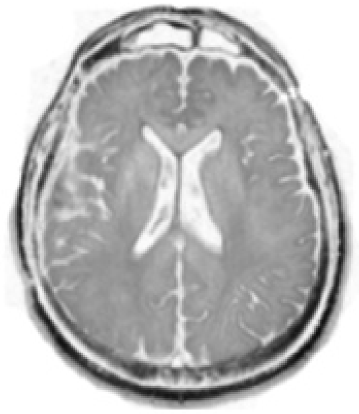

Fig. 4:c F domain

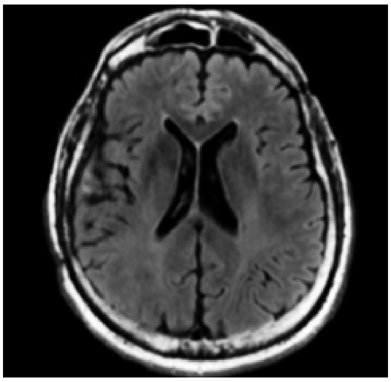

Fig. 4:d Enhanced

Fig. 4:e Binarized T-image

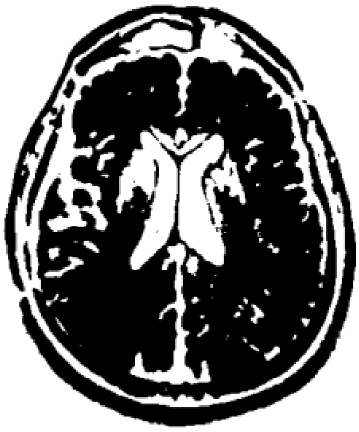

Fig. 4:f Binarized F-image

Fig. 4:g Homogeneity image

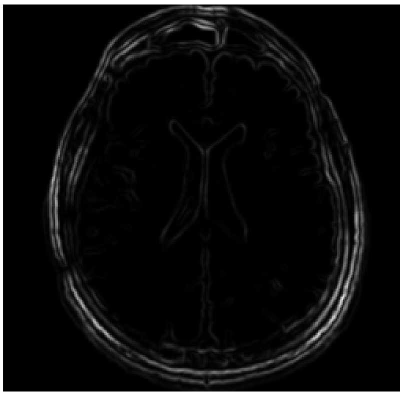

Fig. 4:h Indeterminate image

Fig. 4:i Binary image of T,I,F

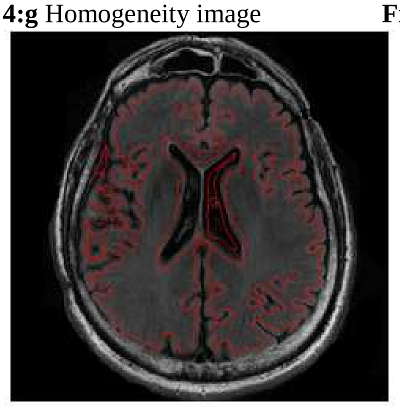

Fig. 4:J Segmented area

Fig. 4:k EFCM output

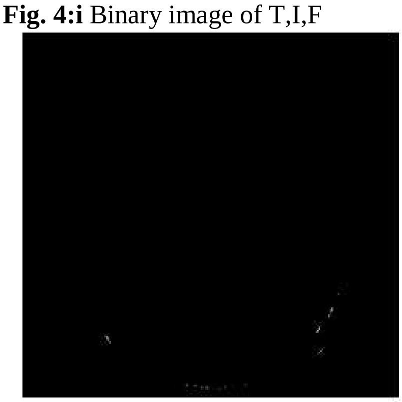

Fig. 4:l Morphological output

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The performances of segmentation algorithms are compared through the performance indices. The image segmentation parameters are used to compare the segmentation results for the same set of images. (i) Rand Index (RI): It counts the fraction of pairs of pixels whose labeling are consistent between the computed segmentation and the ground truth, averaging across multiple ground truth segmentations to account for scale variation in human perception. The Rand index or Rand measure is a measure of the similarity between two data clusters. (ii) Global Consistency Error (GCE): It measures the extent to which the segmentation can be viewed as a refinement of the other. If one segment is a proper subset of the other, then the pixel lies in an area of refinement, and the error should be zero. If there is no subset relationship, then the two regions overlap in an inconsistent manner. (iii) Variation of Information (VOI): It defines the distance between two segmentations as the average conditional entropy of the segmentation given the other, and thus measures the amount of randomness in the segmentation which cannot be explained by the other. The Table 1 shows comparison of the proposed EFCM with FCM and conventional watershed technique in terms of VOI, GCE and RI.

Table 1: Performance metrics of segmentation methods.

Image type	Method	VOI	GCE	RI
Normal	Watershed	5.4365	0	0.1032
Tumor	Watershed	4.7906	0.0246	0.3206
Normal	FCM	5.4354	0.0076	0.1118
Tumor	FCM	4.7670	0.0239	0.3286
Normal	EFCM	0.0368	0	0.0923
Tumor	EFCM	0. 2733	0	0.9105

From the Table 1 it is observed that ECFM performs well ahead of other two methods. The proposed method has the ability to segment the clear images, and too can segment noisy images. This exemplifies the fact that the proposed approach can handle the indeterminacy of the images well. The segmented output using EFCM is considered for further analysis.

Feature Extraction:

The texture features are attained from the statistical appropriation of examined blend of intensities at correct positions regarding each other. Based on the intensity pixels in all combinations, these measurements can be differentiated into first, second-and higher-request imminent. The GLCM is a technique for dividing the second order measurable texture features.

Features are extracted from the tumor regions of MRI images which involves in minimizing the quantity of data required to describe a large set of data accurately. The obtained features are used as inputs to classifiers which assign them to the class which they represent. The motto of feature extraction is to minimize the original data by measuring positive properties which discriminate one input sample from another sample. If the features are excessively used for classification it will lead to shoot the computation time and storage memory is also increases.

Classification Using G-K Fuzzy:

G-K fuzzy is one of the classification technique applied on different fields such as face recognition (Jennifer Huang, *et al*., 2002), text categorization (Veluchamy, M., *et al*.,), cancer diagnosis (Roopali, R., *et al*., 2014), glaucoma diagnosis, microarray gene expression data analysis. G-K fuzzy utilizes binary classification of brain MR image as normal or tumor affected. G-K fuzzy divides the given data into subsets which are gradual. Dimensionality reduction and precise feature set given as input to the G-K fuzzy on the duration of training part as well as during the testing part. The proposed G-K fuzzy classification method is compared with that of SVM.

Table 2 shows the overall performance of G-K fuzzy clustering and SVM algorithm. From the results, it is clear that G-K fuzzy has the most optimal performance.

Table 2: Performance measures of classification methods.

Sample	Accuracy		Specificity		sensitivity	
	G-K Fuzzy	SVM	G-K Fuzzy	SVM	G-K Fuzzy	SVM
Sample1	95.13	94.65	97	85	86.566	83.456
Sample 2	95.67	94.87	98	86	84.446	82.567
Sample 3	95.42	94.81	97	85	85.567	81.341
Sample 4	95.23	94.64	98	86	86.332	84.675

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Conclusion:

Brain tumor diagnosing has becoming a vital one in medical field because which are caused by abnormal and uncontrolled growing of the cells inside the brain. Moreover treatment of a brain tumor basically depends on its size and location. Automatic classification of MRI brain image eliminates the manual errors and accuracy of the test drastically. In this work, EFCM is employed for MRI brain image segmentation and G-K fuzzy classification technique has been adopted for MRI brain image classification. This automated intelligent system results in the improved accuracy rate, specificity and sensitivity. Automation of MRI image classification based on G-K fuzzy will be promising one which aids the physician to make the final decision without any hesitation. From the simulation results it is observed that EFCM based segmentation and G-K fuzzy based classification produces better result when compared with that of FCM and SVM respectively. It also achieves high degree of accurate classification (i.e. more than 95%). From the outcomes it has been concluded that this technique seems to be rapid, easy to operate, non-invasive and cost effective.

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