

Fuzzy Clustering With Spatial Information For Image Segmentation Using Kernel Metric

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Abstract-

In this project the image segmentation using Fuzzy C- means algorithm and kernel metric. In FCM algorithm by introducing a trade-off weighted fuzzy factor and kernel metric. This factor depends on the space distance of all neighboring pixels and their gray-level difference simultaneously. So we propose generalised rough set FCM algorithm in order to further enhance its robustness to noise and outliers, we introduce a kernel distance measure to its objective function. This algorithm determines the kernel parameter by using all data points in the collection. So the segmentation accuracy is high. Furthermore, the trade-off weighted fuzzy factor and the kernel distance measure are both parameter free. The performance of the proposed method is compared with FCM results on synthetic and real images are more effective and efficient.

Index Terms- Fuzzy clustering, gray-level constraint, image segmentation, kernel metric.

I. INTRODUCTION

A. General

Image segmentation is one of the key techniques in image understanding and computer vision. The task of image segmentation is to divide an image into a number of non-overlapping regions. Which have same characteristics such as gray level , color, tone, texture, etc. A lot of clustering based methods have been proposed for image segmentation [1]-[5]. Among the clustering methods one of the most popular methods for image segmentation is fuzzy clustering information than hard clustering.

Fuzzy C-means (FCM) algorithm is one of the most widely used Fuzzy clustering algorithm in image segmentation. Although the conventional FCM algorithm works on most noise free images it fails to segment images corrupted by noise, outliers and other imaging artifacts. Its non-robust results are mainly because of ignoring spatial contextual information in image and the use of non-robust Euclidean distance. To deal with this problem. Many improved FCM algorithm have been proposed by incorporating local spatial information into original FCM objective function [8]-[10]. To reduce the computational time of En-FCM is very small. So we proposed the fast generalised FCM algorithm. This introduces a local similarity measure that combines both spatial and gray level information to form a non-linearly weighted sum image. Clustering is performed on the basis of the gray level histogram

time of the summed image. Thus, its computational time is very small. However, these algorithms do not directly apply on the original image. They need some parameter, to control the trade-off between robustness to noise and effectiveness of preserving the details. The selection these parameters is not an easy task, and has to be made by experience or by using the trail-and-error method.

To overcome the mentioned problems, [1] presents a novel robust fuzzy local information c-means clustering algorithm (FLICM), which is free of any parameter selection, as well as prompting the image segmentation performance. Furthermore, it presents a more robust result. Although RFLICM algorithm can exploit more local context information to estimate the relationship of pixels in neighbours since the local coefficient of variation, it is still unreasonable to ignore the influence of spatial constraint on the relationship between central pixel and in neighbors. In order to further improve the performance of FLICM in retraining noise, another novelty in this study is introducing the kernel distance measure to its objective function. In recent years, kernel methods have received an enormous amount of attention in machine learning community. Its main idea is to transform complex nonlinear problems in original low dimensional feature space to the problems easily solved in the transformed space. Particularly, the clustering algorithms based on kernel methods have been applied to many fields of image segmentation [12-15]. Because of this advantage, introduced a new kernel-induced distance measure for the original

data space into the objective function of FCM to replace the conventional measures. Therefore [9] proposed two variants of KFCM which replace this term using the mean filtered or median filtered image to reduce the computational cost. In general ,the Gaussian RBF kernel [9] is adopted in the kernel function for its facility. But the parameter σ in GRBF has a great influence on the performance of the algorithm. Therefore, we use a fast bandwidth selection rule, which can adaptively compute the parameter σ .

The paper further organized as follows: Section II proposes the motivation. Section III provide algorithm in details. In section IV, experimental results on synthetic images, medical images and natural images. Conclusions is defined in section V.

II MOTIVATION

The goal of my paper is to design a trade-off weighted fuzzy factor for adaptively controlling the local spatial relationship. This factor depends on space distance of all neighboring pixels and their gray level difference simultaneously. In order to improve the performance of image segmentation and introducing the kernel distance measure to its objective function. The segmentation process of a gray-level image can be defined as the minimization of an energy function. Let us suppose that this image has to be segmented into $c(c \geq 2)$ classes. In the FCM approach, the segmentation process of a gray-level image can be defined as the minimization of an energy function. FLICM [1] introduces a novel fuzzy factor G_{ki} as a fuzzy local similarity measure in its objective function, which is aimed at guaranteeing noise insensitiveness and image detail preservation. Its objective function for partitioning a dataset $\{x_i\}_{i=1}^N$ into c clusters is defined in terms of

$$J_m = \sum_{i=1}^N \sum_{k=1}^C \left[U_{ki}^m \|x_i - V_k\|^2 + G_{ki} \right] \quad (1)$$

The parameter m is a weighting exponent on each fuzzy membership and determines the amount of fuzziness of the resulting classification. Here we set $m = 2$ for following experiments. The array $U = \{u_{ki}\}$ represents a membership matrix satisfying

$$U \in \left\{ U_{ki} \in \left[0, 1 \right] \mid \sum_{k=1}^C U_{ki} = 1 \right\} \quad (2)$$

While the fuzzy factor G_{ki} is defined mathematically as follow

$$G_{ki} = \sum_{j \in N_i} \frac{1}{d_{ij} + 1} (1 - U_{kj})^m \|x_j - V_k\|^2 \quad (3)$$

Where the i th pixel x_i is the center of the local window and the j th pixel x_j represents the neighboring pixels falling into the window around x_i , d_{ij} is the spatial Euclidean distance between pixels i and j . N_i stands for the set of neighbours in a window around x_i . U_k represents the fuzzy membership of gray value x_j with respect to the k th cluster. Then the membership function as follow,

$$U_{ki} = \frac{1}{\sum_{j=1}^C \left[\frac{\|x_i - V_k\|^2 + G_{ki}}{\|x_i - V_j\|^2 + G_{ji}} \right]^{1/m}} \quad (4)$$

$$V_k = \frac{\sum_{i=1}^N U_{ki}^m x_i}{\sum_{i=1}^N U_{ki}^m} \quad (5)$$

V is the vectors of the cluster. The maximum membership procedure assigns the pixel i to the class C_k with the highest membership

$$C_k = \arg(\max\{U_{ki}\}) \quad k=1,2,3,\dots,c \quad (6)$$

It is used to convert the fuzzy image achieved by the proposed algorithm to the crisp segmented image.

A. Introducing the Trade-off weighted Fuzzy factor

The fuzzy factor G_{ki} , the corresponding membership values of the non-noisy pixels, as well as the noisy pixels that falling into the local window will converge to a similar, and thereby balance the membership values of the pixels that located in the window. Thus FLICM becomes more robust to outliers. Therefore G_{ki} can reflect the damping extent of the neighbours with the spatial distance from the central pixel. It is described as follows

$$G_{ki} = \begin{cases} 1 \\ \sum_{j \in N_i} \frac{1}{2 + \min((C_u^j/C_u)^2, (C_u/C_u^j)^2)} \\ \text{if } C_u^j \geq C_u \end{cases} \quad (7)$$

Where, C_u represents the local coefficient of variation of central pixel. C_u^j represents the j th local coefficient of variation in neighbours. In addition, the damping extent of the neighbours cannot be accurately calculated, as the same gray-level distribution and different spatial constraint. Hence in this paper, we define a new trade-off weighted fuzzy factor to adaptively control the local

neighbour relationship. This factor depends on space distance of all neighbour pixels and their gray level discrepancy simultaneously

B. Using Non-Euclidean Distance

It can be seen that the measure used in the objective function of FLICM is still the Euclidean metric as in FCM. Although this metric method is computationally simple, the use of Euclidean distance can lead to non-robust results on segmentation of image corrupted by noise, outliers, and other imaging artifacts. In the FCM objective function to reduce the effect of outliers on clustering results. On other hand, there is a trend in recent machine learning work to construct a nonlinear version of a linear algorithm using the kernel method, which aims at transforming the complex nonlinear problems in original low-dimensional feature space to the problems which can be easily solved in the transformed space, and this method can be used in clustering.

A kernel in the feature space can be represented as the following function K

$$K(x,y) = \{ \varphi(x), \varphi(y) \} \quad (8)$$

The different kernels will induce different measure for the original space. Gaussian Radial basis function (GRBF) kernel is a commonly used method. And its mathematical formulation presents as follow

$$K(x,y) = \exp - \left(\frac{\sum_{i=1}^d |x_i - y_i|^a}{\sigma^b} \right) \quad (9)$$

Where d is the dimension of vector x; σ is the kernel bandwidth. The Selection appropriate bandwidth value for a kernel based clustering algorithm could be very troublesome since all the data points are unlabeled and their true classes are unknown. So we use a fast bandwidth selection rule based on the distance variance of all data points in the collection to determine the parameter σ .

III. METHODOLOGY

Motivated by the above descriptions, we improve FLICM by introducing a trade-off weighted fuzzy factor and kernel method. The block diagram shows the step by step procedure for the segmentation process.

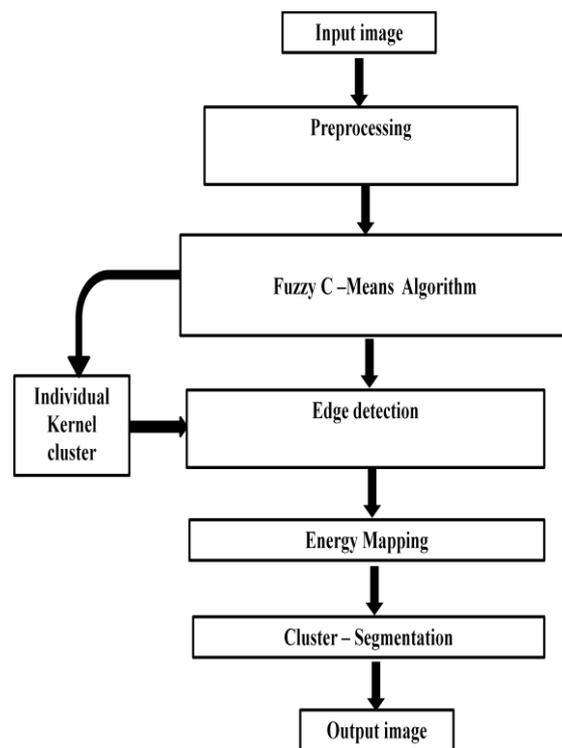


Figure: Block diagram

We take the input brain image. Then preprocessing is performed. In this preprocessing the low frequency background noise and the reflections, masking portions are removed, size can be reduced. Then apply Fuzzy C-means algorithm this algorithm can calculate the mean ,centroid, Euclidean distance from the cluster collection. After edge can be detected by using the edge detection, then energy mapping can be performed. The next process is the image can be segmented. Then the segmented image produce the more accurate output image.

A. Proposed system Algorithm

Input: MRI Brain image.

Output: Segmented result.

Step 1: Set the number c of the cluster prototype, fuzzification parameter m, window size N_i and the stopping condition ϵ .

Step 2: Initialize randomly the fuzzy cluster prototype.

Step 3: Set the loop b = 0.

Step 4: Calculate the trade-off weighted fuzzy factor W_{ij} and the modified distance measurement D_{ik}^2 .

Step 5: Update the partition matrix using Eq(12)

Step 6: Update the cluster prototype using Eq(13)

Step 7: If $\max |V_{new} - V_{old}| < \epsilon$ then stop, otherwise, set b = b+1 and go to step 4.

Where $V = [V_1, V_2, \dots, V_c]$ are the vectors of the cluster prototype.

When the algorithm has converged, a defuzzification process takes place to convert the fuzzy image to the crisp segmented image.

B. Trade-off Weighted Fuzzy Factor

The adaptive trade-off weighted fuzzy factor depends on the local spatial constraint and local gray-level constraint. For each pixel X_i with coordinate (p_i, q_i) the spatial constraint reflects the damping extent of the neighbours with the spatial distance from the central pixel and defined as

$$W_{sc} = 1/(d_{ij}+1) \tag{10}$$

Where the d_{ij} is the spatial Euclidean distance between the j th pixel in neighbours and the central pixel. Therefore, the trade-off weighted fuzzy factor is written as

$$W_{ij} = W_{sc} \cdot W_{gc} \tag{11}$$

Futher more the weight of the neighboring pixel will be increased to suppress the influence of outlier after transformed into the kernel space and added the spatial constraint. Here, two cases are presented they are,

Case 1: The central pixel is not a noise and some pixels within its local window may be corrupted by noise.

Case 2: The central pixel is corrupted by noise, while the other pixels within its local window are homogenous, not corrupted by noise. In this way, a new class of non-Euclidean distance measures in original data space is obtained. The mean, variance can be calculated by the equation as,

$$\bar{d} = \frac{\sum_{i=1}^N d_i}{N} \tag{12}$$

$$\Sigma = \frac{1}{N-1} \sum_{i=1}^N (d_i - \bar{d})^2 \tag{13}$$

From the above description we can see that the trade-off weighted fuzzy factor and the kernel distance measure are both free of the empirically adjusted parameters which can be incorporated into other fuzzy c-means algorithms easily.

C. Fuzzy C-Means Algorithm

FCM method for image clustering compared to hard thresholding clustering methods, FCM is capable of reducing the uncertainty of pixels belonging to one class and therefore in providing improved clustering outcomes. FCM allows data points to be assigned into more than one cluster. The steps of the FCM is first randomly select the cluster center, calculate distance between cluster center, calculate

the membership function minimum. The advantage is to give best result for overlapped data set and comparatively better than k-means algorithm.

IV. EXPERIMENTAL RESULT

The proposed algorithm result is computational consuming, since the fuzzy factor is computed in each iteration step. Furthermore, kernel means, performing a nonlinear data transformation into high dimensional feature space via nonlinear mapping increases the probability of the linear separability of the data within the transformed space. The result improves the performance of image segmentation, as well as the robustness to the type of noises.

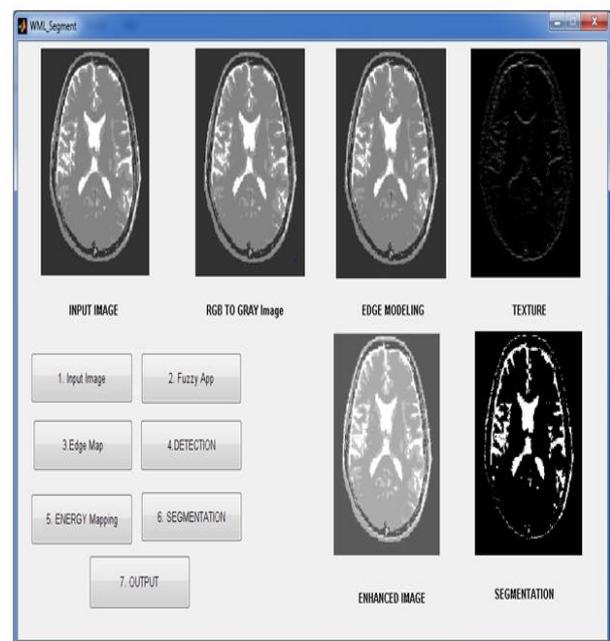


Figure: Input and Output image performance

V. CONCLUSION

The kernel method have been recently applied to unsupervised clustering. In this paper we propose an unsupervised FCM algorithm based on the kernel metric for segmentation of images that have been corrupted by imhomogeneities and noise. The result show the kernel metric is an effective approach to constructing a robust image clustering algorithm. Most of the traditional hybrid approaches produce less accurate result. The proposed generalized rough set based fuzzy C-means algorithm, each cluster is characterized by three automatically determind rough-fuzzy regions. This algorithm is compared to the existing algorithm accuracy is high and the segmentation images are more effective and efficient.

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