

Method Implementation in Magnetic Resonance Image Segmentation Algorithm for Human Brain Tumor

¹Gayatri Shashikant Mirajkar, ²Balaji Vithalrao Barbadekar
and ³Dr. Ing. Yogesh Shriram Sonavane

¹*Ph.D. Scholar, Shivaji University, Kolhapur, Maharashtra, India*
E-mail: gayatrimirajkar@gmail.com

²*112/C/2, Gorakhpur, Satara, Maharashtra, India*
E-mail: balaji.barbadekar@gmail.com

³*Chalmers University of Technology,*
Dept. of Chemical & Biological Engg., Göteborg, Sweden
E-mail: yogeshsonavane2000@googlemail.com

Abstract

In the magnetic resonance image segmentation the k-means algorithm and fuzzy c-means clustering algorithm have been developed and implemented. Simulations have been done in MATLAB 2010b. Applying the expectation-maximization algorithm directly to the MR image of human brain does not provide satisfactory results in the segmentation of human brain tumor. The input to the kmeans algorithm is the final feature image obtained by processing the outputs of Gabor wavelets and the number of desired classes in which the input image must be segmented. The region with the highest intensity in the tumor has been labeled as the darkest in the kmeans algorithm. Kmeans clustering for features extracted from all three levels of approximation has been study thoroughly. Fuzzy c-means clustering is applied to the feature image obtained from combining the Gabor outputs. The clustering algorithm evaluates the six classes in the feature image. Within each class, the candidate pixels showing the greatest tendency of belonging to the particular class are highlighted with the darkest colors. In fuzzy c-means clustering, at every level of decomposition, the tumor is perfectly segmented out showing its presence as an object at all levels of approximation which is definite advantage over kmeans clustering algorithm.

Keywords: Segmentation, magnetic resonance image, Gabor, kmeans, fuzzy c-means

Introduction

Every day, people deal with different types of data coming from all types of measurements and observations. Data describe the characteristics of a living species, depict the properties of a natural phenomenon, summarize the results of a scientific experiment, and record the dynamics of a running machinery system [1]. More importantly, data provide a basis for further analysis, reasoning, decisions, and ultimately, for the understanding of all kinds of objects and phenomena. One of the most important of the myriad of data analysis activities is to classify or group data into a set of categories or clusters [2]. Aim of the present paper is an implementation in magnetic resonance image segmentation algorithm for human brain tumor. Following is a brief discussion about MR image segmentation, the kmeans or isodata clustering algorithms, and fuzzy c-means clustering algorithm.

Clustering

Cluster analysis or clustering is the assignment of a set of observations into subsets (called clusters) so that observations in the same cluster are similar in some sense [3]. Clustering algorithms partition data objects (patterns, entities, instances, observations, units) into a certain number of clusters (groups, subsets, or categories) [2]. Several definitions of clustering have been summarized in [4] and are as follows:

A cluster is “an aggregate of points in the test space such that the distance between any two points in the cluster is less than the distance between any point in the cluster and any point not in it.”, “Clusters may be described as continuous regions of this space (d-dimensional feature space) containing a relatively high density of points, separated from other such regions by regions containing a relatively low density of points.”

Data objects that are classified in the same group should display similar properties based on some criteria. Classification being one of the most primitive activities of human beings [5], [4], it plays an important and indispensable role in the long history of human development. In order to learn a new object or understand a new phenomenon, people always try to identify descriptive features and further compare these features with those of known objects or phenomena, based on their similarity or dissimilarity, generalized as proximity, according to some certain standards or rules. According to [6], naming and classifying are essentially synonymous. With such classification information at hand, we can infer the properties of a specific object based on the category to which it belongs.

Classification systems are either supervised or unsupervised depending on whether they assign new data objects to one of a finite number of discrete supervised classes or supervised categories, respectively [7 – 9].

In supervised classification, the mapping from a set of input data vectors, denoted as $x \in R^d$, where d is the input space dimensionality, to a finite set of discrete class labels, represented as $y \in 1, \dots, C$, where C is a total number of class data types, is modeled in terms of some mathematical function $y = y(x, w)$, where w is a vector of adjustable parameters. In supervised pattern classification, a set of training data are available and the classifier is designed by exploiting this a priori known information.

In unsupervised classification, also called clustering or exploratory data analysis, no labeled data are available [6], [10]. The goal of clustering is to separate a finite, unlabeled data set into a finite and discrete set of “natural,” hidden data structures, rather than to provide an accurate characterization of unobserved samples generated from the same probability distribution [8], [11]. It is clear from the above discussion that a direct reason for unsupervised clustering comes from the requirement of exploring the unknown natures of the data that are integrated with little or no prior information. Sometimes, the process of labeling data samples may become extremely expensive and time consuming, which also makes clustering a good choice considering the great savings in both cost and time. In addition, cluster analysis provides a compressed representation of the data and is useful in large - scale data analysis.

Basic Steps Involved in Clustering

The basic steps that an expert must follow in order to develop a clustering task are viz., feature selection which involves the proper selection of features so as to encode as much information as possible concerning the task of interest satisfying the goal of minimum information redundancy, proximity measure that quantifies how “similar” or “dissimilar” two feature vectors are, Clustering criterion depends on the interpretation the expert gives to the term “sensible,” based on the type of clusters that are expected to underlie the data set, Clustering algorithms refers to the choice of a specific algorithmic scheme that unravels the clustering structure of the data set. Correctness of the algorithm is validated using appropriate tests. In many cases, the expert in the application field must integrate the results of clustering with other experimental evidence and analysis in order to draw the right conclusions. In a number of cases, a step known as clustering tendency should be involved. This includes various tests that indicate whether or not the available data possess a clustering structure. For example, the data may be completely random in nature, thus, trying to unravel clusters would be meaningless. Different choices of features, proximity measures, clustering criteria, and clustering algorithms may lead to totally different clustering results. By using above basic steps clustering algorithms for kmeans and fuzzy c-means have been studied thoroughly and explained in the following section.

The k-means Algorithm

This is one of the most popular and well-known clustering algorithms [9], [12], [13] also known as Isodata or c-means algorithm. It can be viewed as a special case of the generalized hard clustering algorithmic scheme when point representatives are used and the squared Euclidean distance is adopted to measure the dissimilarity between vectors x_i and cluster representatives θ_j .

For this case

$$J(\theta, U) = \sum_{i=1}^N \sum_{j=1}^m u_{ij} \|x_i - \theta_j\|^2 \quad (1)$$

This is trace of the within scatter matrix S_w which can be rewritten as,

$$J(\theta, U) = \text{trace}\{S_w\} \quad (2)$$

For the above choice of distance, equation (1) gives that θ_j , is the mean vector of the j -th cluster. For this specific choice generalized hard algorithmic scheme has been applied. The algorithm converges to a minimum of the cost function. The isodata algorithm recovers clusters which are as compact as possible because the algorithm converges to a minimum of the cost function. However, this convergence result is not valid for other distances, including the Euclidean distance [14]. The k-means algorithm is as follows:

The kmeans algorithm has been implemented as follows:

Choose arbitrary initial estimates $\theta_j(0)$ for the θ_j 's, $j = 1, \dots, m$

Repeat

--- For $i = 1$ to N

Determine the closest representative, say θ_j , for x_i

Set $b(i) = j$

--- End (For)

--- For $j = 1$ to m

Parameter updating: Determine θ_j as the mean of the vectors $x_i \in X$ with $b(i) = j$

--- End {For}

Until no change in θ_j 's occurs between two successive iterations.

Kmeans algorithm includes the parameters, minimization of the cost function, updation of parameters until no change in value between two successive iterations is reached. Computational simplicity is an advantage of this algorithm. Kmeans algorithm is suitable for recovering compact clusters

Experimental Results Obtained for kmeans clustering

Study of detection of tumor in human brain has been done with the help of T2-weighted MRI image [15] showing the axial section of the human brain. The MR image that has been selected for analysis exhibits a diffuse structure in the left occipital lobe. Due to complexity of diffuse structure it is difficult to differentiate the pathological tissue from normal tissue. The thorough analysis of given image has been performed with kmeans algorithm with MATLAB 2010b. Various observations have been made. These are discussed as follows.

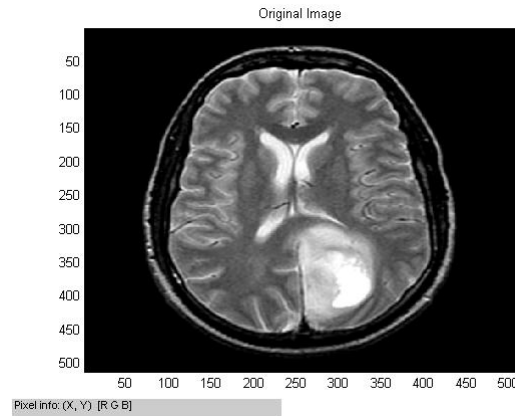


Figure 1: Original Image.

Fig. 1(a) shows T2-weighted MR image showing left parietal anaplastic astrocytoma. T2-weighted image shows the region having mixed signal intensity. A low grade glioma is observed here.

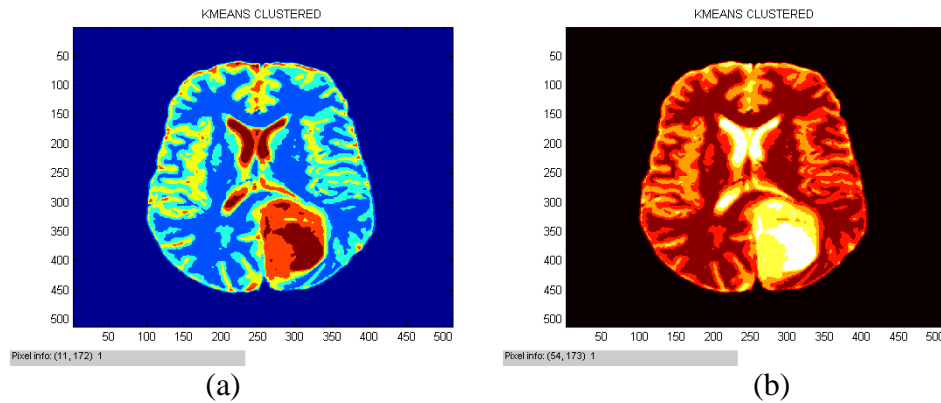


Figure 2: Results of kmeans clustering for original image (Level 0).

Fig. 2 shows the result of applying the kmeans clustering algorithm to the MR image shown in fig. 1. At the level of original image, all of the image features are captured. The tumor region as well as the surrounding edema is very well highlighted. The clustering algorithm has divided the feature image into 5 classes and represents the background a sixth class. The dominant frequency for the tumor as well as the edema region has been obtained using the technique elaborated in [16 – 17]. The size of the Gabor filter chosen for the image analysis is 5×5 . Such a small size of the filter prevents the smoothing effect and also highlights the fine structures within the image.

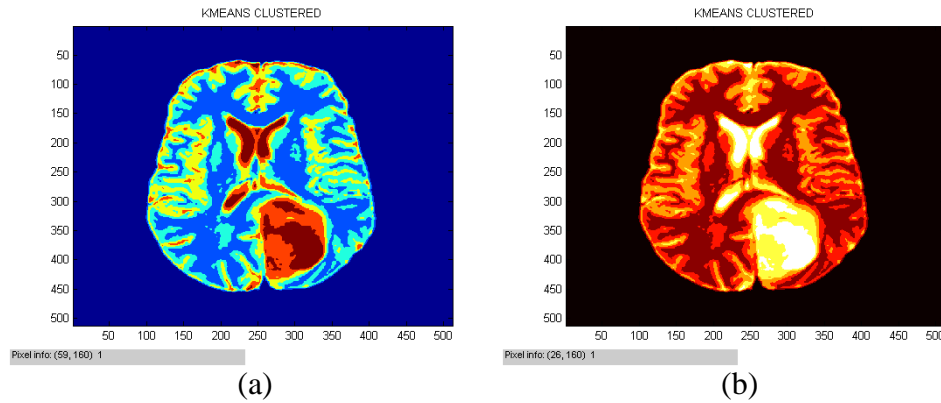


Figure 3: Results of kmeans clustering for Approximation at Level 1.

The clustered image at level 1 of decomposition by stationary wavelet transform shows a slightly coarser clustering. The five classes, namely white matter, grey matter, cerebrospinal fluid, tumor and edema are partitioned.

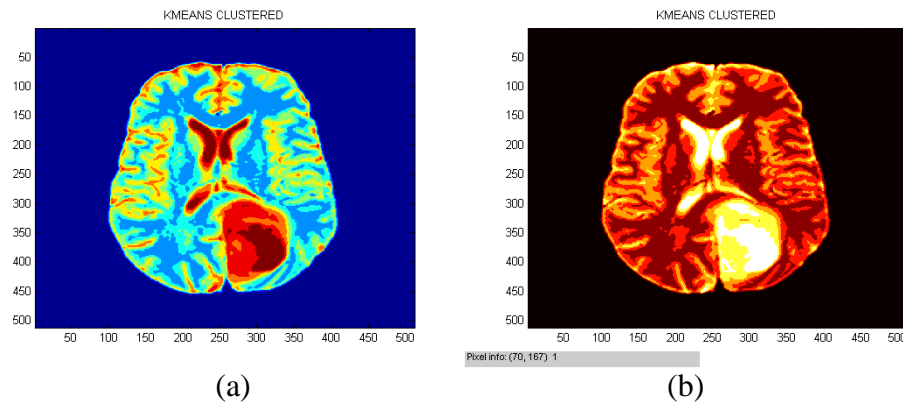


Figure 4: Results for kmeans clustering for Approximation at level 2.

The next level of decomposition, i.e., is the second level of stationary wavelet transform decomposition. Although this is the coarser level than the previous level, it provides an inherent simplicity. Clustering achieved by applying kmeans to the feature image obtained from this level provides a much simplified view of the image.

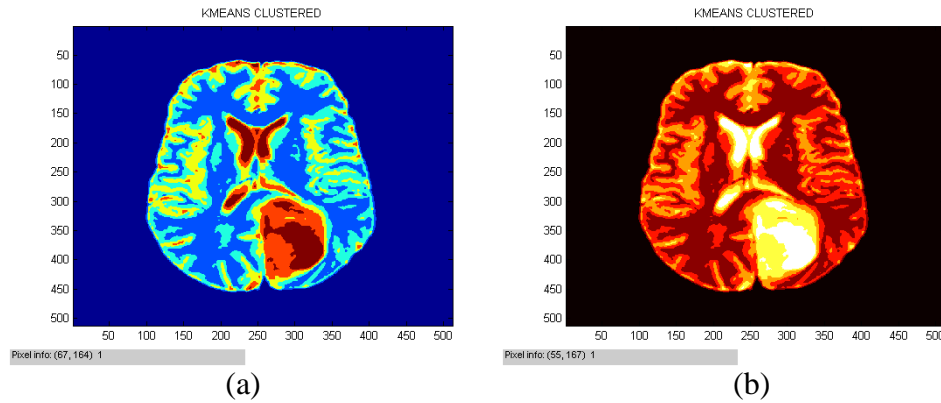


Figure 5: Results for kmeans clustering for features extracted from all three levels of approximation.

The results of clustering applied to the feature image obtained from all 3 levels of decomposition, namely original image, approximation at level 1, approximation at level 2 are presented in fig. 5. An observation of this clustered output shows that it contains the significant features from all the above three clustered outputs. The tumor mass has been efficiently segmented out at all three levels of decomposition and also can be seen in the final combined output.

Similarly, second form of clustering algorithm has been implemented using the same multiscale approach described as follows.

Fuzzy Clustering Algorithms

Fuzzy c-means clustering algorithm is a method that is frequently used in pattern recognition. It has the advantage of giving good modeling results in many cases, although it is not capable of specifying the cluster by itself. Fuzzy c-means is a method of clustering which allows one piece of data to belong to two or more clusters. The reason of using fuzzy models is that formulated problem may not be easier to solve computationally. The difficulty associated with probabilistic algorithm is the involvement of the pdf's, for which a suitable model has to be assumed [14].

A fuzzy clustering of the data set X into the m clusters is as follows

A fuzzy m -clustering of data set X is defined by a set of functions $u_j: X \rightarrow A, j = 1, \dots, m$, where $A = [0, 1]$. In the case where $A = \{0, 1\}$, a hard m -clustering of X has been defined. In this case, each vector belongs exclusively to a single cluster. It has been assumed that the number of clusters as well as their shape is known a priori.

θ_j is the parameterized representative of the j -th cluster, $\theta = [\theta_1^T, \dots, \theta_m^T]^T$, U is an $N \times m$ matrix whose (i, j) element equals $u_j(x_i)$, $d(x_j, \theta_j)$ is the dissimilarity between x_i and θ_j , and $q (> 1)$ is a parameter called a fuzzifier. Most of the well-known fuzzy clustering algorithms are those derived by minimizing a cost function of the form

[14],

$$J_q(\theta, U) = \sum_{i=1}^N \sum_{j=1}^m u_{ij}^q d(x_i, \theta_j) \quad (3)$$

With respect to θ and U , subject to the constraints

$$\sum_{j=1}^m u_{ij} = 1, i = 1, \dots, N \quad (4)$$

Where

$$u_{ij} \in [0,1], i = 1, \dots, N, j = 1, \dots, m \quad (5)$$

$$0 < \sum_{i=1}^N u_{ij} < N, j = 1, 2, \dots, m \quad (6)$$

The grade of membership of x_i in the j -th cluster is related to the grade of membership of x_i to the rest $m - 1$ clusters through eq. Different values of q in eq. bias $J_q(\theta, U)$ toward either the fuzzy or the hard clusterings. More specifically, for fixed θ , if $q = 1$, no fuzzy clustering is better than the best hard clustering in terms of $J_q(\theta, U)$. However, if $q > 1$, there are cases in which fuzzy clustering lead to lower value of $J_q(\theta, U)$ than the best hard clustering.

Fuzzy clustering algorithm has been implemented. The generalized fuzzy algorithmic scheme is presented below. The algorithm begins with a initial estimate for θ_j . The parameter updating has been estimated using equation (10). The results are calculated until a termination criterion is satisfied.

Generalized Fuzzy Algorithmic Scheme (GFAS)

Choose $\theta_j(0)$ as initial estimates for $\theta_j, j = 1, \dots, m$

t = 0

Repeat

--- For i = 1 to N

For j = 1 to m

$$u_{ij}(t) = \frac{1}{\sum_{k=1}^m \left(\frac{d(x_i, \theta_j(t))}{d(x_i, \theta_k(t))} \right)^{\frac{1}{q-1}}} \quad (7)$$

End {For - j}

--- End {For - i}

--- t = t + 1

--- For j = 1 to m

Parameter updating: Solve

$$\sum_{i=1}^N u_{ij}^q (t-1) \frac{\partial d(x_i, \theta_j)}{\partial \theta_j} = 0 \quad (8)$$

With respect to θ_j and set $\theta_j(t)$ equal to this solution.

--- End {For – j}

Until a termination criterion is met

As a termination criterion we may employ $\|\theta(t) - \theta(t-1)\| < \varepsilon$, where $\|\cdot\|$ is any vector norm and ε is a “small” user-defined constant. Specializing this algorithm to point representatives, the fuzzy c – Means (FCM) or Fuzzy k – means algorithm is obtained. A special case of point representatives for fuzzy kmeans has been studied thoroughly.

Special case for point representatives

In the case of compact clusters, a point representative is used for each cluster, that is, θ_j consists of l parameters. In this case, the dissimilarity $d(x_i, \theta_j)$ may be any distance measure between two points. Two common choices for $d(x_i, \theta_j)$ are

$$d(x_i, \theta_j) = (x_i - \theta_j)^T A (x_i - \theta_j) \quad (9)$$

Where A is a symmetric, positive definite matrix, and the Minkowski distance [14],

$$d(x_i, \theta_j) = \left(\sum_{k=1}^l |x_{ik} - \theta_{jk}|^p \right)^{\frac{1}{p}} \quad (10)$$

Where p is a positive integer and x_{ik} , θ_{jk} are the k th coordinates of x_i , θ_j , respectively. The specific form of GFAS under these choices is,

When the distance given in eq. is in use, we have

$$\frac{\partial d(x_i, \theta_j)}{\partial \theta_j} = 2A(\theta_j - x_i) \quad (11)$$

Substituting eq. into eq., we obtain

$$\sum_{i=1}^N u_{ij}^q (t-1) 2A(\theta_j - x_i) = 0 \quad (12)$$

Since A is positive definite, it is invertible. Premultiplying both sides of this equation with A^{-1} and after some simple algebra, we obtain,

$$\theta_j(t) = \frac{\sum_{i=1}^N u_{ij}^q(t-1) x_i}{\sum_{i=1}^N u_{ij}^q(t-1)} \quad (13)$$

The resulting algorithm is also known as fuzzy c-means (FCM) or Fuzzy k-means algorithm.

Fuzzy c-means clustering algorithm implementation

Fuzzy c-means clustering algorithm has been implemented on MR images as shown in fig. 6.

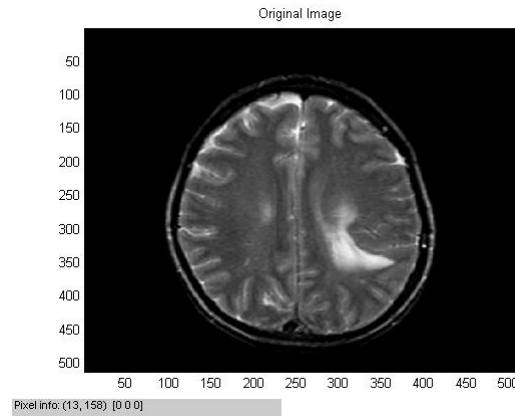
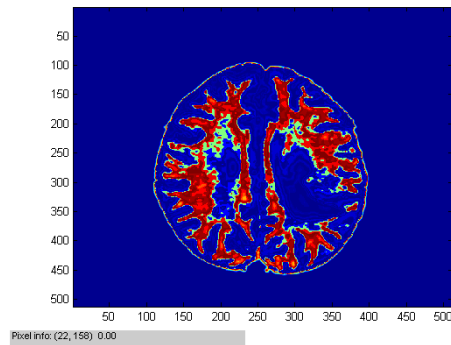
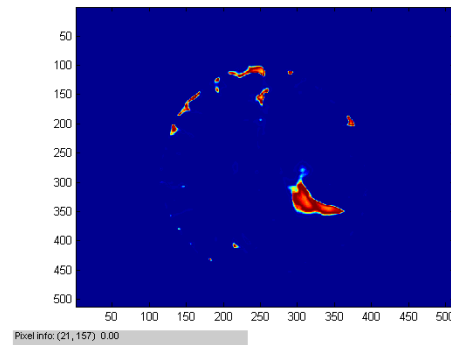


Figure 6: Original image.

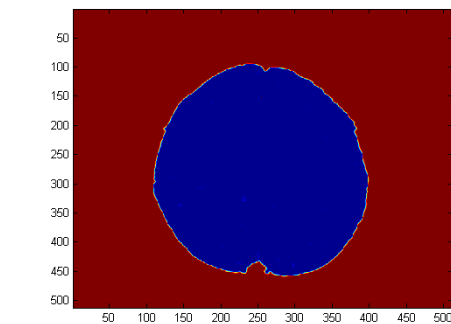
The results of applying fuzzy c-means clustering to the MR image showing metastatic bronchogenic carcinoma are presented in following figures. The MRI also shows a compression of adjacent mid-brain structures. The MR demonstrates the tumor as an area of high signal intensity in the T2-weighted axial scan of the brain. The MR brain image shows a large mass with surrounding edema. Experimental Results for Fuzzy c-means clustering are as shown in figures 6, 7, 8, and 9.



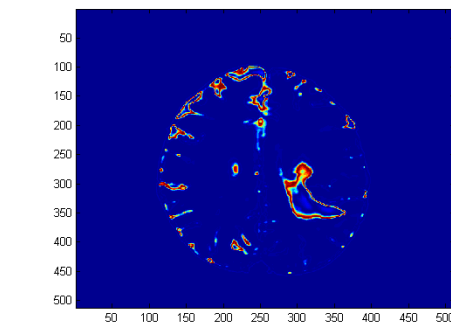
(a)



(b)



(c)



(d)

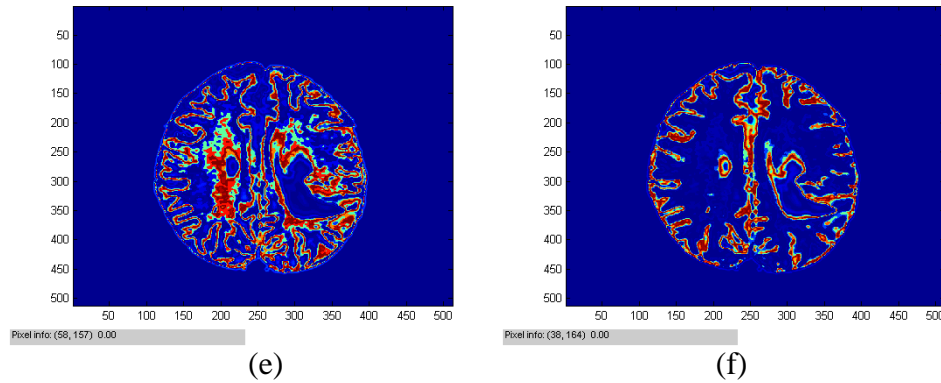
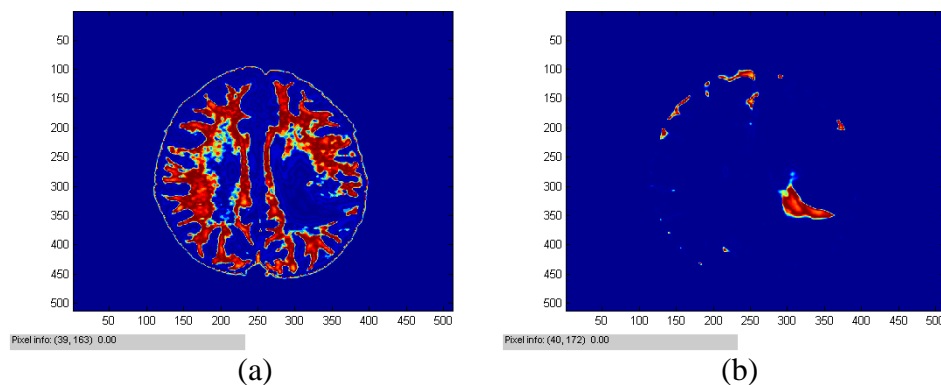


Figure 7: Results of Fuzzy C-means clustering for original image.

The analysis of fuzzy c-means clustering on original image have been studied thoroughly, where fig. 7(a) to 7(f) presents the six classes obtained from fuzzy c-means algorithm. The fuzzy algorithm obtains the required six classes of tissue. In class 2 shown in fig. 7(b), the tumor region is clearly segmented out from the surrounding diffuse edema tissue.

Fig. 7(a) is showing the mid-brain being highlighted at maximum intensity. Fig. 7(b) is showing the lesion being clearly separated as a separate cluster. Also some regions having high signal intensity, probably containing CSF are also highlighted in fig. 7(b). But, these can be removed either manually or by comparing the region size. Fig. 7(c) is showing two classes, one the complete brain and the second class, the background. Fig. 7(d) is showing the surrounding border of the tumor region. Fig. 7(e) is showing the borders of gyri, sulci, and the inter-hemispheric fissure. Along with this, some part of the edema surrounding the lesion is also highlighted. Fig. 7(f) is showing the gyri and sulci as well as a region of high signal intensity in the right hemisphere which can be probably CSF.

In every level of decomposition, the tumor is perfectly segmented out showing its presence as an object at all levels of approximation.



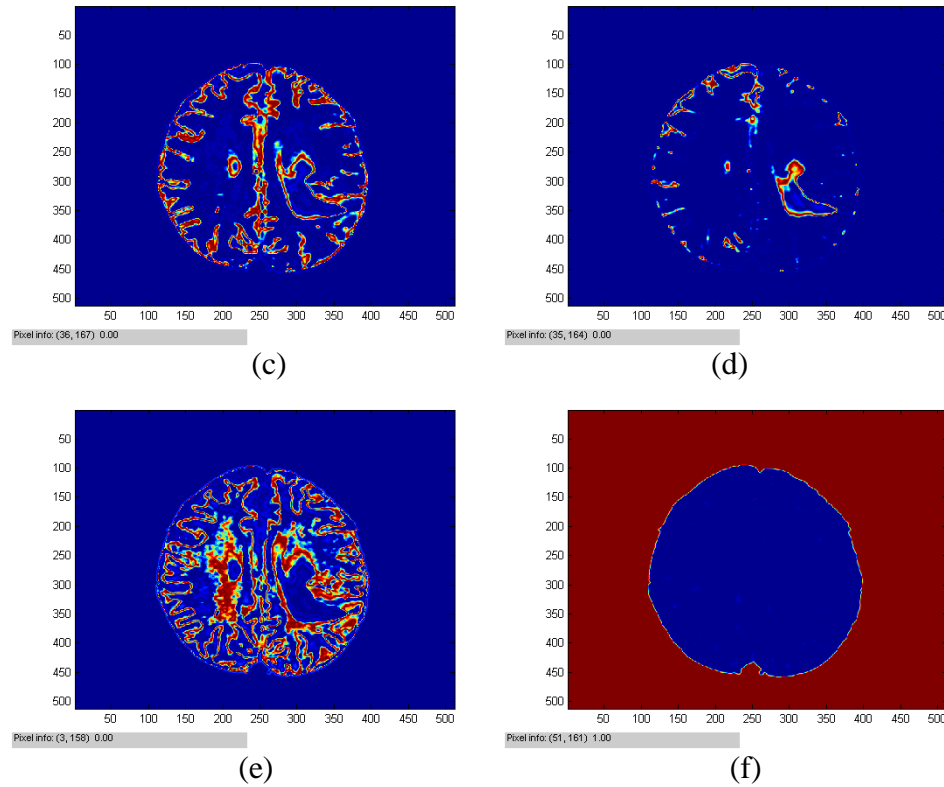


Figure 8: Results of Fuzzy C-means clustering for Approximation at Level 1.

Fig. 8 is showing the results for fuzzy c-means clustering for Level 1 of SWT decomposition. In fig. 8(b), again the tumor region is clearly segmented out, obtained as a separate cluster. Again the surrounding regions containing CSF are also segmented out as a separate cluster. Fig. 8(a) is again showing the mid-brain at maximum intensity. The lesion and the surrounding edema are labeled as a cluster having minimum intensity. Fig. 8(c) is showing the inter-hemispheric fissure labeled as a separate cluster along with the inner region of the edema also being labeled as a separate cluster with high intensity. The gyri and sulci as well as the outer part of the edema are segmented out in fig. 8(d). The midbrain region on the right lobe and the outer regions of the gyri as well as the sulci are clustered out in fig. 8(e). Finally fig. 8(f) is showing the two classes of brain and the background.

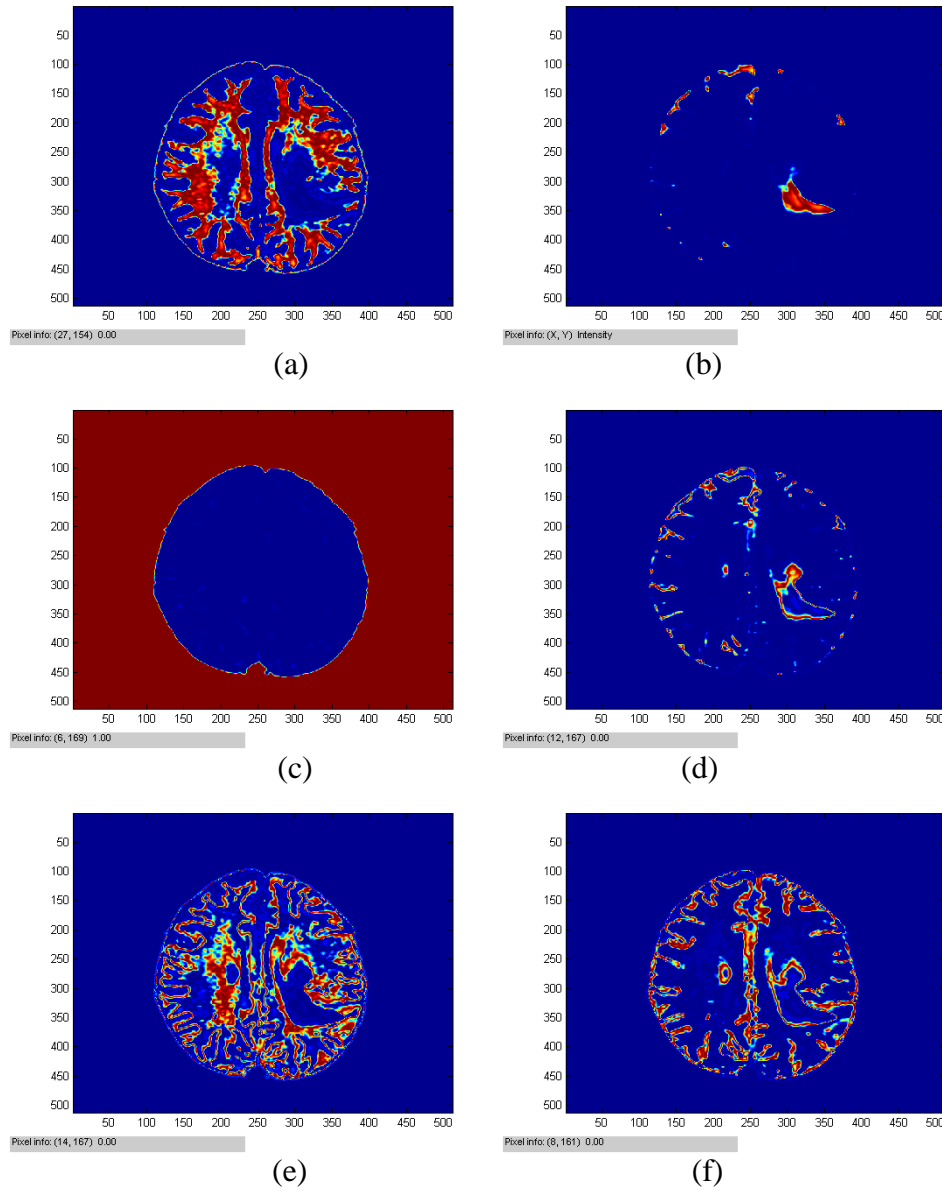


Figure 9: Results of Fuzzy C-means clustering for Approximation at Level 2.

Fig. 9(a) is showing the same mid-brain region being labeled as a separate cluster. The lesion as well as the surrounding edema is left out. Fig. 9(b) is showing the lesion labeled as a separate cluster at the second level of SWT decomposition. The two classes of brain and non-brain regions are differentiated in fig. 9(c). Fig. 9(d) is again showing the inner part of edema being highlighted along with the boundaries of gyri and sulci. Fig. 9(e) is showing the inter-hemispheric fissure boundary as well as boundaries of the gyri and sulci. Some part of the mid-brain region is also highlighted, leaving aside the lesion and surrounding edema. The inter-hemispheric fissure is

clearly segmented out in fig. 7(f).

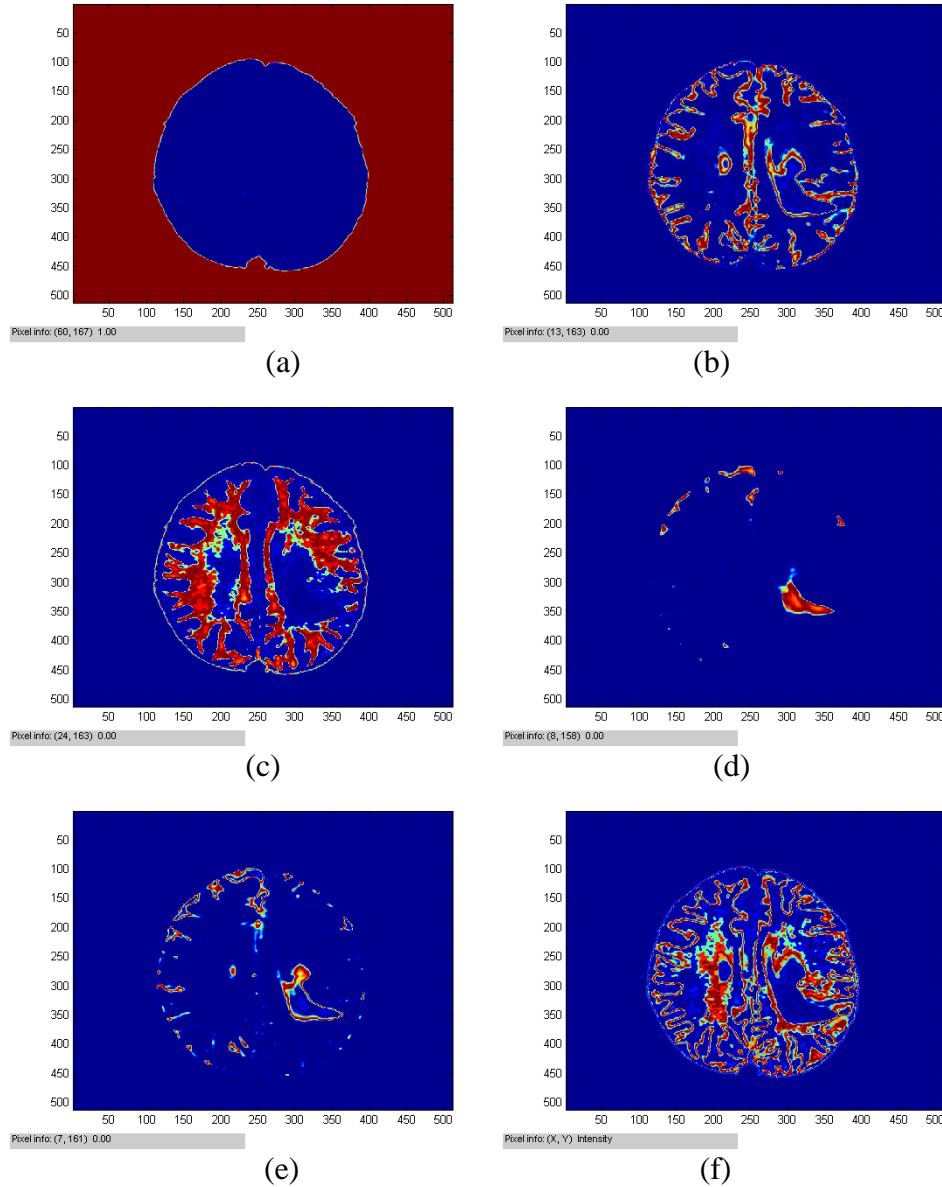


Figure 10: Results of Fuzzy C-means clustering for features captured from all three levels.

The results of applying fuzzy clustering to the feature images obtained from level 0, level 1, and level 2 of Stationary wavelet transform decomposition are presented in fig. 7, 8, 9 and fig. 10. In the fuzzy clustered results for the levels of approximation, the tumor region is clearly differentiated from the surrounding tissue. Its presence across the 3 levels of SWT decomposition clearly indicates the tumor object.

Fig. 10 is showing the results of fuzzy c-means clustering applied to the feature image obtained from all the three feature images at the three approximation levels. The surrounding edema is obtained in class 4 of the approximations. In the clustered results obtained for the final feature image shown in fig. 9, the tumor is obtained in class 4 and edema in class 5 for this image. This will vary in accordance with the input image to the fuzzy clustering algorithm. From above study fuzzy clustering is superior and giving detailed information than kmeans. The advantage of fuzzy clustering is it focuses upon the tumor object as a single class, thus facilitating its extraction, contour tracing for further analysis.

Conclusion

The method implementation in magnetic resonance image segmentation has been studied significantly with kmeans and fuzzy c –means algorithm. The output of the clustering algorithm must be the delineation of tumor region from the unaffected brain tissue. Applying the expectation-maximization algorithm directly to the MR image of human brain does not provide satisfactory results. Same is the case with fuzzy c-means clustering. The input to the kmeans algorithm is the final feature image obtained by processing the outputs of Gabor wavelets and the number of desired classes in which the input image must be segmented. The region with the highest intensity in the tumor has been labeled as the darkest in the kmeans algorithm. Kmeans clustering for features extracted from all three levels of approximation has been study thoroughly. Fuzzy c-means clustering is applied to the feature image obtained from combining the Gabor outputs.

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Authors Biography

Gayatri Shashikant Mirajkar has received the B. E. degree in Electronics Engineering from Karmaveer Bhaurao Patil College of Engineering & Polytechnic, Satara, in 2001, the M. Tech degree in Electronics & Telecommunication Engineering from Dr. Babasaheb Ambedkar Technological University, Lonere, Raigad, in 2005. She is currently pursuing her Ph. D in Electronics Engineering in Shivaji University, Kolhapur, Maharashtra. She has a teaching experience of 6 years and her research interests include Image Processing, Digital Signal Processing, Microwave Engineering

Dr. Balaji Vithalrao Barbadekar has received the B. E. degree in Electrical Engineering from College of Engineering and Polytechnic, Pune in 1980, the M. E. degree in Electronics Engineering from Walchand College of Engineering, Sangli in 1988 and the Ph. D degree in Electronics Engineering from Shivaji University, Kolhapur in 2000. He has a teaching experience of 35 years and his research interests include Microwave Engineering, Power Electronics, Image Processing, and Wireless Technology.

Dr. Ing. Yogesh Shriram Sonavane has received the B. E. degree in Chemical Engineering from Pravara Rural College of Engineering, Loni in 2000, the M.S. degree in Process Engineering & Design from Otto Von Guericke University, Magdeburg, Germany in 2005, and the Ph. D degree from Otto Von Guericke University, Magdeburg, Germany in 2010. He is currently employed as a scientist at Chalmers University of Technology, Sweden.