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Robust level set image segmentation algorithm using local correntropy-based fuzzy c-means clustering with spatial constraints

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ABSTRACT

Accurate image segmentation is a challenge task in image analysis and understanding, while fuzzy *c*-means clustering (FCM) with spatial constraints (FCM_S) is an effective algorithm suitable for this challenge. However, FCM_S has high computational complexity and still lacks enough robustness to noise and outliers, which will limit its usefulness. To overcome these difficulties, a local correntropy-based fuzzy *c*-means clustering algorithm with spatial constraints (LCFCM_S) and its simplified model (LCFCM_S_1) are proposed in this paper. By utilizing the correntropy criterion, the clustering algorithm can efficiently emphasize the weights of the samples that are close to their corresponding cluster centers. Then, the proposed clustering algorithms are incorporated into a variational level set formulation with a level set regularization term. Finally, the iteratively re-weighted algorithm is adopted to solve the LCFCM_S and LCFCM_S_1 based level set method. Experimental results on synthetic and real images show the superiority of our methods in terms of accuracy and robustness for segmenting images with intensity inhomogeneity and noise, when compared with several state-of-the-art approaches.

1. Introduction

Image segmentation is one of the most difficult topics in image understanding and pattern recognition. The purpose of image segmentation is to divide an image into a number of non-overlapping regions and extract interest targets. Until now, many segmentation algorithms have been proposed, such as edge detection [1,2], clustering [3–6], level set [7–9], graph cut [10,11], and so on. Among the clustering segmentation methods, fuzzy *c*-means (FCM) algorithm [12,13] has been broadly applied to image segmentation. The main characteristic of fuzzy clustering is that it allows pixels belonging to multiple clusters with different degrees of membership. Thus, the FCM algorithm retains more information from original images. However, it is very sensitive to noise and other imaging artifacts, since it does not consider any spatial information.

To solve these problems, many improved algorithms which introduce local spatial information into the original FCM algorithm were applied to improve the segmentation performance [14–18]. Ahmed et al. [14] presented FCM_S algorithm by introducing the spatial information to the objective function of FCM which enabled every pixel to be influenced by its immediate neighborhood. However, FCM_S is very time-consuming because of the calculation of the spatial neighborhood term in each iteration step. Subsequently, in order to reduce the time consumption of FCM_S, Chen and Zhang [15] proposed two variants, FCM_S1 and FCM_S2. These two algorithms substituted the neighborhood term by utilizing the mean-filtered image and median-filtered image respectively. Thus, the computational times are reduced significantly. Moreover, based on the fact that the number of gray-levels is smaller than that of the pixels of the summed image, Szilagyi et al. [16] proposed the enhanced fuzzy *c*-mean (EnFCM) algorithm. In this algorithm, a linearly-weighted sum image is obtained from both the original image and its neighborhood average image. Hence, the computational time of EnFCM algorithm is dramatically reduced. More recently, Cai et al. [17] proposed the fast generalized fuzzy *c*-means algorithm (FGFCM). This algorithm utilizes local spatial and gray-level information to form a nonlinearly-weighted sum image. The quality of the segmented image is well enhanced. However, EnFCM and FGFCM, still lack enough robustness to noise and intensity inhomogeneity.

The level set method, originally introduced by Osher and Sethian [19], has been extensively applied to image segmentation with noise and intensity inhomogeneity. In [20,21], Li et al. proposed an efficient region-based level set method by introducing a local binary fitting (LBF) energy with a kernel function. The LBF model which draws upon spatially varying local image

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information as constraints, can well segment objects with intensity inhomogeneities. Some related methods which have similar capabilities of dealing with intensity inhomogeneity as the LBF model were recently proposed in [22,23]. Wang and Pan [22] proposed a novel segmentation algorithm via a local correntropy-based K-means (LCK) clustering and it can be robust to the outliers. In [23], Huang et al. presented a level set model using local region robust statistics and correntropy-based K-means method. This model can efficiently segment images with intensity inhomogeneity and noise. However, as pointed out in [22,23], these two methods are still sensitive to the noise to some extent.

In this paper, we propose a novel level set algorithm for image segmentation by introducing the local correntropy-based fuzzy c-means clustering with spatial constraints (LCFCM_S) and then simplify it, to corresponding robust version LCFCM_S$_1$. In the proposed models, the correntropy criterion can reduce the weights of the samples that are away from their corresponding cluster centers. As a result, LCFCM_S and LCFCM_S$_1$ based clustering algorithm can provide enough robustness to noise and outliers. In addition, we have also made some comparisons with several state-of-the-art models to show the superiority of our methods.

The remainder of this paper is organized as follows. In Section 2, we review several related backgrounds. Our model is presented in Section 3. The experimental results are provided in Section 4, followed by some discussions in Section 5. Finally, this paper is summarized in Section 6.

2. Backgrounds

Given a dataset $X = \{x_i\}_{i=1}^{N}$, the K-means clustering is to minimize the following objective function:

$$\min_{\{v_c\}_{c=1}^{K}} \sum_{c=1}^{K}\sum_{i=1}^{N} u_{ic}\|x_i - v_c\|_2^2, \tag{1}$$

where K is the number of clusters, N is the total number of pixels, v_c is the center of each cluster, and u_{ic} represents the membership function of the ith pixel, with respect to the cth cluster center. The membership function satisfies two conditions as $u_{ic} \in \{0,1\}$ and $\sum_{c=1}^{K} u_{ic} = 1$. The objective function of Eq. (1) uses the mean square error (MSE) criterion to measure the distance between samples and cluster centers which are sensitive to outliers. In order to deal with this difficulty, the correntropy-based K-means (CK) algorithm [24] is proposed. Thereby, the object function of CK is reformulated as

$$\min_{\{v_c\}_{c=1}^{K}} -\sum_{c=1}^{K}\sum_{i=1}^{N} u_{ic}\rho^2 g(\|x_i - v_c\|_2), \tag{2}$$

where $g(s) = \exp\left(-s^2/2\rho^2\right)$ is a Gaussian function with the kernel width ρ. Due to the Gaussian kernel, the CK algorithm can emphasize the weights of samples that are close to their corresponding cluster centers. Recently, considering the pixels in a local region, Wang and Pan [22] proposed the local correntropy-based

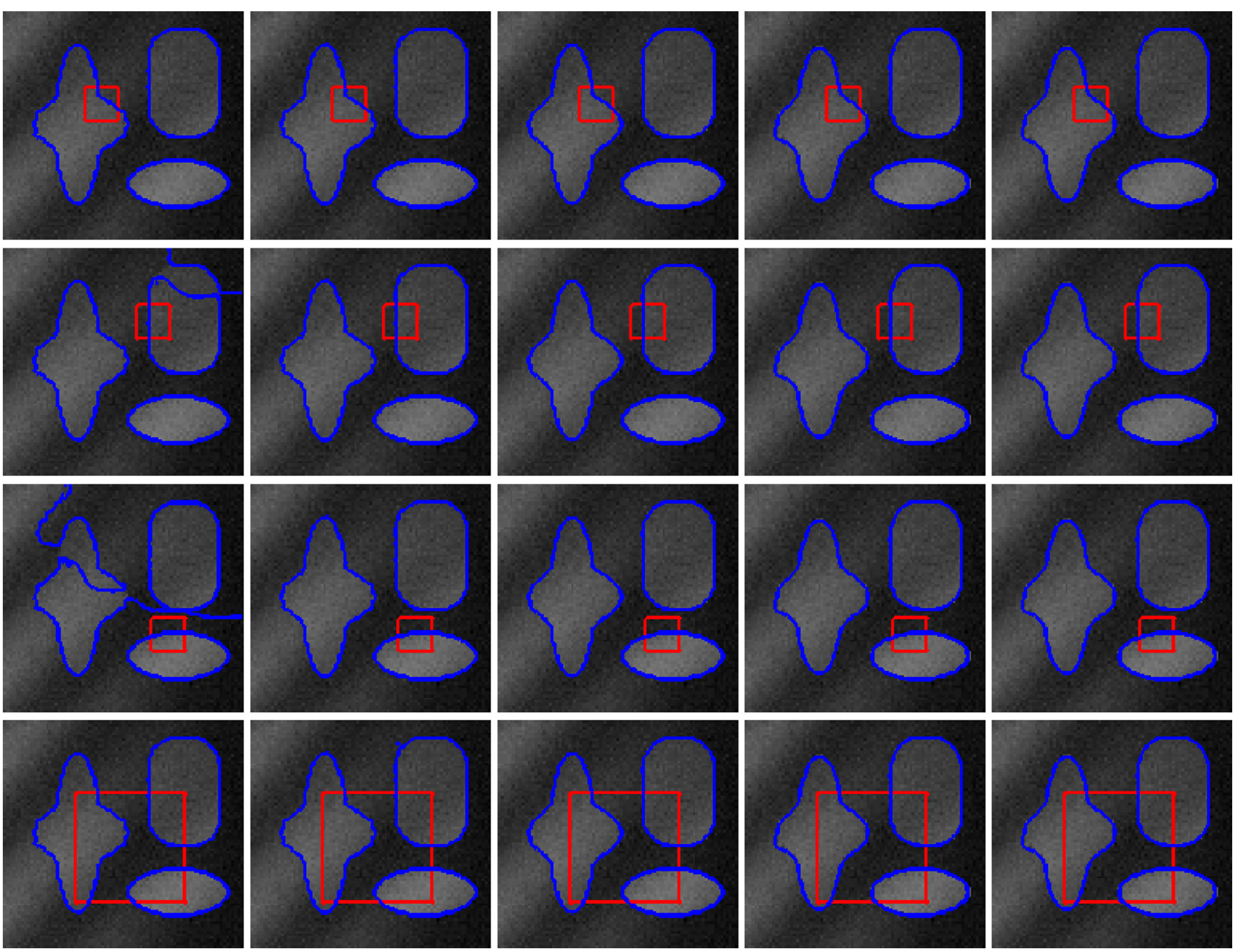

Fig. 1. Comparison results for a synthetic image with heavy noise. The first column: results of LBF. The second column: results of LGDF. The third column: results of LCK. The fourth column: results of LCFCM_S. The last column: results of LCFCM_S$_1$. The red contours are initial contours, while the blue are the segmentation results. The other figures are the same.