ABNORMALITY DETECTION OF BRAIN MRI IMAGES USING A NEW SPATIAL FCM ALGORITHM

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Abstract

Fuzzy C-Means (FCM) is a unsupervised clustering technique that has been extensively used in image segmentation. Conservative FCM algorithm has an inadequacy, it is not consider spatial information into the account. This causes the FCM algorithm to work only on definite images with stumpy level of noise. In this paper an improvement to fuzzy clustering is describe. An earlier spatial constraint is introduced into FCM algorithm, in which the spatial information is encoded through mutual influences of neighboring sites. To detect the abnormalities of Brain MRI images using a new spatial FCM and compare the results with k-means and FCM techniques. Twenty MRI Brain images have been tested and evaluated the similarity of the metrics.

Index Terms: Fuzzy-C means, k-means, clustering, spatial information, image segmentation, Brain-MRI.

1. INTRODUCTION

Image segmentation is of great interest in a variety of scientific and industrial areas, with applications in biomedicine, remote sensing, control of quality and many others. The main purpose of image segmentation is to extract information from the images to distinguish different objects of interest. Several methods for supervised and unsupervised image segmentation and classification have been proposed in the past. FCM (Fuzzy-Cmeans) is unsupervised technique that has been successfully applied to future analysis, clustering, and classifier designs in the fields such as astronomy, geology, medical imaging, target recognition, and image segmentation. An image can be represented in different feature spaces, and the FCM method classifies the image by grouping similar data points in the feature space into clusters. There has been considerable interest recently in the use of fuzzy segmentation methods, which retain more information from the original image than hard segmentation methods (e.g. Bezdek et al. [1], Udupa et al. [2], Pham [3]). The fuzzy C-means method (FCM), in particular, can be used to obtain segmentation via fuzzy pixel classification. Unlike hard classification methods which force pixels to belong exclusively to one class, FCM allows pixels to belong to multiple classes with varying degrees of membership. This approach allows additional flexibility in many applications and has recently been used in processing of magnetic resonance image (MRI) [4]. For example, in their segmentation of MRI brain images, Pham et al. [5] threshold the FCM memberships in order to extract pixels which a high confidence of correct classification. Xu et al. [6] used deformable surfaces that converged to the peaks of the memberships. The FCM method, however, does not address the intensity in homogeneity artifact that occurs in nearly all MRI [7]-[8].

2. FUNDAMENTAL THEORY

2.1 Magnetic Resonance Imaging

In this section, we give a brief description of the principles of Magnetic Resonance Imaging (MRI) which are referred to [9]. MRI is an imaging technique used primarily in medical settings to produce high quality images of the inside of the human body. In MRI, the image is a map of the local transverse magnetization of the hydrogen nuclei. This transverse magnetization in turn depends on several intrinsic properties of the tissue. The magnetic resonance phenomenon relies on the fundamental property that protons and neutrons that make up a nucleus possess an intrinsic angular momentum called spin. When protons and neutrons combine to form nucleus, they combine with oppositely oriented spins. Thus, nuclei with an even number of protons and neutrons have no net spin, whereas nuclei with an odd number of protons or neutrons possess a net spin. Hydrogen nuclei have an signal since its nucleus is made up of only a single proton and possess a net spin. The human body is primarily fat and water,
which have many hydrogen atoms. Medical MRI primarily images the magnetic resonance signal from the hydrogen nuclei in the body tissues. The net spin of the nucleus around its axis gives it an angular moment. Since the proton is a positive charge, a current loop perpendicular to the rotation axis is also created, and as a result the proton generates a magnetic field. The joint effect of the angular moment and the self generated magnetic field gives the proton a magnetic dipole moment parallel to the rotation axis. Under normal condition, one will not experience any net magnetic field from the volume since the magnetic dipole moments are oriented randomly and on average equalize one another. When placed in a magnetic field, a proton with its magnetic dipole moment processes around the field axis. The frequency of this precession, \( \nu \), is the resonant frequency and is called the Larmor frequency. The precession frequency is directly proportional to the strength of the magnetic field, i.e.,

\[
\nu = \frac{\gamma B}{2\pi} \tag{1}
\]

Where \( J \) is the main magnetic field strength and \( \gamma \) is a constant called gyro magnetic ratio which is different for each nucleus (42.58 MHz/Tesla for protons). Given a specimen, the application of a magnetic field \( J \) would create a net equilibrium magnetization \( M_0 \) per cubic centimeter, which is aligned to the \( J \) field. The \( M_0 \) is the net result from summing up the magnetic fields due to each of the \( H \) nuclei and is directly proportional to the local proton density or spin density. However, \( M_0 \) is many orders of magnitude weaker than \( J \) and is not directly observable. By ripping \( M_0 \) away from the \( J \) field axis with an appropriate RF pulse having a frequency equals to the Larmor frequency, a longitudinal magnetization component ML and a transverse magnetization component MT is produced. Then the RF pulse is turned off, the longitudinal magnetization component ML recovers to \( M_0 \) with a relaxation time \( T_1 \), and the transverse magnetization component MT diphase and decays zero with a relaxation time \( T_2 \). Ruining relaxation, the protons lose energy by emitting their own RF signal with the amplitude proportional to MT. This signal is referred to as the free induction decay (FID) response signal. \( T_2 \) indicates the time constant required for the FID response signal from a given tissue type to decay. The FID response signal is measured by an RF coil placed round the object being imaged. When MRI images are acquired, the RF pulse is repeated at a predetermined rate. The period of the RF pulse sequence is the repetition time, TR. The FID response signals can be measured at various images within the TR interval. The time between which the RF pulse is applied and the response signal is measured is the echo delay time, TE. The TE is the time when the spin echo occurs due to the refocusing effects of the 180 degree refocusing pulse applied after a delay of TE/2 from the RF pulse. The TR and TE control how strongly the local tissue relaxation times, \( T_1 \) and \( T_2 \), affect the signal. By adjusting TR and TE the acquired MR image can be made to contrast different tissue types.

### 2.2 Magnetic Resonance Imaging

Much past work on medical image segmentation relied strictly on human graphical interaction to define regions, using methods such as manual slice editing, region painting and interactive thresholding. Rajapakse [10] classified the different methods of image segmentation as four main categories. (1) The classical methods such as thresholding region growing and edge based techniques. (2) The statistical methods such as the maximum-likelihood classifier (MLC). These methods are basically supervised and depend on the prior model and its parameters. Vannieret al. [11] reported satisfactory preliminary results with Bayesian MLC. Ozkan et al. [12] made a comparison between the MLC and the neural network classifier which showed the superiority of the neural network. New methods of segmentation that could be classified as statistical methods have been introduced in the past few years. Hansel [13] used a probabilistic supervised relaxation technique for segmenting 3D medical images. The method introduced the use of cues to guide the segmentation. Those cues marked by the user have the mean and standard deviation as description parameters. (3) The neural networks methods one example of which is the work of Ahmed et al. [14] who used a two stages neural network system for CT/MRI image segmentation. The first stage is a self-organized principal component analysis (SOPCA) network and the second stage consists of a self-organizing feature map (SOFM). The results obtained compare favorably with the classical and statistical methods. (4) The Fuzzy Clustering methods. In [15] a comparison between the fuzzy clustering and neural network techniques in segmenting magnetic resonance images of the brain debated for the need of unsupervised technique in segmentation which was provided using the unsupervised fuzzy c-mean algorithm. However the long IN time taken by the fuzzy c-mean algorithm was documented. In [18] the standard fuzzy clustering algorithm does not correctly segment the regions of abnormality images.

### 3. METHODOLOGY

#### 3.1 K-means clustering

The K-means method is the simplest method in unsupervised classification. The clustering algorithms do not require training data. K-means clustering is an iterative procedure. The K-means clustering algorithm clusters data by iteratively computing a mean intensity for each class and segmenting the image by classifying each pixel in the class with the closest
The steps involved in the K-means clustering algorithm are given below:

1. Choose K initial clusters \(z_1(l), z_2(l), \ldots, z_K(l)\).

2. At the \(K^{th}\) iterative step, distribute the samples \(x\) among the K clusters using the relation
   \[x \in C_j(k)\] if \(||x - z_j(k)|| < ||x - z_i(k)||\]
   where \(C_j(k)\) denotes the set of samples whose cluster center is \(z_j(k)\).

3. Compute the new cluster centers \(z_j(K+1) = 1/N_j \sum_{x \in C_j(k)} x\), \(j = 1, 2, \ldots, K\) (2)
   where \(N_j\) is the number of samples in \(C_j(k)\).

4. If \(z_j(k+1), j = 1, 2, \ldots, K\), the algorithm has converged and the procedure is terminated. Otherwise go to step 2.

The drawback of the K-means algorithm is that the number of clusters is fixed, once K is chosen and it always returns K cluster centers.

### 3.2 Fuzzy C-Means Clustering

The FCM algorithm assigns pixels to each class by using fuzzy memberships. Let \(X=(x_1, x_2, \ldots, x_N)\) denotes an image with \(N\) pixels to be partitioned into \(c\) clusters, where \(x_i\) represents multispectral (features) data. The algorithm is an iterative optimization that minimizes the cost function defined as follows [16]:

\[
J = \sum_{j=1}^{N} \sum_{i=1}^{c} u_{ij}^m ||x_j - v_i||^2
\]  

where \(u_{ij}\) represents the membership function of pixel \(x_j\) in the \(i^{th}\) cluster, \(v_i\) is the \(i^{th}\) cluster center, and \(m\) is a constant. The parameter \(m\) controls the fuzziness of the resulting partition, and \(m = 2\) is used in this study. The cost function is minimized when pixel close to the centroid of their clusters are assigned high membership values, and low membership values are assigned to pixels with data far from the centroid. The membership function represents the probability that a pixel belongs to a specific cluster. In the FCM algorithm, the probability is dependent solely on the distance between the pixel and each individual cluster center in the feature domain.

The membership functions and cluster centers are updated by the following:

\[
u_{ij} = \frac{1}{\sum_{k=1}^{c} \left( \frac{||x_j - v_i||}{||x_j - v_k||} \right)^{2/(m-1)}}
\]  

where \(u_{ij} \in [0, 1]\). Starting with an initial guess for each cluster center, the FCM converges to a solution for \(v_i\) representing the local minimum or a saddle point of the cost function. Convergence can be detected by comparing the changes in the membership function or the cluster center at two successive iteration steps. One of the important characteristics of an image is that neighboring pixels possess similar feature values, and the probability that they belong to the same cluster is great. This spatial relationship is important in clustering, but it is not utilized in a standard FCM algorithm.

### 3.3 Spatial FCM

To exploit the spatial information, a spatial function is defined as:

\[
h_{ij} = \sum_{k \in NB(x_i)} u_{ik}
\]  

where \(NB(x_i)\) represents a square window centered on pixel \(x_i\) in the spatial domain. A 3 x 3 window was used throughout this work. Just like the membership function, the spatial function \(h_{ij}\) represents the probability that pixel \(x_i\) belongs to \(i^{th}\) cluster. The spatial function of a pixel for a cluster is large if the majority of its neighborhood belongs to the same cluster. The spatial function in incorporated into membership function as follows:

\[
u_{ij} = \frac{u_{ij}^P h_{ij}^q}{\sum_{k=1}^{c} u_{ik}^P h_{ik}^q}
\]
4. IMAGE DATA

In this paper, we are used 20 images are taken from two patients at Guntur Government hospital. An abnormality of the images was marked by HOD of Radiology department, Guntur. The images were divided into four clusters: gray matter (GM), white matter (WM), cerebrospinal fluid (CSF) and other features. In addition, two synthetic images with four gray levels are generated to serve as ‘ground truth’ images for segmentation evaluation.

5. RESULTS AND DISCUSSION

5.1 Jaccard Coefficient:

The first measure similarity is the Jaccard Index known as Jaccard similarity coefficient, which is very popular and used mostly as similarity indices for binary data. The area of overlap \( A_j \) is calculated between the original image \( B_j \) and its corresponding gold standard image \( G_j \) as shown in equation - (8).

\[
A_j = \frac{|B_j \cap G_j|}{|B_j \cup G_j|} \quad ---- (8)
\]

If the original object and corresponding gold standard image \( G_j \) (associated ground truth image) are exactly identical then the measure is 1 and the measure 0 represents they are totally disjoint, but the higher measure indicates more similarity. Jaccard index of the proposed method is compared with the K-means and Fuzzy-C means algorithms. The results shown in Table. 1 and the Fig. 2 demonstrate the superiority of the proposed method.

<table>
<thead>
<tr>
<th>IMAGE</th>
<th>JACCARD INDEX(%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>K-means</td>
</tr>
<tr>
<td>Img1</td>
<td>77.92</td>
</tr>
<tr>
<td>Img2</td>
<td>81.78</td>
</tr>
<tr>
<td>Img3</td>
<td>79.56</td>
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<tr>
<td>Img4</td>
<td>78.32</td>
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<tr>
<td>Img5</td>
<td>80.44</td>
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<td>Img6</td>
<td>76.77</td>
</tr>
<tr>
<td>Img7</td>
<td>82.32</td>
</tr>
<tr>
<td>Img8</td>
<td>80.08</td>
</tr>
<tr>
<td>Img9</td>
<td>79.12</td>
</tr>
<tr>
<td>Img10</td>
<td>81.48</td>
</tr>
<tr>
<td>Img11</td>
<td>78.99</td>
</tr>
<tr>
<td>Img12</td>
<td>77.59</td>
</tr>
</tbody>
</table>

Table 1: Efficiency comparison using Jaccard Index
From the experiments for each test image we obtain Jaccard Index values computed from equation (8) is compared with gold standard images by all three different methods including Proposed, K-means and Fuzzy are in TABLE 1. The proposed method surpasses both the other methods by demonstrating mean (μ) as 95.50% and standard deviation (σ) as 1.55 %.

The proposed method confirms the qualitative improvement over the existing methods.

5.2 Dice coefficient:

The other method Dice coefficient which is another similarity measurement related to Jaccard Index method is as follows. In order to evaluate the performance, two measurements of similarity and diversity between the results of the image and its associated gold standard image are considered as shown in equation (9).

\[ s = \frac{2|X \cap Y|}{|X| + |Y|} \quad (9) \]
From the experiments for each test image we obtain Dice Index values computed from equation -(9) is compared with gold standard images by all three different methods including Proposed, K-means and Fuzzy are in TABLE 2. The proposed method surpasses both the other methods by demonstrating mean (μ) as 94.05% and standard deviation (σ) as 1.03 %.

The new spatial FCM successfully classifies the MRI images into four clusters. However, spurious blobs of GM appear inside the WM cluster. The spatial function modifies the membership function of a pixel according to the membership statistics of its neighborhood. Such neighboring effect biases the solution toward piecewise-homogeneous labeling. Both SFCM techniques reduce the number of spurious blobs, and the segmented images are more homogeneous. The SFCM algorithm with a higher q parameter shows a better smoothing effect. The possible disadvantages of using higher spatial weighting are the blurring of some of the finer details. However, this is Difficult to judge from the results. Because no similar cluster is present in the neighborhood, the weight of the noisy cluster is greatly reduced with SFCM, Furthermore, the membership of the correct cluster.

6. CONCLUSION

Unsupervised FCM clustering is a technique applied to segment images into clusters with similar haunted properties. It utilizes the distance between pixels and cluster centers in the haunted domain to compute the membership function. The pixels on an image are highly correlated, and this spatial information is an important characteristic that can be used to aid their labeling. On the other hand, the spatial relationship between pixels is rarely utilized in FCM. In this paper, we proposed a new spatial FCM that incorporates the spatial information into the membership function to get better the segmentation results. The membership functions of the neighbors centered on a pixel in the spatial domain are enumerated to obtain the cluster sharing statistics. These statistics are transformed into a weighting function and incorporated into the membership function. This neighboring effect reduces the number of erroneous blobs and bias the solution towards piecewise homogeneous labeling and evaluated by using various cluster quality metric functions. Preliminary results revealed that the new spatial algorithm yielded good results compared with K-means and Fuzzy-C means algorithms.

7. FURTHER SCOPE

The spatial fuzzy method can be extended to fuzzy MRF model. Our further research is focused on MRI images by using this model to segment the images finely.

REFERENCES


BIOGRAPHIES

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