Image Binarization Focusing On Objects

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Abstract: In this paper, an image binarization method based on a new discriminant criterion is proposed. The criterion emphasizes much the homogeneity of the object gray level distribution and while intentionally de-emphasizes the heterogeneity of the background such that the new binarizing or thresholding method can overcome some shortcomings of famous Otsu's method. Experimental results on the three real images show that compared to both Otsu's and recent Kwon's binarizing methods, the proposed method has not only visually better or comparable segmentation effect but also, more favorably, removal ability for noise.

Keywords: Image binarization; Otsu's method; discriminant analysis; threshold selection; image segmentation.

1 Introduction

Separating the foreground out from the background of an image is an important preprocessing in image analysis [1], its purpose is to acquire some useful information in the image for higher level image processing. Binarization or thresholding is such a widely-used method and generally, its process is to first determine a gray threshold according to some objective criteria and then assigns each pixel to one class (such as the foreground) if its gray level or gray value is greater than the determined threshold and otherwise to the other class (such as the background). Examples of thresholding applications include document image analysis [2], map processing [3], quality inspection of materials [4], and so on. In [5], the authors described the 40 thresholding algorithms, analyzed and evaluated their performances. According to the image information contents these algorithms exploited, the 40 thresholding methods are categorized into the six classes: histogram shape-based methods, clustering-based methods, entropy-based methods, object attribute-based methods, the spatial methods and local methods based on the local characteristics of each pixel. Among these classes, many thresholding algorithms are based on their independently defined criteria to acquire the optimal segmenting threshold, for example, the famous Otsu's method is a thresholding technique based on a linear discriminant criterion [6] and the recent Kwon's threshold selection method [7] is another technique based on a clustering criterion. Among the aforementioned typical, simple and relatively effective methods based on criteria, their authors paid equal attention to both the foreground object(s) and the background and ignored the heterogeneity and diversity of the background that existed more likely in some real images and at the same time, these methods in themselves also fail to partially remove noise existing in the background. For purpose of mitigating the methods' shortcomings, in this paper, we develop a new binarization method for gray images by defining such a

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discriminant criterion that puts much emphasis on the homogeneity of the object gray distribution and intentionally de-emphasizes the heterogeneity of the background. By "de-emphasize" here, we mean that we do not to care whether the background is homogeneous or not but just concern the homogeneity of the foreground, which is a major difference from the existing similar criterion-based methods such as Otsu's and recent Kwon's methods. Experimental results on three real images show that the proposed method yields not only visually better or comparable to segmentation effect but also has a relatively obvious removal ability for noise in comparison with both Otsu's and recent Kwon's methods.

The rest of this paper is organized as follows: In section 2, we review briefly Otsu's algorithm and then propose a threshold selection method based on a new discriminant criterion in section 3, which takes not only gray level of each pixel but also its local average gray level around the pixel. In section 4, we give our experimental results on three gray images and finally, Section 5 concludes this paper.

2 Brief review of Otsu's thresholding method

With loss of generality of discussion, we just concentrate on analysis for Otsu's method [6] but the same exposition can be straightforwardly applied to Kwon's method [7] and thus the review for it is omitted here.

Otsu's binarizing method selects an optimal threshold Th^* for a given image by maximizing a discrimimant criterion, i.e., the separability of the resultant classes in gray levels. Concretely, assume that the gray level of the given image ranges in {0, 1, 2, …, L-1}, where L is the total number of gray levels of the image. Otsu's method searches for an optimal threshold value Th^* in the range such that the objective function $J_{Otsu}(T)$, defined below, achieves its maximum:

$$J_{Otsu}(T)=\frac{P_1(T)P_2(T)[m_1(T)-m_2(T)]}{\sigma^2} \tag{1}$$

And thus

$$Th^*=\arg\max_{0\le T\le L-1} J_{Otsu}(T) \tag{2}$$

where $\sigma^2=\sum_{l=0}^{L-1}[l-m(T)]^2h(l)$ is the variance of the gray levels of the image; the $m(T)=\sum_{l=0}^{L-1}lh(l)$ is the mean of the total gray levels; $\{h(l), l=0, 1, \ldots, L\text{-}1\}$ is the gray level histogram or distribution of a given image and $h(l)$ denotes the number of the pixels in the image with gray level of l; $P_1(T)=\sum_{l=0}^{T}h(l)/\sum_{l=0}^{L-1}h(l)$ denotes the prior probability of the foreground (the object class); $P_2(T)=\sum_{l=T+1}^{L-1}h(l)/\sum_{l=0}^{L-1}h(l)$ the prior probability of the background (the non-object class); $m_1(T)=\sum_{l=0}^{T}lh(l)/\sum_{l=0}^{T}h(l)$ is the mean of the foreground and $m_2(T)=\sum_{l=T+1}^{L-1}lh(l)/\sum_{l=T+1}^{L-1}h(l)$ the mean of the background. The foreground and the background contain respectively those pixels with the gray levels in $\{0, 1, \ldots, T\}$ and $\{T+1, \ldots, L-1\}$. From the criterion (1), maximizing the criterion equivalently maximizes the between-class separation in the foreground and background and while at the same time, minimizes the total variance in both fore- and back-ground classes. It has been shown [6] that the above criterion can achieve its maximum when the distributions of both classes are two-peaked, especially Gaussian with the same class variance. Again from (1), we can also see that Otsu's criterion (and its variants such as Kwon's criterion [7]) pays almost equal attention to both the foreground and background of a given image to be segmented and thus relatively suits to segment those images with separate homogeneities, i.e., such a method focuses on both the foreground and the background simultaneously. Generally we seem able to consider the object as foreground having homogeneity of gray levels to some extent, however, for the background, we generally do not consider so as well. Conversely, it tends to have a heterogeneity or diversity of gray level distribution. Consequently, this case may more likely lead to the above similar method failure to segment the background. Moreover, when not so interested in the background with heterogeneity, one could more hopefully completely or partially remove it from the image. To this end, in this paper, we propose such a new effective method by defining an alternative discriminant criterion to achieve a purpose of partially counterbalancing shortcomings of the abovementioned methods.

3 Binarization method based on alternative discriminant criterion

As stated in section 2. In nature, Otsu's method views both the object and the background as having uniformity or homogeneity of gray levels to some degree so as to be able to use separate means to represent them respectively. However, such a case just holds partially. More intuitively, the pixels of an object may have more uniformity or homogeneity in gray level distribution than the pixels in the background, meaning that the background possesses more likely a heterogeneous and non-uniform distribution and naturally produces many different and diverse gray levels. Therefore, adopting a single mean to represent the background will possibly result in a biased threshold estimate. In addition, Otsu's criterion only takes the gray levels of the pixels into account but neglects their spatial distribution and contextual relationship of the pixels themselves belonging to the foreground or background at the same time as its extension [7]. Although Kwon's criterion incorporates the spatial distribution or neighboring information of the pixel coordinates in a given image, it neglects the continuity of the object gray levels and thus more likely over-stresses a role played by the numbers of the two class pixels in the image rather than the gray levels themselves.

In order to remedy such shortcomings of both Otsu's method and its variant [7], in this paper, we will define an alternative (new) discriminant criterion $J_{LC}(T)$ but focus primarily on the object to be segmented in a given image and at the same time, only assume that the object has gray level homogeneity. As a result, the threshold selection problem can still be considered as a classification problem as done in Otsu's method, i.e., selecting an optimal gray level $T^* \in \{0, 1, 2, \ldots, L-1\}$ makes the following new criterion $J_{LC}(T)$ minimized:

$$J_{LC}(T) = (\frac{P_1(T)}{P_2(T)})^{\alpha} \frac{\sum_{(x,y)\in O} [\lambda(g(x,y)-m)^2 + (1-\lambda)(\bar{g}(x,y)-m)^2]}{\sum_{(x,y)\notin O} [\lambda(g(x,y)-m)^2 + (1-\lambda)(\bar{g}(x,y)-m)^2]} \quad (3)$$

And thus

$$T^* = \arg\min_{0\le T\le L-1} J_{LC}(T) \quad (4)$$

where $m = \frac{1}{|O|}\sum_{(x,y)\in O} g(x,y)$, $P_1(T) = \frac{1}{|O|}$, $P_2(T) = \frac{1}{N-|O|}$, O the set of pixels belonging to the object, $g(x, y)$ denotes the gray level of the pixel at (x, y), $\bar{g}(x,y)$ is the local (or neighboring) average gray level of the pixel and defined as $\bar{g}(x,y) = \frac{1}{|W|}\sum_{(u,v)\in W} g(u,v)$, W is a window centered at (x, y) and its size $|W|$ is usually taken as 3x3 or 5x5, and m the mean of gray levels of the object foreground, N the total number of pixels in a given image, α ($\alpha \ge 0$) is an exponent and adjusts $(P_1(T)/ P_2(T))^{\alpha}$ to achieve some trade-off and λ ($0 \le \lambda \le 1$) also is an adjustable parameter to trade off the proportion between gray levels of each pixel and its local average gray levels. The numerator in (3) *only* measures the object-class similarity or scatter degree, in which the second term reflects local spatial continuity or homogeneity among the object pixels. This is so-called nature of "focusing on the object". The more similar (compact) the pixels in the object class, the smaller the scatter and thus the smaller the value of the numerator is. And the denominator in (3) measures the background-class dissimilarity to the object class. A larger value of the denominator implies that the two classes are better separated even when the background is heterogeneous. Therefore, the proposed criterion more focuses on both the similarity of the object class itself and the dissimilarity of the background to the object, aiming to better avoid the problem probably incurred by the heterogeneity of the background. Such an idea seems somewhat consistent with a human intuition of segmenting image: an object with a uniform distribution in a diverse and non-uniform scene can easier be discerned and identified by our human eyes. As a result, it is desired to yield a better segmentation effect in a situation with both heterogeneous background and uniform foreground (object), and while at the same time, the noise in the image is also appropriately reduced and even removed due to the introduction of the local neighbor average of the pixel.

4 Experimental results

In the experiments we use the three images shown in Fig.1 to compare segmenting effects with both Otsu's and Kwon's threshold selection methods respectively. All thresholded images are shown in Fig. 2 to Fig. 4, respectively and their corresponding optimal threshold value T^* with respect to each image and the values of parameters (λ, α) achieving the best objective value are listed in Table 1. The thresholded image $b(x, y)$ of the input image $g(x, y)$ is formed in terms of $b(x, y) = 0$, if $g(x, y) \le T^*$; $b(x, y) = 1$, if $g(x, y) > T^*$.

In all the experiments, we choose a 3x3 local neighbor of each pixel to obtain local average gray level $\bar{g}(x, y)$ of the pixel at position (x, y). From Table 1, we find that the three compared methods select different threshold values for the same image and different images, and further those optimal values selected by our method seem all more prone to the low end of {0, 1,…, L-1}, i.e., gray levels of the objects and especially distinct for image1 and Blood images when (λ, α)=(1, 0.5) and (0.5, 1), respectively (here, λ=1 means that the second terms are zero in both the numerator and denominator of (3) and thus the local information of each pixel does not come into effect in segmentation. In contrast, λ=0.5 means that not only gray value but also the local information of each pixel contributes to the selection of the optimal threshold value) but for Image2, such a difference in value is not so distinct. The thresholded images with the proposed method exhibit visually better or comparable segmenting quality as shown in Fig.2-4 (a-c), respectively, and at the same time, we can observe that our method can remove noise in the images and focuses primarily on the object to be segmented, and yields especially distinct results for Image1, which seems somewhat consistent with our attention mechanism intuitively. However, the other methods do not have such an effect. For the thresholded Image2, Otsu's method behaves visually best and preserves more details of the image while at the same time, Kwon's method yields the worst segmenting effect visually. Our method is, on the whole, only slightly inferior to Otsu's method. On the thresholded Blood image, our method not only eliminates noise but also better preserves the edges and contours of each cell than Kwon's method, while Otsu's method preserves more pixels inside the cells as shown in Fig. 4 (a). In the same case, although still able to identify shapes of the cells, Kwon's method includes more noise than both Otsu's and our methods. On the aspect of eliminating noise in the Blood image, visually, Kwon's method is the worst and thus so is its segmentation quality, Otsu's method is better than the former but our method is still best. To sum up, the proposed method is feasible for segmenting the images used here and exhibits better noise removal ability, which is partially due to not only the introduction of the local neighbor average gray levels to the proposed criterion but also especially more focus on the object(s).

5. Conclusions

In this paper, we propose an effective binarization or threshold selection method for gray image and obtain optimal threshold values by examining different combinations between parameters λ and α based on a newly-constructed discriminant analysis criterion to binarize those given images. Compared to the other two methods, our method can not only remove noise in the images but also yield visually better or comparable segmenting quality on the three images but at the price of computational increase. These relatively good results mainly contribute to both the introduction of each pixel's gray level and its local neighbor average gray level into the discriminant criterion and in particular to putting more emphasis on the object to be segmented. Our further study work is to apply the proposed method to more real-life images.

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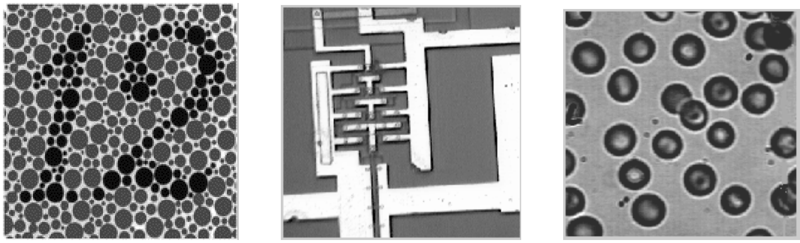
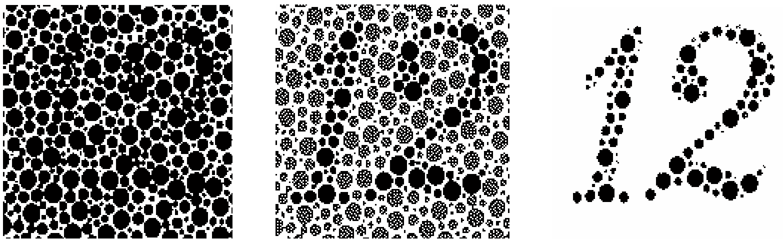


(a) (b) (c)

Fig.1 Original images

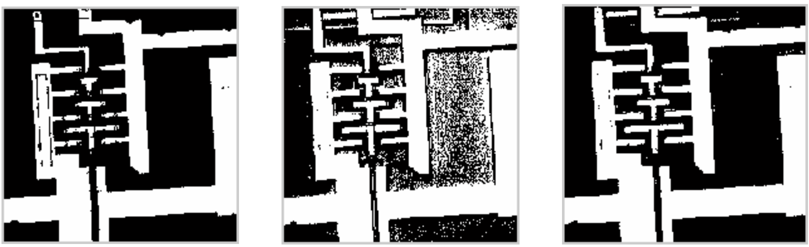
(a) Image1 for color blindness test; (b) Image2 and (c) Blood image



(a) (b) (c)

Fig.2 Thresholded images for Image1

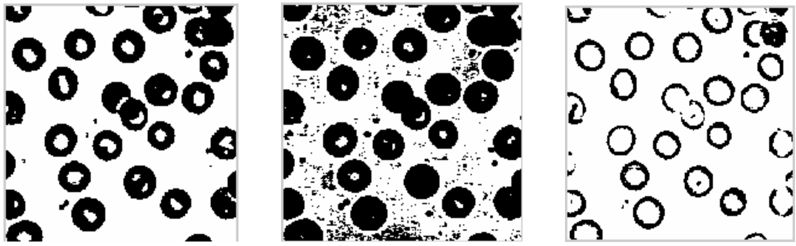
(a) Otsu's method; (b) Kwon's method; (c) the proposed method.



(a) (b) (c)

Fig.3 Thresholded images for Image2

(a) Otsu's method; (b) Kwon's method; (c) the proposed method.



(a) (b) (c)

Fig.4 Thresholded images for Blood image

(a) Otsu's method; (b) Kwon's method; (c) the proposed method.

Table 1 Threshold values determined by three methods

image	Otsu's method	Kwon's method	proposed method (λ, α)
Image1	127	76	25 (1, 0.5)
Image2	173	113	125 (0.5,1)
Blood	96	151	47 (0.5,1)