Optik 125 (2014) 5234–5240

Contents lists available at ScienceDirect

Optik

journal homepage: www.elsevier.de/ijleo

Two-dimensional Otsu's thresholding segmentation method based on grid box filter

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ARTICLE INFO

Article history:
Received 25 August 2013
Accepted 10 May 2014

Keywords:
Image segmentation
Otsu
Two-dimensional histogram
Integral image
Particle swarm optimization

ABSTRACT

Otsu algorithm, an automatic thresholding method, is widely used in classic image segmentation applications. In this paper, a novel two-dimensional (2D) Otsu thresholding algorithm based on local grid box filter is proposed. In our method, firstly by utilizing the coarse-to-fine idea, the 2D histogram is divided into regions by grid technique, and each region is used as a point to form a new 2D histogram, to which 2D Otsu thresholding algorithm and an improved particle swarm optimization (PSO) algorithm are applied to get the region number of the new 2D histogram threshold. Then on the result region, the mean of the 2D histogram is computed base on box filter, and the two algorithms are applied again to obtain the final threshold for the original image. Experimental results on real data show that the proposed algorithm gets better segmentation results than the traditional recursion Otsu algorithm. It significantly reduces the time of segmentation process and simultaneously has the higher segmentation accuracy.

1. Introduction

Otsu algorithm [1], also known as the maximum between-class variance method, is one of the commonly used methods in image segmentation for selecting threshold [2] automatically that remains a challenging problem at present. With its simple calculation and good adaptation, the algorithm has a widespread application prospect in future.

Due to one-dimensional Otsu algorithm's poor adaptability to noise image segmentation, a two-dimensional (2D) gray histogram and a 2D Otsu algorithm [3] are introduced. In recent years 2D Otsu algorithm has well adapted to classic image segmentation due to its contents-independent characteristics. However, its application has been limited by its shortcomings that include: (1) it has the higher time complexity, which cannot satisfy the requirements of real-time processing; (2) for the criterion of segmentation result, the cohesion of within-class is ignored, which leads to the poor accuracy quality.

To overcome the first aforementioned shortcoming, a lot of fast methods emerged. Wang et al. [4] proposed a fast algorithm for 2D Otsu adaptive threshold algorithm, which greatly improved the calculation speed of 2D threshold in iterative way. Lang et al. [5] improved the original algorithm with integral image and put forward a fast algorithm, of which the computation time was significantly reduced. Fan et al. [6] gave a 2D cross-entropy linear-type threshold segmentation method for gray-level images, which was viewed as an available threshold selection method. Besides, Jun et al. [7] built an improved 2D Otsu algorithm for SAR image. Later, Zhu et al. [8] proposed a fast method that can obtain ideal segmentation results and decrease the computation cost reasonably to achieve the goal of fast segmentation. Moreover, Zhang et al. [9] presented a fast and precise 2D Otsu's histogram of image thresholding method with much less runtime. In addition, He et al. [10] proposed a new fast algorithm, which was to find out every threshold that was equal to the integer part of the average of the mean levels of two classes, and then selected one threshold with Otsu criterion. Unfortunately, most of the above algorithms only considered between-class variances and ignored the information, i.e., the within-class cohesion, contained in each pixel classification.

To overcome the second aforementioned shortcoming, Pei [11] in his paper put forward an improved Otsu segmentation algorithm that considered not only the difference between-class but also the divergence of each class. Jiao et al. [12] introduced an improved Otsu method through the Gray level and Gradient Mapping (GGM) function. Based on image regions, Long et al. [13] presented an interactive document images thresholding segmentation algorithm, which was greatly influenced by artificial factors. Besides,

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http://dx.doi.org/10.1016/j.ijleo.2014.05.003
0030-4026/

Gao et al. [14] proposed a patch part segmentation based on modified Otsu method in their paper and Sathya et al. [15] employed a bacterial foraging (BF) algorithm based multilevel thresholding. Recently, Xu et al. [16] described a new weighted threshold algorithm based on the estimation of optimal threshold for achieving minimal centroid error in the processed image, which indicated a higher accuracy. However, it involved too many parameters. Jumb et al. [17] used an approach for color image segmentation using Otsu's adaptive thresholding. For this method, because the result of Otsu's multi-thresholding might consist of over segmented regions, so K-means clustering was applied to merge the over segmented regions, which was more suitable for color images. These methods obtained effective segmentation results. However, their computation was complex.

In view of the above-mentioned facts, many scholars contribute lots of algorithms for different backgrounds. They either ensure the segmentation accuracy as high as 96% or reduce its time complexity from $O(L^4)$ to $O(L^2)$ or $O(L)$ (L is the image's gray level).

At present, more and more genetic algorithms are applied to fitting Otsu's threshold. Such as, Li [18] in her paper presents an Otsu image segmentation method based on improved genetic algorithm. In general, the genetic algorithm is better for one target optimization effect, but it has obviously deficiencies in multi-objective optimization. To overcome the aforementioned shortcoming, according to the biological principle, various artificial intelligence multi-objective optimization models attempt to be utilized to perform Otsu's threshold and fortunately they have received better results. Nonetheless, with the artificial intelligence (AI) algorithm having been developed, we argue that AI algorithm using other conventional method will provide a discriminative solution to Otsu's thresholding problems.

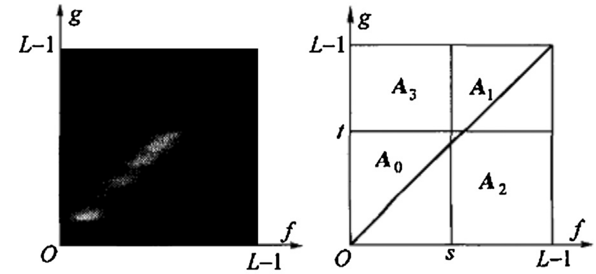
In future, for 2D Otsu algorithm, it is prefer a higher segmentation result and lower time consumption. In this paper, we mainly focus on how to improve its efficiency and a fast 2D Otsu's thresholding segmentation method is proposed. In our algorithm, the histogram of an image is divided into several sub-areas with sliding window, and box filter is adopted to calculate the average gray value of pixels in local area on integral image [19,20]. Finally a multi-objective model of the particle swarm optimization (PSO) [21] converted by classification discriminant function is introduced to get the optimal threshold.

The rest of the paper is organized as follows. Section 2 roughly provides a description of 2D Otsu algorithm. Section 3 is devoted to the improved algorithm using the principle of Otsu as well as an improved PSO algorithm, and how to utilize it to get the final threshold for original image. Section 4 gives experiments and comparative results in detail, and Section 5 summarizes our contributions and sketches future work.

2. 2D Otsu algorithm

Suppose an image with the size of $M \times N$, of which the gray level is L. The pixel neighborhood average gray, whose level is also L, of each pixel is calculated. It forms a dual group: pixel gray value i and the average gray j of its neighbors. Here, we make the emerging frequency of binary group as (i, j), and the number of the pixel points of which the gray value is i and its neighbors gray level is j as $h(i, j)$, then the corresponding joint probability density $p_{i,j}$ is defined as:

$$p_{i,j} = p(i,j) = \frac{h(i,j)}{M \times N}$$
$$\text{And} \sum_{i=0}^{L-1}\sum_{j=0}^{L-1} h(i,j) = M \times N, \quad \sum_{i=0}^{L-1}\sum_{j=0}^{L-1} p_{i,j} = 1 \tag{1}$$



(a) Corresponding 2D histogram (b) Projection of 2D histogram

Fig. 1. 2D histogram of a gray image. (a) Corresponding 2D histogram. (b) Projection of 2D histogram.

The average vector of 2D histogram is written as:

$$\mu' = \left[\mu_1{}', \mu_2{}'\right] = \left[\sum_{i=0}^{L-1}\sum_{j=0}^{L-1} i p_{i,j}, \sum_{i=0}^{L-1}\sum_{j=0}^{L-1} j p_{i,j}\right] \tag{2}$$

Fig. 1 shows 2D histogram of a gray image and its projection. Suppose segmentation threshold is $[s, t]$, then the straight line $f = s$ and $g = t$ divided the projection plane of 2D histogram into four regions, shown in Fig. 1(b), which is expressed as A_0, A_1, A_2, A_3, actually, in 2D histogram the region away from the diagonal is negligible, that is, regional A_2 and A_3 in the probability is negligible, then the background and objectives are located in the region A_0 and A_1, assuming that there are two classes in 2D histogram, they represent objects and backgrounds respectively, and has a different distribution of the probability density function, then the two types of probabilities are computed respectively as:

$$\begin{aligned} \omega_1 &= \sum_{A_0} p_{i,j} = \sum_{i=0}^{s-1}\sum_{j=0}^{t-1} p_{i,j} \\ \omega_2 &= \sum_{A_1} p_{i,j} = \sum_{i=s}^{L-1}\sum_{j=t}^{L-1} p_{i,j} \end{aligned} \tag{3}$$

Two types corresponding mean vectors:

$$\begin{aligned} \mu_1 &= \left[\mu_{1i}, \mu_{1j}\right]^T = \left[\frac{\sum_{A_0} i p_{i,j}}{\omega_1}, \frac{\sum_{A_0} j p_{i,j}}{\omega_1}\right]^T \\ \mu_2 &= \left[\mu_{2i}, \mu_{2j}\right]^T = \left[\frac{\sum_{A_1} i p_{i,j}}{\omega_2}, \frac{\sum_{A_1} j p_{i,j}}{\omega_2}\right]^T \end{aligned} \tag{4}$$

As the probability of diagonal away from the histogram is negligible, so there is $\omega_1 + \omega_2 \approx 1$, the between-class variance is defined as:

$$BCV = \omega_1(\mu_1 - \mu)(\mu_1 - \mu)^T + \omega_2(\mu_2 - \mu)(\mu_2 - \mu)^T \tag{5}$$

So, we get the best threshold, which makes the maximum value of BCV, namely, the optimal segmentation threshold satisfies the following:

$$[s_0, t_0] = arg \max_{\substack{1 \le s \le L-1 \\ 1 \le t \le L-1}} \left\{BCV\right\} \tag{6}$$

3. Improved 2D Otsu algorithm

In this section, we emphasize the segmentation algorithm using the principle of Otsu based on an improved PSO algorithm: firstly, by utilizing the coarse-to-fine idea, the initial 2D histogram is divided into several sub-areas based on sliding window, and local