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2-D direction histogram based entropic thresholding

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ABSTRACT

Local image features are effective descriptors for image analysis and are also important cues for image segmentation. In this paper, we propose a novel entropic thresholding approach. This approach incorporates local features into a conventional entropic method to implement the thresholding. The local features are obtained from an orientation histogram to describe the edge property of the local neighborhood. To verify the performance of our method, thresholding was carried out on different types of images and compared with some well-known entropic approaches. Experimental results show that using the local edge property can give a better thresholding result.

1. Introduction

It is important in image processing and analysis to extract or segment objects from background for the success of image recognition, image compression, image retrieval, etc. The objects can be the regions, shapes, textures, which can be used independently or combined to each other. For segmentation, many different types of approaches have been proposed. All of the methods can be commonly divided into four groups: thresholding, boundary-based, region-based, and hybrid techniques [1]. Among the techniques, the thresholding is a simple but effective one for the segmentation based on the differences of gray level between the objects and background. For the simplest case, the thresholding can be seen as an operation for converting a gray level image into a binary image by selecting an appropriate threshold value. If the values of pixels are below the threshold, then the pixels belong to the object, and if above the threshold, then to the background, or vice versa.

During the past decades, many thresholding techniques have been devoted to the threshold selection, and most of these methods can be classified into two categories [2–14]. One is global thresholding, where a single threshold value is computed from the gray level histogram of the image for bi-level thresholding, and it is easy to extend this thresholding to multilevel thresholding. The other is local thresholding, where the input image is thresholded by using the local threshold values which are determined locally, e.g. pixel by pixel, or region by region. Then, a specified region can have a 'single threshold' that can be changed from region to region according to the threshold candidate selection for a given area [2]. In comparison with the local thresholding, global thresholding methods are easy to implement and often used as popular tools in various image processing applications. One of the most common approaches in global thresholding techniques is an entropic approach [3]. Pun [4] proposed the first entropic method by introducing the entropic concept in threshold selection in which the optimal threshold was obtained by maximizing the upper bound of the *a posteriori* entropy. Later, Kapur et al. [5] corrected and improved Pun's method by maximizing the sum of the two class entropies of the object and background. Then, Albuquerque et al. [6] generalized it to Tsallis's entropy. Following Kapur's idea, Yen et al. [7] optimally thresholded the image by maximizing the entropic correlation. And then, both of Kapur's and Yen's methods were extended to Renyi's entropy by Sahoo et al. [8]. Due to the fact that all these methods mentioned above are based on the 1-D histogram, which is the first-order statistic, their method can be regarded as one of the 1-D entropic approaches. According to the Refs. [5,9], the 1-D approaches have a shortcoming, that is different images with the same histogram resulted in the same threshold value. In other words, they do not take the spatial correlation between pixels into consideration.

To account for the shortcoming of 1-D entropies and to obtain better results, a lot of literature has appeared to take into account the spatial correlation. Abutaleb [10] defined a 2-D entropy and found the optimal threshold pair by maximizing the sum of entropies. In his approach, the 2-D entropies were computed from the 2-D histogram which was determined by using the gray value

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of the pixels and the local average gray value of the pixels. Later, Brink [11] improved Abutaleb's method by maximizing the smaller of two entropies of the background and object. And then, Sahoo et al. [9,12] refined the extension by Abutaleb, based on their earlier work [8] using 2-D Renyi's entropies, and extended the 1-D methods by Pavesic and Ribaric [13] and Albuquerque et al. [6] to 2-D Tsallis–Havrda–Charvat entropies one after another. Beside the disadvantage of large computational cost, all these 2-D methods also had the disadvantage of losing information, when entropies were computed from the conventional 2-D histogram, where the domain of the 2-D histogram was divided into four quadrants: only two of them relative to the object and background were used to calculate the entropies, while the other two relative to the edges were ignored, even if they contained important information between the object and background. Hence, Xiao et al. [14] tried to use pixel similarity to describe the edge, and extended Kapur's method, based on the gray level spatial correlation (GLSC) histogram. The GLSC histogram takes into account the local property of the image by using the gray value of the pixels and their similarity with neighboring pixels.

In this paper, we present a novel 2-D entropic thresholding method taking into consideration the local features, which are computed from the orientation histogram of the local neighborhood in a gradient image. This method extends a well-known 1-D entropic method proposed by Kapur et al. [5]. It uses a different type of 2-D histogram from conventional 2-D histogram for the computation of 2-D entropies. 2-D direction histogram is determined by the gray levels of the pixels and the local features of corresponding local neighborhoods. This paper is organized as follows. In Section 2, two relative 2-D entropic algorithms are briefly reviewed. Section 3 presents the construction of a 2-D direction histogram, the threshold selection method, and a simple recursive method for computation. Section 4 reports on the experimental results from some real-world images and discussions. We draw some conclusions in Section 5.

2. Related works

Since the concept of entropy, which is a measure of uncertainty introduced by Shannon into information theory to interpret how much information is contained in a source, was introduced in image thresholding [4], many entropic methods have been developed in rapid succession. Consequently, the entropic approach has become a major category of thresholding. Most of these methods can be generally divided into 1-D entropic methods and 2-D entropic methods. Compared with the former, the latter has an advantage of simultaneously adjusting the threshold pairs to get a better image quality. However, computational cost is an issue which has to be dealt with, when the size of image and total number of gray levels are large. In this section, we will give a brief review of Abutaleb's method and Xiao's method.

2.1. Abutaleb's approach

Suppose that a digital image of size $M \times N$ has L gray levels denoted by $\Omega = \{0,1,\ldots,L-1\}$. Let $f(x,y)$ be the gray level of the pixel located at the spatial location (x,y). Then, the image can be represented by $F = \{f(x,y)|x = 0,1,\ldots,M-1; y = 0,1,\ldots,N-1\}$. At each point (x,y) of F, average gray value of local neighborhood with the size $W \times W$ centered at the pixel (x,y) can be calculated by

$$g(x,y) = Rround\left(\frac{1}{W^2}\sum_{j=-(W-1)/2}^{(W-1)/2}\sum_{i=-(W-1)/2}^{(W-1)/2} f(x+i,y+j)\right), \tag{1}$$

where $Round(\mu)$ denotes the integer part of μ. Then, using the pixel's gray value $f(x,y)$, and the average gray value $g(x,y)$ as a pair

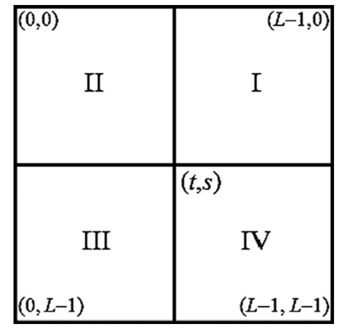

Fig. 1. Conventional 2-D histogram.

vector (t,s), the 2-D histogram can be obtained from the frequency of occurrence of the pair vectors as follows:

$$p(i,j) = \frac{1}{MN}\sum_{x=0}^{M-1}\sum_{y=0}^{N-1}\delta_{ij}, \tag{2}$$

where

$$\delta_{ij} = \begin{cases} 1, & f(x,y) = i \text{ and } g(x,y) = j, \\ 0 & \text{Otherwise.} \end{cases} \tag{3}$$

As shown in Fig. 1, the 2-D histogram can be defined as a matrix with the horizontal axes for the gray value and the vertical axes for the local average gray value. When assuming the pair (t,s) as a threshold vector, the domain of the histogram is divided into four quadrants. Furthermore, these four can be classified into diagonal quadrants II and IV, and off-diagonal quadrants I and III. Based on the difference between the gray levels and the local average gray levels, the diagonal quadrants, which have small gray level variations, are regarded as containing the object and background, and the off-diagonal quadrants, which have large variations, are regarded as the edges and noises that are ignored in calculation. According to above assumptions, the probabilities of the object class and background class can be calculated by

$$P_B(t,s) = \sum_{j=0}^{s}\sum_{i=0}^{t} p(i,j), \tag{4}$$

$$P_O(t,s) = \sum_{j=s+1}^{L-1}\sum_{i=t+1}^{L-1} p(i,j). \tag{5}$$

Then, the two normalized *a posteriori* probabilities distributions of the object and background classes are obtained by using $P_B(t,s)$ and $P_O(t,s)$. Using these two probabilities distributions, Abutaleb [10] defined the entropies associated with the object and background classes as follows:

$$H_B(t,s) = -\sum_{j=0}^{s}\sum_{i=0}^{t} \frac{p(i,j)}{P_B(t,s)}, \tag{6}$$

$$H_O(t,s) = -\sum_{j=s+1}^{L-1}\sum_{i=t+1}^{L-1} \frac{p(i,j)}{P_O(t,s)}. \tag{7}$$

Following the idea suggested in Ref. [10], the optimal threshold vector (t^*,s^*) can be obtained by solving the following maximization problem:

$$(t^*,s^*) = \arg\max_{(t,s)\in\Omega\times\Omega}\{H_B(t,s) + H_O(t,s)\}. \tag{8}$$

2.2. Xiao's approach

In Ref. [14], Xiao et al. defined another type of 2-D histogram, the GLSC histogram, by using the pixel similarity of local neighborhood instead of local average gray level. For a pixel located at point (x,y), the pixel similarity $q(x,y)$ in the corresponding $W*W$