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Multi-objective evolutionary fuzzy clustering for image segmentation with MOEA/D

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ABSTRACT

In order to achieve robust performance of preserving significant image details while removing noise for image segmentation, this paper presents a multi-objective evolutionary fuzzy clustering (MOEFC) algorithm to convert fuzzy clustering problems for image segmentation into multi-objective problems. The multi-objective problems are optimized by multi-objective evolutionary algorithm with decomposition. The decomposition strategy is adopted to project the multi-objective problem into a number of sub-problems. Each sub-problem represents a fuzzy clustering problem incorporating local information for image segmentation. Opposition-based learning is utilized to improve search capability of the proposed algorithm. Two problem-specific techniques, an adaptive weighted fuzzy factor and a mixed population initialization, are introduced to improve the performance of the algorithm. Experiment results on synthetic and real images illustrate that the proposed algorithm can achieve a trade-off between preserving image details and removing noise for image segmentation.

1. Introduction

Image segmentation, which is often the first and most critical step in many image applications, plays a significant role in computer vision and image understanding. The definition of image segmentation is to divide an image into multiple segments with similar characteristics (such as gray level, color, intensity or texture). Among the methods proposed for image segmentation in recent years, image clustering, especially fuzzy clustering [1], has been widely applied in different areas such as remote sensing, medical image, and etc. [2–8].

Fuzzy c-means (FCM) [9,10] algorithm is one of the most popular fuzzy clustering methods for image segmentation. Although the traditional FCM algorithm works well on lots of noise-free images, it is relatively sensitive to noise because of its ignorance about spatial information in images. To deal with the misclassification errors caused by noise, many improved FCM algorithms [2–8] have been proposed by incorporating local spatial information into original FCM objective function. Ahmed et al. [2] proposed a bias-corrected fuzzy c-means (FCM_S) algorithm, which introduced a spatial neighborhood term into original FCM objective function to ensure that the labeling of a pixel is determined by the labels of its neighbor pixels. However, FCM_S was time-consuming for computing the spatial neighborhood term in each iteration step. To reduce the time cost by computing the spatial neighborhood term in each iteration step of FCM_S, Chen and Zhang [3] proposed two variants of FCM_S algorithm, FCM_S1 and FCM_S2, which respectively replaced the spatial neighborhood term in FCM_S with an extra mean-filtered image and a median-filtered image computed in advance. Meanwhile, Szilágyi et al. [4] proposed an enhanced FCM (EnFCM) algorithm performed on the basis of gray level histogram of a linearly-weighted summation image to speed up the image segmentation process. Similarly, the fast generalized FCM (FGFCM) algorithm proposed by Cai et al. [5] was performed on the basis of gray level histogram, and it utilized both local spatial information and local gray information to enhance the qualities of the segmented results. However, these above-mentioned algorithms did not apply on original images and needed some parameters α (or λ), which have a crucial impact on the performances of the algorithms, to control the influence of local information. Hence, Krinidis and Chatzis [6] presented a fuzzy local information c-means (FLICM) algorithm which introduced a novel fuzzy factor based on local spatial information to replace the parameter α in the above algorithms. Recently, Gong et al. [7,8] proposed two variants of FLICM algorithms. In [7], RFLICM replaced the spatial distance with a local coefficient of variation as a local similarity. To make the segmentation results more accurate, a tradeoff weighted fuzzy

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factor based on the space distances and gray level differences of all neighbor pixels was designed in [8], and a kernel distance measure was employed to improve the performance on restraining noise. Although FLICM and its variants can achieve well performance for image segmentation, some problems still exist in their frameworks. In [11,12], it is claimed that the local minimizers of FLICM and its variants do not truly minimize their energy functions. Celik and Lee [11] pointed out that the minimization of the term based on local information may contradict the minimization of original FCM objective function sometimes. Also, Szilágyi [12] presented that the influence of original FCM objective function may be suppressed by the local information term with larger value in the clustering process. Hence, it is still a difficult task to incorporate local information of images into fuzzy clustering adaptively and effectively. In this regard, a multi-objective evolutionary fuzzy clustering (MOEFC) algorithm for image segmentation is proposed in this paper. The proposed algorithm converts fuzzy clustering problems for image segmentation into multi-objective optimization problems (MOPs).

In recent years, a variety of fuzzy clustering methods based on evolutionary algorithm (EA) are proposed [13,14,62,63] for image applications [15–19] and many other applications [20–26]. Among them, some fuzzy clustering algorithms based on multi-objective evolutionary algorithm (MOEA) [15,16,20] are proposed to optimize original FCM energy function and the Xie-Beni [27] index simultaneously. However, these two measures are not completely independent to each other, and it may lead to not good enough solutions. Hence, Zhao et al. [19] proposed a multi-objective spatial fuzzy clustering algorithm (MSFCA) for image segmentation to optimize the global fuzzy compactness with spatial information and fuzzy separation among the clusters simultaneously. Unlike these above algorithms, this paper concerns a trade-off between preserving significant image details and removing noise for image segmentation. The original FCM energy function to preserve image details and the function based on local information to restrain noise are optimized simultaneously. The decomposition strategy is adopted to project the multi-objective fuzzy clustering problem into a number of sub-problems. Each sub-problem represents a fuzzy clustering problem with different set of weights to balance the influences of preserving image details and restraining noise. Hence, the fuzzy clustering problem, which is the most suitable sub-problem for image segmentation, can be taken into consideration.

To improve the search capability of the algorithm, opposition-based learning (OBL), a kind of machine learning techniques proposed by Tizhoosh [28], is adopted. It has been widely used in many optimization problems, such as reinforcement learning [28], differential evolution [29,30], and neural networks [31]. The main idea of OBL is to generate the opposites of the solutions for a better covering of the problem's search space. Therefore, we utilize OBL to achieve a better convergence speed for searching the robustness in multi-objective optimization. Additionally, to improve the performance of the algorithm, two problem-specific techniques, an adaptive weighted fuzzy factor and a mixed population initialization, are introduced. As a conclusion, our algorithm has the following attractive characteristics: (1) it can achieve a trade-off between preserving image details and restraining noise for image segmentation by optimizing the functions to preserve image details and restrain noise simultaneously; (2) it can achieve robust performance for image segmentation by introducing two problem-specific techniques, an adaptive weighted fuzzy factor and a mixed population initialization; (3) it can achieve optimal solutions with a better convergence speed by incorporating OBL into multi-objective optimization. These above characteristics make MOEFC a more suitable and general evolutionary algorithm for image segmentation.

1.414	1	1.414
1		1
1.414	1	1.414

Fig. 1. The spatial Euclidean distance between pixel x_i and its neighbor pixel x_j in a 3×3 square window.

The remainder of this paper is organized as follows. Section 2 presents related works and the main ideas of the proposed approach. The details of the proposed algorithm are described in Section 3. Section 4 presents experimental results, showing how the performance of MOEFC compares against seven popular techniques. Concluding remarks are drawn in Section 5.

2. Background works

2.1. Fuzzy-C means clustering algorithms with local information

In recent years, for image segmentation, many improved FCM algorithms [2–8] are proposed to incorporate local image information into original FCM energy function. Some parameters, which are generally chosen by experience or trial and error experiments, are utilized to control the influence of local information and have a crucial impact on the performances of the improved FCM algorithms. It is not easy to find the optimal parameters which will lead to the best segmentations of observed images. To deal with this drawback, FLICM [6] defined a fuzzy factor to replace the parameters in the above algorithms and applied on original observed images. Let us set $\{x_i\}_{i=1}^{N}$ be the observed image, where x_i is the ith pixel and its value equals to the gray level value of the ith pixel. N represents the total number of pixels. If the number of clusters is c, the energy function of FLICM for partitioning the image $\{x_i\}_{i=1}^{N}$ into c clusters can be defined by:

$$J_m = \sum_{i=1}^{N}\sum_{p=1}^{c}[u_{ip}^{m}\|x_i - z_p\|^2 + G_{ip}] = \sum_{i=1}^{N}\sum_{p=1}^{c}u_{ip}^{m}\|x_i - z_p\|^2 + \sum_{i=1}^{N}\sum_{p=1}^{c}G_{ip} \tag{1}$$

where $G_{ip} = \sum_{\substack{j \in \mathbf{N}_i \\ j \neq i}} \frac{1}{d_{ij}+1}(1-u_{jp})^m\|x_j - z_p\|^2$, z_p is the pth cluster center, u_{ip} is the fuzzy membership of pixel x_i in the pth cluster, and m is the weighting parameter on each fuzzy membership. $\mathbf{N}_i$, a 3×3 square window with pixel x_i in its center, represents a neighborhood of pixel x_i, and pixel x_j is one of the neighbor pixels in $\mathbf{N}_i$. d_{ij} stands for the spatial Euclidean distance between pixel x_i and pixel x_j as shown in Fig. 1. FLICM works by updating the fuzzy memberships and the cluster centers computed as follows:

$$u_{ip} = \frac{1}{\sum_{q=1}^{c}\left(\frac{\|x_i - z_p\|^2 + G_{ip}}{\|x_i - z_q\|^2 + G_{iq}}\right)^{1/(m-1)}} \tag{2}$$

$$z_p = \frac{\sum_{i=1}^{N}u_{ip}^{m}x_i}{\sum_{i=1}^{N}u_{ip}^{m}} \tag{3}$$

Let us employ the Lagrange multipliers to the energy function of FLICM in Eq. (1) and set m to 2 [6], the clustering centers and the