

An Improved Classifier for Image Segmentation Quality through Initialization of Cluster Centers

Jenita Mary.L^{*1} and Chelladurai.T²

PG Scholar, Department of Electronics and Communication Engineering, PSNA college of Engineering and Technology, Dindigul -624622, India

Assistant Professor, Department of Electronics and Communication Engineering, PSNA college of Engineering and Technology, Dindigul -624622, India

ABSTRACT:

An improved fuzzy classifier based image segmentation algorithm which takes some spatial features into account is proposed. The experimental results show that the proposed algorithm is more noise than the standard fuzzy, with more certainty and less fuzziness. This will lead to its practicable and effective applications in medical image segmentation. We have used a new cluster center initialization method in order to efficiently improve segmentation quality results. Our approach starts from an over segmented image, which is obtained by applying a standard morphological watershed transformation on the original image. We have to apply proposed approach to brightness segmentation on different standard test images, with good visual and objective segmentation quality results. Through the comparison with the base work which uses Random Forest classifier (RF) and other methods, the results show that the new improved algorithm has the advantages such as high segmentation precision and low computational cost.

Index Terms: FCM clustering, RF classifier, Feature Selection, Grey Scale image, Cluster center Initialization, minimum distance threshold.

I. INTRODUCTION

Digital image processing is the use of computer algorithms to perform image processing on digital images. As a subfield of digital signal processing, digital image processing has many advantages over analog image processing; it allows a much wider range of algorithms to be applied to the input data, and can avoid problems such as the build-up of noise and signal distortion during processing. Since images are defined over two dimensions (perhaps more) digital image processing can be modeled in the form of Multidimensional Systems.

Image segmentation is the process of partitioning a digital image into multiple segments (sets of pixels, also known as super-pixels). The main goal of segmentation is to simplify and/or change the representation of an image into something that is more meaningful and easier to analyze. Image segmentation is typically used to locate objects and boundaries (lines, curves, etc.) in images. More precisely, image segmentation is the process of assigning a label to every pixel in an image such that pixels with the same label share certain characteristics. The result of image segmentation is a set of segments that collectively cover the entire image or a set of contours extracted from the image. Each of the pixels in a region is similar with respect to some characteristic or computed property such as color, intensity or texture. Adjacent regions are significantly different with respect to the same characteristic(s).

II. INTRODUCTION TO FUZZY BASED CLASSIFICATION

Over the past few decades, fuzzy logic has been used in a wide range of problem domains. Although the fuzzy logic is relatively young theory, the areas of applications are very wide such as process control, management, decision making operations, research economies and classification. Dealing with simple „black“ and „white“ answers is no longer satisfactory enough; a degree of membership became a new way of solving the problems.

A fuzzy set is a set whose elements have degrees of membership. A element of a fuzzy set can be full member (100% membership) or a partial member (between 0% and 100% membership). That is, the membership value assigned to an element is no longer restricted to just two values, but can be 0, 1 or any value in-between. Mathematical function which defines the degree of an element's membership in a

fuzzy set is called membership function. Fuzzy logic is relatively young theory. This advantage of dealing with the complicated systems in simple way is the main reason why fuzzy logic theory is widely applied in technique. Fuzzy c-means (FCM) clustering is an unsupervised technique that has been successfully applied to feature analysis, clustering and classifier designs in fields such as astronomy, geology, medical

imaging, target recognition and image segmentation. FCM algorithm classifies image by grouping similar data points in the feature space into clusters. This clustering is achieved by iteratively minimizing a cost function that is dependent on the distance of the pixels to the cluster centers in the feature domain.

III. RELATED WORKS

Hitesh Gupta and Mahesh Yambal, July 2013, "Image Segmentation using Fuzzy C Means Clustering: A survey" International Journal of Advanced Research in Computer and Communication Engineering Vol. 2, Issue 7 presented a latest survey of different technologies used in medical image segmentation using Fuzzy C Means (FCM). The conventional fuzzy c-means algorithm is an efficient clustering algorithm that is used in medical image segmentation. Their survey includes Brain Tumor Detection Using Segmentation Based on Hierarchical Self Organizing Map, Robust Image Segmentation in Low Depth of Field Images, Fuzzy C-Means Technique with Histogram Based centroid Initialization for Brain Tissue Segmentation in MRI of Head Scans. Modifying and generalizing the FCM algorithm is a prevailing research stream in fuzzy clustering in recent decades. Low Depth of Field (DOF) is a method used to give special importance to a part of image which is essential or which has to be focused. This method can be used in the fields like sports, photography & medical.

H. Costin, April, 2013, "A Fuzzy Rules-Based Segmentation Method for Medical Images Analysis" INT J COMPUT COMMUN, ISSN 1841-9836 reported a new (semi)automated and supervised method for the segmentation of brain structures using a rule-based fuzzy system. In the field of biomedical image analysis fuzzy logic acts as a unified framework for representing and processing both numerical and symbolic information, as well as structural information constituted mainly by spatial relationships. The developed application is for the segmentation of brain structures in CT (computer tomography) images. Promising results show the superiority of this knowledge-based approach over

best traditional techniques in terms of segmentation errors. Though the proposed methodology has been implemented and used for model driven in medical imaging, they may be applied to any imagistic object that can be expressed by expert knowledge and morphological images. The application of fuzzy logic for biomedical image segmentation proved superior results in terms of segmentation errors, in comparison with other methods. A main advantage of this method is that knowledge is directly represented in the image space by means of fuzzy sets.

The automatic detection of contour points is facilitated by using a data fusion approach by combining information brought by fuzzy rules with that coming from each used searched direction. Thus, the obtained average accuracy of 5.6% was found very well by the medical neuro-surgeon who helped them during experiments. Another advantage of this method is that the computing time when implementing this non-iterative algorithm is kept at a low value and it is possible to be lowered by further parallelization.

IV. RANDOM FOREST BASED CLASSIFICATION

Random forests (RFs) are being used increasingly by many medical applications like tissue segmentation, abnormality detection, coronary artery stenoses identification, grading disease, segmenting Crohns Disease, kidney segmentation and multiple lesion structures. Prior shape is incorporated in the form of zero level set shape templates, elliptical shape priors, registration information, orientation histograms and flux maximization to segment multiple objects in medical and natural images.

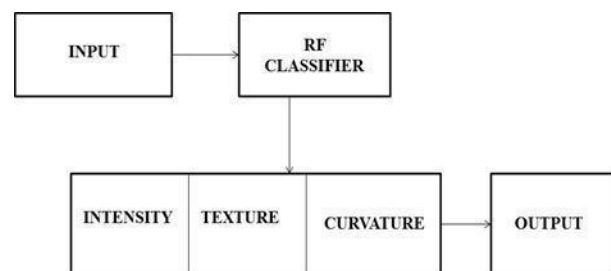


Fig.1. Block Diagram Representation For Random Forest Based Classification

An RF is an ensemble of decision trees, where each tree is typically trained with a different subset of the training set ("bagging"), thereby improving the generalization ability of the classifier. Samples are processed along a path from the root to a leaf in each

tree by performing a binary test at each internal node along this path. The binary test compares a certain feature with a threshold. Training a forest amounts to identifying the set of tests at each node that best separate the data into the different training classes. At each node a random feature subset is examined to select the best subset. This decreases the correlation between outputs of different trees, but improves the performance of the forest as a whole.

DRAWBACKS WITH RANDOM FOREST BASED CLASSIFICATION

The knowledge from random forests is particularly useful when the number of samples is low when compared with the number of feature elements. In such a case the trained RF may not generalize well to novel samples. So they choose to discard those feature elements that have minimal influence on the classification performance. Random Forest based classification suits the best only for hierarchial images and may not give best results for sequential images.

V. IMPROVED CLASSIFICATION USING FCM CLUSTERING

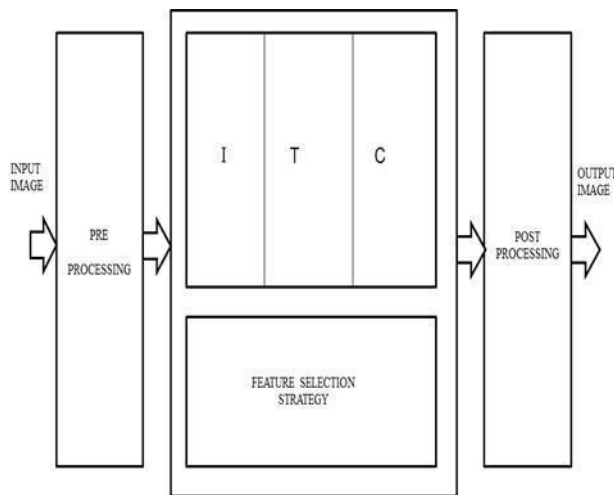


Fig.2. Block Diagram Representation for Fuzzy Based Classification

Image pre-processing can significantly increase the reliability of an optical inspection. Several filter operations which intensify or reduce certain image details enable an easier or faster evaluation. Users are able to optimize a camera image with just a few clicks.

Examples:

- Normalization
- Edge filters
- Soft focus, selective focus
- User-specific filter
- Static/dynamic binarization
- Image plane separation
- Binning

A.FEATURE SELECTION STRATEGY

Two levels of features selection may be done. They are Low level and context feature method. Low level has intensity (I), texture (T) and curvature (C) as their features whereas context level has the combination of above three features.

Intensity

Traditionally, image intensities have been processed to segment an image into regions or to find edge-fragments. Analyzing intensity features involves finding the contrast in image. Grey Scale image contains only pixels of two intensity values, one for background and one for object pixels and the contrast of the object would be a difference of those values.

Texture analysis

Purpose of texture analysis is to identify different textured and non-textured regions in an image, to classify or segment different texture regions in an image and to extract boundaries between major texture regions. Part of the problem in texture analysis is defining exactly what texture is. There are two main approaches:

1. Structural approach: Texture is a set of primitive texels in some regular or repeated relationship.
2. Statistical approach: Texture is a quantitative measure of the arrangement of intensities in a region.

While the first approach is appealing and can work well for man-made, regular patterns, the second approach is more general and easier to compute and is used more often in practice. We have to identify a filter which can give sharp edges for the given image.

Curvature Entropy

Curvature maps are obtained from the gradient maps of tangent along the 3D surface. The second fundamental form (F2) of the curvature maps is identical with the Weingarten mapping and the trace of the F2 matrix gives the mean curvature. This means curvature map is used for calculating anisotropy. Context information is particularly important for medical images because of the regular arrangement of human organs. Context features have been used to segment brain structures in MRI, the

prostate from CT images, cardiac structures from MRI, localizing anatomical structures and registration. Fig.3.(b) shows the template for context information where the circle center is the voxel in question and the sampled points are identified by a red „X“.

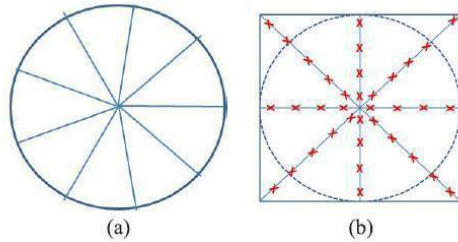


Fig.3.(a) Partitioning of patch for calculating anisotropy features; (b) template for calculating context features.

B. INITIALIZATION OF CLUSTER CENTERS

In the FCM algorithm, the adjacent two iterations can get two cluster centers. If the distance between these two cluster centers is less than some threshold, we can determine that the FCM algorithm has converged. If the initial cluster centers are selected in the vicinity of a local minimum, it may cause the algorithm to converge to a local minimum. It means that the algorithm is sensitive to initial value and its classification accuracy rate is decreased.

To solve these problems, we propose an improved FCM algorithm. Let $X = X_1, X_2, \dots, X_n$ be a set of classified samples. Minimum distance threshold between classes is R . Cluster center initialization steps are shown as follows:

Step1 Calculate the distance between any two samples to generate the distance matrix D . Put the nearest two samples into a category and let the midpoint of the two samples as the cluster center of the first class.

Step2 Using the distance matrix D , find all samples which distance to the first cluster center greater than R . In these samples, classify the nearest two samples into a category and let the midpoint of the two samples as second category cluster center.

Step3 Similarly, like step1 and step2, find two nearest samples in remain samples. Classify the two samples into a category and let the midpoint of the two samples as new category cluster center.

Step4 Repeat step 3 until the category c is found.

In accordance with the requirements of steps 1 and 2, the samples should be divided into two categories. The selection process of initial cluster center is shown as Fig.4. As can be seen from Fig.4, initialization of cluster centers is executed in multiple

areas. This method can make the clustering process avoid local convergence; thereby reduce the dependence of FCM algorithm on initialize cluster centers.

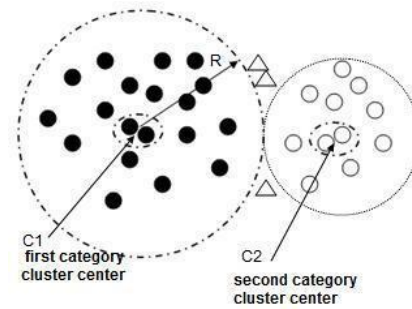


Figure.4. Initialization of cluster centers

Finally, post-processing returns the Median value of array. Median filter is used to replace the central value of an M -by- N neighborhood with its median value.

Syntax

$M = \text{median}(A)$
 $M = \text{median}(A, \text{dim})$

Description

$M = \text{median}(A)$ returns the median values of the elements along different dimensions of an array. A should be of type `single` or `double`.

If A is a vector, $\text{median}(A)$ returns the median value of A .

If A is a matrix, $\text{median}(A)$ treats the columns of A as vectors, returning a row vector of median values.

If A is a multidimensional array, $\text{median}(A)$ treats the values along the first nonsingleton dimension as vectors, returning an array of median values.

$M = \text{median}(A, \text{dim})$ returns the median values for elements along the dimension of A specified by scalar `dim`.

VI. RESULTS AND DISCUSSIONS

A. INPUT IMAGES

Here, we have analyzed both normal image and MRI image without abnormalities. The results have been enclosed here for two sample input images represented as follows.

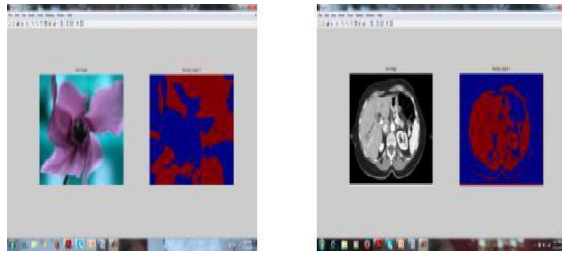


Fig.5.Input and its corresponding RGB image

B.TABULATION FOR INTENSITY AND TEXTURE VALUES

IMAGE	INTENSITY VALUE	TEXTURE VALUE
1	0.0079	1.0000
2	0.0072	0.9546

After extracting the intensity and texture features from input image we perform fuzzy based clustering to get our segmented output. Depending upon the features of each image the clustering values will vary. We can get the clustering values for each image by loading and executing each image separately. After clustering we get the sub-sampled and updated image at the output end. The final segmented output of each image is given below.

C.OUTPUT IMAGES

The segmented image after basic fuzzy clustering without initialization of cluster centers is given below.

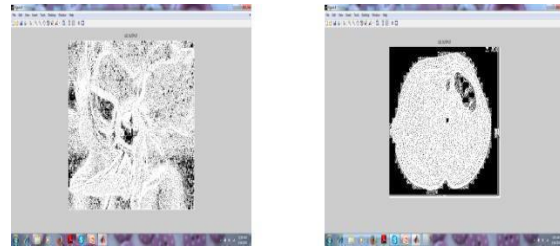


Fig.6.Before cluster center initialization

The output of each image after initialization of cluster centers is given below.

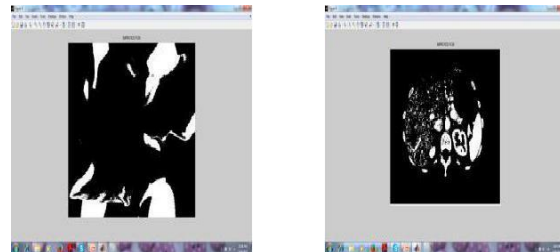


Fig.7.After cluster center initialization

We have classified each image into 3 clusters. The cluster center values for the 2 images in Fig.7 are as follows. For the first image the center values are 0.1099, 0.4498, 0.7276 and for the second image it is 0.0490, 0.5811, 0.9069.

D.PERFORMANCE PARAMETERS

We have successfully implemented the method of using fuzzy classifier for improving the image segmentation results. The following performance parameters were evaluated to compare its efficiency with other methods.

1. Accuracy/Success Rate
2. Overall Error
3. Percentage of Correct Classification (PCC)
4. Test Statistics

Test Statistics

This provides definitions and some results for tests that detect the presence of a condition (a test result is either “positive” or “negative”, which may be “true” or “false”).

Definition 1. A true positive test result is one that detects the condition when the condition is present.

Definition 2. A true negative test result is one that does not detect the condition when the condition is absent.

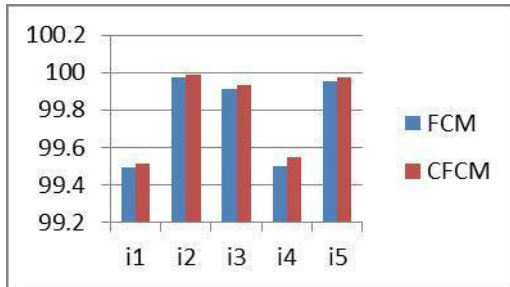
Definition 3. A false positive test result is one that detects the condition when the condition is absent.

Definition 4. A false negative test result is one that does not detect the condition when the condition is present.

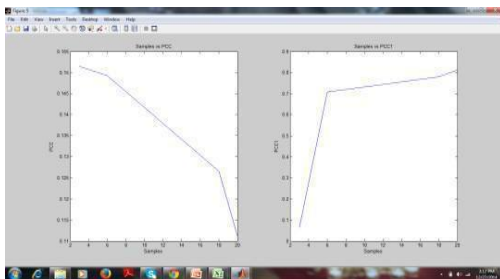
The analysis of performance parameters are given below.

ACCURACY RATE

The comparison of accuracy rate before and after using cluster centric operation is represented in the below graph.



PCC



TEST STATISTICS

IMAGE	TP	TN
1	0.2117	0.7883
2	0.0045	0.9955
3	0.0019	0.9981
4	0.0926	0.9074
5	0.3036	0.6964

VII.CONCLUSION

We have proposed an image segmentation method that exploits knowledge from the training process of fuzzy classifiers. An improved fuzzy

classifier based medical image segmentation algorithm which takes some spatial features into account. Here, we have used a cluster center initialization technique that efficiently improve segmentation quality results. Our approach starts from an over segmented image, which is obtained by applying a standard morphological watershed transformation on the original image. We have efficiently applied the proposed approach to brightness segmentation on different standard test images, with good visual and objective segmentation quality results. Higher segmentation accuracy and better generalization is achieved using fuzzy classifier with cluster center initialization technique.

VIII. REFERENCES

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