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Optimal multi-level thresholding with membrane computing

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ABSTRACT

The conventional methods are not effective and efficient for image multi-level thresholding due to time-consuming and expensive computation cost. The multi-level thresholding problem can be posed as an optimization problem, optimizing some thresholding criterion. In this paper, membrane computing is introduced to propose an efficient and robust multi-level thresholding method, where a cell-like P system with the nested structure of three layers is designed as its computing framework. Moreover, an improved velocity-position model is developed to evolve the objects in membranes based on the special membrane structure and communication mechanism of objects. Under the control of evolution-communication mechanism of objects, the cell-like P system can efficiently exploit the best multi-level thresholds for an image. Simulation experiments on nine standard images compare the proposed multi-level thresholding method with several state-of-the-art multi-level thresholding methods and demonstrate its superiority.

1. Introduction

Image segmentation is one of the most important tasks in computer vision and video applications. Thresholding has been widely used as a popular image segmentation technique [1]. The goal of thresholding is to separate objects from background image or discriminate objects from objects that have distinct gray levels. The existing thresholding methods can be roughly classified as two categories: bi-level thresholding and multi-level thresholding [2–4]. Bi-level thresholding segments an image into two different regions. The pixels with gray values greater than a certain threshold are classified into object, and those with gray values lower than the threshold are regarded as background. Thresholding problem can be posed as an optimization problem. Otsu's method [5] and Kapur's method [6] are simple and effective bi-level thresholding, which maximize the between-class variance of gray levels and the entropy of the histogram to optimize single threshold for an image respectively. Multi-level thresholding determines more than one threshold for an image and segments the image into several distinct regions, which correspond to one background and several objects. The Otsu's and Kapur's methods can be extendable to multi-level thresholding, however, they are inefficient because gray level histograms of most of the real-life images are multimodal. Thus, multi-level thresholding has received much attention in recent years. In order to solve the multi-level thresholding problem, some natural computing methods have been applied to solve the multi-level thresholding problem, for example, genetic algorithms (GA), particle swarm optimization (PSO), ant colony optimization (ACO), differential evolution (DE), artificial bee colony (ABC), and bacterial foraging (BF) algorithm. Tao et al. [7] presented a three-level thresholding method that used the GA to find the best thresholds. Hammouche et al. [8] proposed a multi-level thresholding method, which allowed the determination of the appropriate number of thresholds as well as the adequate thresholds. However, GA has several shortcomings, for example, slow convergence rate and premature convergence to local minima. Thus, some PSO-based multi-level thresholding methods have been developed [9–11]. In addition, Tao et al. [12] used the ACO to obtain the best parameters of the presented entropy-based object segmentation method, while Sathya et al. [13] proposed a multi-level thresholding method using the bacterial foraging algorithm. Akay et al. [14] presented a study on PSO and ABC algorithms for multilevel thresholding. Agrawal et al. [15] presented an optimal multi-level thresholding method using cuckoo search algorithm. Osuna-Enciso et al. [16] reported a comparison study of PSO, ABC and DE for multi-threshold image segmentation. Fan et al. [17] proposed a molecular kinetic theory optimization algorithm (MKTOA) to solve the multi-level thresholding problem. Yin et al. [18] proposed a multilevel image segmentation through fuzzy entropy maximization and graph cut optimization.

Membrane computing initiated by Gh. Păun [19], as a new branch of natural computing, is inspired from the structure and functioning of living cells as well as interaction of living cells in

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tissues and organs. Membrane computing is a novel class of distributed parallel computing models, known as P systems [20]. In the past years, a variety of variants of P systems have been proposed [21–27], including membrane algorithm of solving global optimization problems [28]. The research results on a variety of optimization problems have indicated that compared to the existing evolutionary algorithms, membrane algorithm offers a more competitive method due to its three advantages: better convergence, stronger robustness and better balance between exploration and exploitation [29–31].

Based on the above consideration, this paper introduces membrane computing to deal with multi-level thresholding problem and proposes a novel multi-level thresholding method. A cell-like P system with the nested structure of three layers, including several evolution membranes, several local store membranes and a global store membrane, is considered as its optimization framework to exploit the best thresholds for an image. Moreover, based on the special membrane structure and communication mechanism of objects, an improved velocity-position model is developed to evolve the objects in the system. In recent, Peng et al. [32] presented a multi-level thresholding method based on tissue-like P systems, where fuzzy entropy is used as the objective function to optimize the thresholds. However, there are three differences with Peng's method [32]: (1) this paper uses the between-class variance criterion and entropy criterion as objective functions respectively, and the existing works have indicated that they are two most effective measures in histogram-based thresholding; (2) a variant with a special membrane structure, namely, a cell-like P system with the nested structure of three layers, is considered in this paper, so the proposed method is inspired from the different mechanism from Peng's method; (3) the external best objects are used to guide the evolution of objects in Peng's method, which can cause the degradation of the objects when initial objects in evolution membranes are very close to each others in solution space.

The rest of this paper is organized as follows. Section 2 reviews two multi-level thresholding problems to be solved, which use the between-class variance criterion and entropy criterion as objective functions, respectively. Section 3 describes the proposed multi-level thresholding method based on cell-like P systems. Experimental results are provided in Section 4, and conclusions are discussed in Section 5.

2. Problem statement

Assume that a given image I has L gray levels, $\{1, 2, \ldots, L\}$. Let h_i denotes the number of pixels with gray level i, thus total number of pixels equals $N = h_1 + h_2 + \ldots + h_L$. The occurrence probability of gray level i is given by

$$p_i = \frac{h_i}{N}, \qquad p_i \geq 0, \qquad \sum_{i=1}^{L} p_i = 1. \tag{1}$$

For the image I, a multi-level thresholding method determines m thresholds, $(t_1, t_2, \ldots, t_m)$, and divides the image into $m+1$ classes: C_0 for $[1, \ldots, t_1]$, C_1 for $[t_1+1, \ldots, t_2]$, …, and C_m for $[t_m+1, \ldots, L]$. Therefore, the gray level probability distributions for the $m+1$ classes are as follows:

$$C_0\left(\frac{p_1}{\omega_0}, \ldots, \frac{p_{t_1}}{\omega_0}\right), \qquad C_1\left(\frac{p_{t_1+1}}{\omega_1}, \ldots, \frac{p_{t_2}}{\omega_1}\right), \quad \cdots, \quad C_m\left(\frac{p_{t_m+1}}{\omega_m}, \ldots, \frac{p_L}{\omega_m}\right) \tag{2}$$

where

$$\omega_0 = \sum_{i=1}^{t_1} p_i, \qquad \omega_1 = \sum_{i=t_1+1}^{t_2} p_i, \quad \ldots, \quad \omega_m = \sum_{i=t_m+1}^{L} p_i. \tag{3}$$

Mean levels for the $m+1$ classes, $\mu_0, \mu_1, \ldots, \mu_m$, respectively, are

$$\mu_0 = \sum_{i=1}^{t_1} \frac{ip_i}{\omega_0}, \qquad \mu_1 = \sum_{i=t_1+1}^{t_2} \frac{ip_i}{\omega_1}, \quad \ldots, \quad \mu_m = \sum_{i=t_m+1}^{L} \frac{ip_i}{\omega_m}. \tag{4}$$

Let μ_T be the mean intensity for whole image. Thus, we have

$$\mu_T = \omega_0\mu_0 + \omega_1\mu_1 + \cdots + \omega_m\mu_m, \quad \omega_0 + \omega_1 + \cdots + \omega_m = 1. \tag{5}$$

Multi-level thresholding can be posed as an optimization problem, which optimizes the m thresholds by maximizing some thresholding criterion (objective function). Usually, there are two thresholding criterions broadly used in literature, between-class variance criterion and entropy criterion, which can be used as the objective function of the optimization problem.

2.1. Case 1: between-class variance criterion

The between-class variance criterion is firstly used in Otsu's bi-level thresholding method [33,34], and then is extended to multi-level thresholding. For the m thresholds, the between-class variance of the image I can be defined by

$$\sigma_B^2 = \sigma_0 + \sigma_1 + \cdots + \sigma_m \tag{6}$$

where $\sigma_0 = \omega_0(\mu_0 - \mu_T)^2, \sigma_1 = \omega_1(\mu_1 - \mu_T)^2, \ldots, \sigma_m = \omega_m(\mu_m - \mu_T)^2$. Thus, the multi-level thresholding problem can be configured as the following optimization problem:

$$\max_{1 \leq t_1 \leq \cdots \leq t_m \leq L} J_1(t_1, t_2, \ldots, t_m) = \max_{1 \leq t_1 \leq \cdots \leq t_m \leq L} \sigma_B^2(t_1, t_2, \ldots, t_m) \tag{7}$$

where $t_1, t_2, \ldots, t_m$ are m parameters (thresholds) to be optimized.

2.2. Case 2: entropy criterion

The entropy criterion has been developed by Kapur in bi-level thresholding [6,35], and has been extended to multi-level thresholding. For the m thresholds, the entropy criterion can be defined as follows:

$$H_e = H_0 + H_1 + \cdots + H_m \tag{8}$$

where

$$H_0 = -\sum_{i=1}^{t_1} \frac{p_i}{\omega_0} \ln \frac{p_i}{\omega_0}, \quad \omega_0 = \sum_{i=1}^{t_1} p_i,$$

$$H_1 = -\sum_{i=t_1+1}^{t_2} \frac{p_i}{\omega_1} \ln \frac{p_i}{\omega_1}, \quad \omega_1 = \sum_{i=t_1+1}^{t_2} p_i,$$

$$\cdots\cdots \qquad \cdots\cdots \qquad \cdots\cdots$$

$$H_m = -\sum_{i=t_m+1}^{L} \frac{p_i}{\omega_m} \ln \frac{p_i}{\omega_m}, \quad \omega_m = \sum_{i=t_m+1}^{L} p_i.$$

Based on the entropy criterion, the multi-level thresholding problem can be configured as the following optimization problem:

$$\max_{1 \leq t_1 \leq \cdots \leq t_m \leq L} J_2(t_1, t_2, \ldots, t_m) = \max_{1 \leq t_1 \leq \cdots \leq t_m \leq L} H_e(t_1, t_2, \ldots, t_m) \tag{9}$$

where $t_1, t_2, \ldots, t_m$ are m parameters (thresholds) to be optimized.