Applied Soft Computing 30 (2015) 48–57

Contents lists available at ScienceDirect

Applied Soft Computing

journal homepage: www.elsevier.com/locate/asoc

A multiobjective spatial fuzzy clustering algorithm for image segmentation

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ARTICLE INFO

Article history:
Received 15 October 2012
Received in revised form
11 November 2014
Accepted 22 January 2015
Available online 31 January 2015

Keywords:
Image segmentation
Multiobjective optimization
Fuzzy clustering
Non-local spatial information
Cluster validity measure

ABSTRACT

This article describes a multiobjective spatial fuzzy clustering algorithm for image segmentation. To obtain satisfactory segmentation performance for noisy images, the proposed method introduces the non-local spatial information derived from the image into fitness functions which respectively consider the global fuzzy compactness and fuzzy separation among the clusters. After producing the set of non-dominated solutions, the final clustering solution is chosen by a cluster validity index utilizing the non-local spatial information. Moreover, to automatically evolve the number of clusters in the proposed method, a real-coded variable string length technique is used to encode the cluster centers in the chromosomes. The proposed method is applied to synthetic and real images contaminated by noise and compared with k-means, fuzzy c-means, two fuzzy c-means clustering algorithms with spatial information and a multiobjective variable string length genetic fuzzy clustering algorithm. The experimental results show that the proposed method behaves well in evolving the number of clusters and obtaining satisfactory performance on noisy image segmentation.

1. Introduction

Image segmentation is one of the most difficult tasks and challenging problems in image analysis since the segmentation result plays an important role in further image processing [1]. It aims to divide an image into several non-overlapping meaningful regions with homogeneous characteristics [2]. In the past few decades, many researchers have proposed various segmentation algorithms, such as thresholding techniques [3,4], clustering algorithms [5–8], region-based approaches [9] and combination of some presented approaches [10,11]. Generally, image segmentation is basically clustering of the pixels in the image according to some criteria. Therefore, as the popular unsupervised pattern classification technique that can partition a set of objects into k groups, clustering algorithms are easily applied to image segmentation and have been proved its efficiency.

The idea of data clustering is very close to the way of human thinking, which is the similar samples or pixels in the image are put into one group. One easiest method is utilizing the distance between the observed data to perform clustering. The distance between the data points in the same cluster should be shorter, and the distance between the data points in different clusters should be larger. According to this thought, one can design a clustering objective function and optimize it to achieve the final clustering result. In this kind of clustering algorithms, k-means (KM) and fuzzy c-means (FCM) clustering algorithm are the most popular algorithms and have been applied to various areas. In KM, the optimal partition is obtained by minimizing the total distance within the clusters and every data point either belongs to a certain cluster or not. Relying on the basic idea of KM, FCM also designs an objective function to perform a fuzzy partitioning such that the given data point can belong to several groups with the degree of belongingness. However, when KM and FCM applied to image segmentation, they are both sensitive to noise, outliers and other imaging artifacts due to not considering any spatial information in the image.

In order to overcome the sensitivity of FCM to noise in the image, many researchers introduced the spatial information derived from the neighborhood of the pixel in the image (this kind of spatial information can be called local spatial information) into the objective function of FCM [7,12–15]. Ahmed et al. [12] modified the objective function of FCM by incorporating a spatial neighborhood term and proposed FCM algorithm with spatial information (FCM_S). Subsequently, Chen and Zhang [7] presented two variants of FCM_S (FCM_S1 and FCM_S2) to reduce the computational complexity of FCM_S. Furthermore, in Ref. [7], Chen and Zhang utilized a kernel-induced distance to replace the Euclidean distance and presented the kernel versions of FCM_S1 and FCM_S2 (KFCM_S1 and KFCM_S2). To speed up the image segmentation process of FCM with spatial information, Szilagyi et al. [13] generated a linearly-weighted sum image and proposed an enhanced fuzzy c-means (EnFCM) clustering algorithm. This algorithm is performed on the gray level histogram of the generated sum image instead of the pixels. Similar to EnFCM, Cai et al. [15] defined a non-linearly-weighted sum image and proposed a fast generalized fuzzy c-means (FGFCM) clustering algorithm. These two weighted sum image in EnFCM and FGFCM are both computed by using the neighborhood of the pixel. When the image is heavily contaminated by noise, the adjacent pixels of a pixel may also contain abnormal features and the above fuzzy c-means clustering algorithms with local spatial information cannot obtain satisfying segmentation performance. Instead of using the adjacent pixels of the pixel to generate the spatial constraint term, Zhao et al. [16] introduced a non-local spatial information derived from a large image domain of the pixel to construct the spatial constraint term and proposed a fuzzy c-means

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http://dx.doi.org/10.1016/j.asoc.2015.01.039
1568-4946/

clustering algorithm with non-local spatial information (FCM_NLS). The non-local spatial information of a pixel is obtained by utilizing the pixels with a similar configuration of the given pixel. FCM_NLS can achieve better segmentation results than the existing fuzzy c-means clustering algorithms with local spatial information.

It is well known that the clustering performance relies on the objective function or cluster criteria. Both the traditional FCM and FCM algorithms with spatial information only consider the total distance within the clusters and utilize the single objective function for data clustering. These methods tend to be very effective for spherical or well-separated clusters, but they may fail to detect more complicated cluster structures. Moreover, these methods are quite sensitive to the initialization and may get into the local optimum. In order to solve these problems, many researchers attempted to optimize several cluster validity measures and proposed many multiobjective clustering approaches [17–23]. Among these approaches, a multiobjective evolutionary clustering proposed by Handl and Knowles [17] is an important work. In this method, the deviation and connectivity are used as two objective functions to be simultaneously optimized and the number of clusters can be automatically evolved. However, the chromosome length in this work is equal to the number of data points to be clustered. To reduce the search space, a special mutation operator which maintains a list of nearest neighbors for each data point is used in this method. It should be mentioned that this method is only suitable for crisp clustering. Some works of multiobjective fuzzy clustering can be found in Refs. [18–23]. In these methods, center based encoding technique is used and several cluster validity measures are utilized as the objective functions to be optimized. The method in Ref. [18] optimizes two cluster validity measures, J_m [24] and Xie–Beni (XB) index [25]. However, these two validity measures are not completely independent to each other, especially that these two validity measures are similar when the fuzzy exponent is 2. Therefore they may not obtain good Pareto-optimal solutions. In [21], Mukhopadhyay et al. utilized three cluster validity measure namely XB, J_m and PBM [26] as the objective functions and adopted clustering ensemble to obtain the optimal solution from the final non-dominated solution set. In [18–22], the number of clusters is priorly specified. In contrast, the method in [23] uses a variable string length coded strategy to encode cluster centers, by which the number of clusters can be automatically evolved. Moreover, this method utilizes the global fuzzy compactness and fuzzy separation as objective functions and adopts a validity index I [27] to obtain a single solution from the final non-dominated solution set. This method has been successfully applied to MR brain image segmentation.

When the existing multiobjective fuzzy clustering algorithms applied to image segmentation, the used cluster validity measures do not consider the spatial information derived from the image. Therefore, when the image is heavily contaminated by noise, these methods may not obtain satisfactory segmentation performance. To overcome the sensitivity to image noise and obtain effective segmentation results, a multiobjective spatial fuzzy clustering algorithm (MSFCA) for image segmentation is proposed. In this method, the non-local spatial information derived from the image is introduced into the fitness functions which respectively consider the global fuzzy compactness and fuzzy separation among the clusters. MSFCA uses Non-dominated Sorting Genetic Algorithm-II (NSGA-II) [28] as the underlying optimization strategy. After obtaining the final non-dominated solution set, the best solution is selected according to a cluster validity index with the non-local spatial information in MSFCA. Moreover, MSFCA adopts the real-coded variable string length technique to encode the cluster centers in the chromosomes. So this method can automatically evolve the number of clusters. In the experiments, KM, FCM, FGFCM, FCM_NLS and the multiobjective variable string length genetic fuzzy clustering (MOVGA) method [23] are chosen as comparative methods. The experimental results on a synthetic image and some Berkeley segmentation images contaminated by noise show that MSFCA behaves well in evolving the number of clusters and obtaining satisfactory segmentation performance.

The rest of this paper is organized as follows. Section 2 reviews the existing fuzzy c-means clustering algorithms. Then multiobjective spatial fuzzy clustering algorithm (MSFCA) is proposed in Section 3. In Section 4, MSFCA is verified by segmentation experiments on synthetic and real images. Finally, some concluding remarks and discussions are given in Section 5.

2. Fuzzy c-means clustering algorithms

2.1. Standard fuzzy c-means clustering algorithm

Fuzzy c-means (FCM) clustering algorithm is a method which allows a data point to belong to two or more clusters. Let $X = \{x_1, x_2, \ldots, x_n\}$ denote an image with n pixels, where x_i represents the gray value of the ith pixel. The objective function of standard FCM algorithm is

$$J = \sum_{k=1}^{K}\sum_{i=1}^{n} u_{ki}^{m} ||x_i - v_k||^2 \tag{1}$$

where v_k $(1 \le k \le K)$ denotes the center of the kth cluster and u_{ki} $(1 \le k \le K,\ 1 \le i \le n)$ represents the membership degree function value of the ith pixel belonging to the kth cluster. Moreover, u_{ki} needs to satisfy the following constraints

$$\sum_{k=1}^{K} u_{ki} = 1, \quad u_{ki} \in [0, 1], \quad 0 \le \sum_{i=1}^{n} u_{ki} \le n \tag{2}$$

In Eq. (1), $|| \ ||$ denotes the Euclidean norm and the parameter m $(m > 1)$ is a weighting exponent that determines the amount of fuzziness of the resulting partition. Through minimizing Eq. (1), the update equations of the membership degree function u_{ki} and the cluster center v_k are

$$u_{ki} = \frac{1}{\sum_{l=1}^{K} (||x_i - v_k||^2 / ||x_i - v_l||^2)^{1/(m-1)}} \tag{3}$$

$$v_k = \frac{\sum_{i=1}^{n} u_{ki}^{m} x_i}{\sum_{i=1}^{n} u_{ki}^{m}} \tag{4}$$

2.2. Fuzzy c-means clustering algorithms with spatial information

2.2.1. Spatial information

In order to overcome FCM′s sensitivity to noise and artifacts in the image, several modified FCM algorithms utilize the spatial information derived from the neighborhood window around each pixel [7,12–15]. This kind of spatial information is called local spatial information. Up to now, the local spatial information has had a lot of expression forms. Mean spatial information and median spatial information are two common kinds of local information. The mean spatial information of the ith pixel can be defined as

$$\delta_i = \frac{1}{|S_i|} \sum_{p \in S_i} x_p \tag{5}$$

where S_i is the set of neighboring pixels in a window centered at the ith pixel and $|S_i|$ is its cardinality. Similarly, the median spatial information of the ith pixel is expressed as

$$\varsigma_i = \text{median}\{x_p\},\ p \in S_i \tag{6}$$

Most of the FCM algorithms with spatial information introduce the above local spatial information into the objective function of FCM. Although FCM algorithms with local spatial information can obtain satisfying segmentation performance on an image with low noise level, the local spatial information obtained from the adjacent pixels of a pixel is not the most efficient when the image is heavily contaminated by noise. Actually, there are many pixels possessing a similar neighborhood configuration in an image [29]. Utilizing the pixels with a similar neighborhood configuration to the given pixel to obtain the spatial information is more reasonable than only using the adjacent pixels of the given pixel. We call this kind of spatial information as non-local spatial information.

For the ith pixel, its non-local spatial information $\bar{x}_i$ is computed by

$$\bar{x}_i = \sum_{j \in W_i^r} w_{ij} x_j \tag{7}$$

In this equation, W_i^r denotes a $r \times r$ search window centered at the ith pixel. The non-local spatial information of ith pixel is computed by utilizing the pixels in this window. w_{ij} $(j \in W_i^r)$ is the