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XIII
ON THE MAXIMIZATION OF THE CRISPNESS OF 2D GRAYSCALE
HISTOGRAM FOR IMAGE THRESHOLDING

Qing Wang†, Jing Xue‡, Rongchun Zhao†, Zheru Chi‡, and David Feng†

† Dept. of Computer Science and Engineering
Northwestern Polytechnical University
Xi’an 710072, P.R. China
E-mail: {qwang, saip}@nwpu.edu.cn

‡ Dept. of Electronic and Information Engineering
The Hong Kong Polytechnic University
Hung Hom, Hong Kong, P.R. China
{enzheru, enfeng}@polyu.edu.hk

Abstract

In this paper, a novel image thresholding approach based on the crispness maximization of the 2D grayscale histogram is proposed. The threshold vector \((T,S)\) is obtained by an exhaustive searching algorithm. In this approach, the difference between these two components is guaranteed to be within a relatively small range. This cannot be achieved in fuzzy entropy-based methods, such as Abutaleb’s method. Experimental results show that our proposed approach not only performs well and effectively but also is more robust when applied to noisy images.

1. Introduction

A number of thresholding approaches have been proposed for image segmentation [1-2]. Because of the complexity of image segmentation, efforts to apply new ideas and concepts to image thresholding continued during the last decade [3]. The objective of most of the existing methods is to find the optimal threshold which depends on the gray level histogram of an image. However, more information contained in the image can be utilized to obtain a better segmentation.

In last decades, fuzzy set theory has been applied to pattern classification and object recognition, and especially image thresholding [3-6]. One-dimensional entropic thresholding was first introduced by Pun [5]. Kapur et al. refined the Pun’s method by deriving the two entropies from the original grayscale distribution of an image [6]. Huang and Wang applied a fuzzy entropy measure to image segmentation based on the 1D grayscale histogram [7]. They defined the image pixel membership functions as being dependent on a threshold value. The membership functions were used to reflect the distributions of the pixels in the background and object classes. As a result, the classification error is reduced to a certain degree. The image thresholding methods mentioned above are solely based on the 1D gray level histogram. One drawback of these methods is that only the distribution of the pixel gray scales of an image is considered, whereas the spatial information – the correlation between different gray levels, is ignored.

More recently, 2D entropic techniques using local neighborhood as well as pixel information have been proposed to optimize the global threshold. The concept of 2D grayscale histogram originated from the research work by Kapur et al. [6] and that of Kirby et al. Abutaleb proposed the optimal selection by maximizing the total entropy defined on the 2D (grayscale and local average grayscale) histogram [8]. In the work that followed, Brink refined Abutaleb’s method by maximizing the class entropies, which was achieved by using a single threshold vector to maximize the entropy derived from both the background and object classes [9]. To speed up the search process, Chen et al. proposed a fast two-phase algorithm [10]. In the first phase, a set of quantized threshold vectors was obtained by Brink’s method. In the second phase of the search process, the search space was greatly reduced while the quality of the thresholding for image segmentation was maintained.

All of the above-mentioned approaches based on the 2D grayscale histogram employ an entropy measure. In the case of noisy images, we found that the fuzzy entropic method has some drawbacks. In this paper, in order to adequately utilize the intrinsic information of an image, we employ the concept of the 2D grayscale histogram and propose a non-fuzziness measure – crispness to optimize the threshold vector.

2. 2D Grayscale Histogram

The conventional 1D thresholding methods focus on the selection of the peaks or valleys by analyzing the gray level histogram, seeking to determine the best threshold \(T\) from the gray level histogram. Assuming gray scale image is \(f(x,y)\), which contains \(MN\) pixels with gray level ranging from 0 to \((L-1)\). A gray level histogram is a function that shows, for each gray level, the number of pixels in the image that have that gray level. The abscissa is a gray level and the ordinate is the frequency of occurrence (number of pixels), as shown in Fig 1.c. The 1D thresholding function \(f_t(x,y)\) is defined as

\[
f_t(x,y) = \begin{cases} \mathcal{b}_t, & \text{if } f(x,y) < T \\ \mathcal{h}_t, & \text{if } f(x,y) \geq T \end{cases}
\]

where \(T\) is a threshold. \(\mathcal{b}_t\) and \(\mathcal{h}_t\) are the pre-determined values for the background and object(s), respectively.

From the viewpoint of information processing, 1D thresholding techniques do not utilize all the information available in the image. The drawback for not fully utilizing the information in an image becomes apparent as the signal to noise ratio (SNR) decreases. Thus, one could expect an improvement in image thresholding if the spatial relationships among pixels are exploited. Consequently we can say that a 2D thresholding method utilizes
not only the grayscale of each pixel, but also its neighborhood average grayscale.

The 2D gray level histogram is defined by the set,
\[ H_{i,j} = \{ r_c | r_c = \text{number of bin } (i,j), \ 0 \leq r_c \leq MN \} \] (2)
where element \( r_c \) stands for the number of grayscale bins with (gray level, local average) \( = (i,j) \).

The local average values of an image represent the spatial information except the precise point information reflected by each pixel. The local value from a small square window centered at the pixel \((x,y)\) is defined as
\[ g(x,y) = \frac{1}{3 \times 3} \sum_{i=-1}^{1} \sum_{j=-1}^{1} f(x+i, y+j) \] (3)

Hereby, we define thresholding function \( f_{T,S}(x,y) \) as
\[ f_{T,S}(x,y) = \begin{cases} h_s & \text{if } f(x,y) < T \lor g(x,y) < S \\ h_i & \text{if } f(x,y) \geq T \land g(x,y) \geq S \end{cases} \] (4)
where \((T,S)\) is called the 2D threshold vector.

Fig 1b shows the 2D grayscale histogram of an image, in which the T-axis represents the gray level and S-axis denotes the neighborhood average grayscale level. Since the grayscale image \( f(x,y) \) contains \( L \) levels, there are \( L^2 \) elements in the 2D histogram. As well, we illustrate 1D histogram of gray level and that of local average grayscale showing the relationship between 1D and 2D histograms.

Similar to the threshold in the 1D histogram, an optimal threshold vector \((T,S)\) should be determined to separate the two groups within the planar function. Consequently, the 2D histogram is partitioned into four regions by a threshold vector \((T,S)\), as shown in Fig 2. On the one hand, since the pixels belonging to the object or background class make more contributions to the diagonal quadrants, region 0 and 1 are mainly used to represent the distribution of the object and background classes. On the other hand, off-diagonal quadrants, region 2 and 3, mainly reflect the distribution of the edge pixels and noise in an image.

3. Membership Function

It is important to define a proper membership function for a fuzzy set, which can be sketched by four commonly used functions: triangular, trapezoidal, bell-shaped, and S-shape functions. It is obvious that the (grayscale, local average) pair should be considered when we define the membership function \( \mu_r(i;j,s) \) for element \( r \) in the 2D grayscale histogram. Hereby, we give the basic definition of the membership function used in our method and a detailed procedure for its computation.

3.1 Definition of membership function

The membership function for the 2D gray level histogram \( H_{i,j} \) is defined as
\[ \mu_r(i;j,s) = \min \{ \mu_o(i;t), \mu_b(j;s) \} \] (7)
where \( \mu_o(i;t) \) and \( \mu_b(j;s) \) are derived from the histogram according to the criterion proposed by Huang and Wang [12], which will be discussed in detail in Section 3.2. Actually, the item \( \mu_r(i;j,s) \) denotes the possibility that an arbitrary pixel, whose grayscale is \( i \) and whose local average level is \( j \), belongs to the background (or object) class.

3.1 Computation of membership

Step 1: Derive the 2D histogram \( H_{i,j} \) from \( f(x,y) \). Note that the T-axis and S-axis represent the gray level and local average level, respectively.

Step 2: Project the 2D grayscale histogram \( H_{i,j} \) onto the T-axis to obtain a 1D histogram \( H(i) \), which denotes the number of occurrences at gray level \( i \).
\[ H(i) = \sum_{r_c} r_c, \ i = 0, 1, \ldots, L-1 \] (8)

Step 3: Given an arbitrary \( t \), compute the membership measure \( \mu_o(i;t) \) for value \( i \) in the 1D histogram \( H(i) \),
\[ \mu_o(i;t) = \begin{cases} 1 & \text{if } i \leq t \\
1 + \frac{m^o(t) - m^o(i)}{C_i} & \text{if } i > t
\end{cases} \] (9)
where, \( C_i \) is a constant to ensure \( \mu_o(i;t) \) be within \([1/2,1]\).

\( m^o(t) \) is the mean of gray levels of the background class and \( m^o(i) \) is that of the object class, respectively, obtained by
\[ m^o(t) = \frac{\sum_{k=0}^{L-1} k H(k)}{\sum_{k=0}^{L-1} H(k)} \] (10)
and
\[ m^o(i) = \frac{\sum_{k=0}^{L-1} k H(k)}{\sum_{k=0}^{L-1} H(k)} \] (11)
Step 4: Same as 2, project the 2D histogram onto the S-axis to get the 1D histogram $N(j)$ of the local average grayscale,

$$N(j) = \sum_{s=0}^{L-1} r_s, \ j = 0, 1, \ldots, L - 1$$

(12)

Step 5: Given an arbitrary $s$, compute the $\mu_s(j;s)$ of the average gray level $j$ in the 1D histogram $N(j)$,

$$\mu_s(j;s) = \begin{cases} 1 & j \leq s \\ \frac{1}{1 + \left| j - m_s(o)/C_s \right|} & j > s \end{cases}$$

(13)

where, $C_s$ is again a constant to be chosen such that $0.5 \leq \mu_s(j;s) \leq 1$. $m_s(o)$ is the mean of the local average gray levels of the background class and $m_s(o)$ is that of the object class.

Step 6: After computing $\mu_s(i;t)$ and $\mu_s(j;s)$, the membership function is derived by the minimum of two measures, that is,

$$\mu_{rs}(t,s,t) = \min \{\mu_s(i;t), \mu_s(j;s)\}$$

(14)

4. Crispness Measure and Optimal Solution

Unlike the conventional fuzzy thresholding methods, which can utilize any kind of fuzzy measure, our approach should adopt the crispness of the 2D histogram as a measure. We propose a crispness measure of the 2D histogram in a way that is different from typical fuzzy measures such as the fuzzy entropy measure proposed by, the index of fuzziness, the index of non-fuzziness, and Yager measure.

4.1 Our proposed crispness measure

We define the crispness of 2D gray level histogram as

$$\eta(t,s) = \sum_{s=0}^{L-1} \left[ 2 \mu(r_s,t,s) - 1 \right] r_s + \sum_{r,s} \left[ 2 \mu(r_s,t,s) - 1 \right] r_s$$

(15)

Since the object and background classes mainly concentrate on the diagonal regions, the measure function $\eta(t,s)$ is composed of these two parts as well. The following is the computational procedure to maximize the crispness measure.

4.1 Computation procedure

Step 1: Initialization. As defined in Section 3, $\mu(r_s,t,s)$ is given by $\mu(r_s,t,s) = \min \{\mu_s(i;t), \mu_s(j;s)\}$.

Step 2: Compute the sum of the crispness measure $\eta(t,s)$ of the 2D histogram of the input image in diagonal quadrants 0 and 1, as Eq.(15).

Step 3: Iteration. Increase $t$ from $l_{\min}$ to $l_{\max}$ and $s$ from $g_{\min}$ to $g_{\max}$ step by step in order to seek the global optimal threshold vector $(T,S)$ to maximize $\eta(t,s)$, that is,

$$\eta(T,S) = \max_{l_{\min}, l_{\max}, g_{\min}, g_{\max}} \{\eta(t,s)\}$$

(16)

where, $l_{\min} = \min_{x,y} \{f(x,y)\}$, $l_{\max} = \max_{x,y} \{f(x,y)\}$, $g_{\min} = \min_{x,y} \{g(x,y)\}$ and $g_{\max} = \max_{x,y} \{g(x,y)\}$.

Besides the above three steps to obtain the optimal threshold vector $(T,S)$, it is also important to select a learning algorithm. On the one hand, if we adopt a supervised thresholding approach and the thresholding level is set to $K$, the top $K-1$ threshold vectors corresponding to the top $K-1$ crispness measures should be selected from a total of $L^2$ crispness values. On the other hand, if an unsupervised thresholding is employed, a threshold vector corresponding to each maximum crispness measure is needed.

5. Experimental Results and Discussion

5.1 Results on benchmark images

Our proposed 2D crispness based approach was compared to the approaches proposed by Abutaleb and Brink. Abutaleb took the sum of two entropies derived from the background and foreground classes as the objective function and searched globally for the optimal solution by maximizing the 2D entropy summation. Brink refined the objective function to be the minimum of the entropy of the background class and of that of the object class. His algorithm maximizes the minimum of two entropies, which means the maximization of class entropies. In experiments, we compared the thresholding performance of our proposed non-fuzziness measure – crispness with that of the fuzzy entropy measure.

The thresholding results on benchmark images using our approach and the approaches proposed by Abutaleb and Brink are shown in Fig 3. All these images have a size of $256 \times 256$ with 256 gray levels. In four images, (a) is the original image, and (d) is the binarized image using our approach. (b) and (c) are obtained by using Abutaleb’s and Brink’s method, respectively. In order to compare each method’s ability to deal with the ambiguous pixels most of which are distributed near the off-diagonal quadrants, we reported the number of unprocessed pixels and the threshold vector obtained by each method in Table 1. The table shows that the results of our proposed method are very encouraging.

5.1 Results on noisy images

In these experiments, the proposed 2D crispness based approach was compared to three existing methods when they were applied to noisy images of different SNRs. The referenced methods include the 1D fuzzy thresholding method proposed by Huang and Wang, the 2D entropy based thresholding method proposed by Abutaleb, and its improved version by Brink. Gaussian noise with various variances was added to these images and was dependent with images. SNR was defined as 10 times the logarithm of the ratio of the noise-free image power to the noisy image power.

The binarized results of different methods are shown in Fig 4. The 2D grayscale histogram and the 1D grayscale and local average grayscale histograms can be found in Fig 1. In terms of human perception, there is little difference among the binarized results of a noise-free image produced by the 1D fuzzy measure and those produced by the three methods based on the 2D grayscale histogram. However, quite different results were obtained when these
thresholding methods were applied to noisy images. Fig 4 shows the binarized results of a Gaussian noise degraded image with an SNR of 20 db. It can be observed that the 1D fuzzy entropy based method is much less robust when dealing with noisy images. Abutaleb’s method and Brink’s method have a certain degree of robustness to low-level noise. However, when the level of Gaussian noise increases, the binarized results are relatively poor. The experimental results show that our approach is rather robust to Gaussian noise.

6. Conclusions

A new thresholding method is proposed based on a crispness measure on the 2D gray level histogram. In our approach, the threshold vector \((T, S)\) is determined by an exhaustive searching algorithm within the quadrants. Experimental results show that the difference between \(T\) and \(S\) is sometimes relatively large when the fuzzy entropy is used as a measure. This large difference between \(T\) and \(S\) will result in fewer pixels belonging to the quadrant 0 or 1.

In order to avoid the large difference between \(T\) and \(S\), we propose in this paper a crispness measure by which the difference between two variables is guaranteed to be within a relatively small range. As a result, better thresholding outcomes can be achieved by using our approach. Experimental results on noise-free gray level images and Gaussian noise corrupted images show the effectiveness of our approach for image thresholding. Our method has a better robustness when dealing with noisy images and can also be applied to the segmentation of multi-class gray scale images.

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References