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Thresholding technique with adaptive window selection for uneven lighting image

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Abstract

By adaptively selecting image window size based on the pyramid data structure manipulation of Lorentz information measure, a new technique for image thresholding is proposed. The advantage of this technique is its effectiveness in eliminating both uneven lighting disturbance and ghost objects. When applied to Otsu's thresholding approach, it can provide accurate result under uneven lighting disturbance while using Otsu's method alone cannot. Experimental results show the effectiveness of this method.

Keywords: Image segmentation; Thresholding; Adaptive window selection; Lorentz information measure

1. Introduction

Thresholding is one of the most powerful tools for image segmentation. The segmented image obtained from thresholding has the advantages of smaller storage space, fast processing speed and ease in manipulation, compared with gray level image which usually contains 256 levels. Therefore, thresholding techniques have drawn a lot of attention during the past 20 years.

The thresholding techniques, which can be divided into bilevel and multilevel category, must be performed on gray level image in order to obtain the results. In bilevel thresholding, a threshold is determined to segment the image into two brightness regions which correspond to background and object. Several methods have been proposed to automatically select the threshold. Abutaleb (1989) uses two-dimensional entropy to calculate the threshold. Tsai (1985) selects the threshold through moment preservation such that the resulting threshold image best preserves mathematical moments of the original gray level image. Wang et al. (2002) propose an image thresholding

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approach based on the index of nonfuzziness maximization of the 2D grayscale histogram. Otsu (1979) formulates the threshold selection problem as a discriminant analysis where the gray level histogram of image is divided into two groups and the threshold is determined when the variance between the two groups is the maximum. Even in the case of unimodal histogram images, that is, the histogram of a gray level image does not have two obvious peaks, Otsu's method can still provide satisfactory result. Therefore, it is referred to as one of the most powerful methods for bilevel thresholding (Sahoo et al., 1988) and used as a classical method in real thresholding applications (Cao et al., 2002).

In multilevel thresholding, more than one threshold will be determined to segment the image into certain brightness regions which correspond to one background and several objects. Boukharouba et al. (1985) define the zeros of a curvature function as the multithreshold values by using a distribution function. Spann and Wilson (1985) present a hybrid selection method through a quad-tree approach which combines both statistical and spatial information. Papamarkos and Gatos (1994) specify the multilevel threshold values as the global minima of the rational functions which approximate the histogram segments by using hill-clustering technique to determine the peak locations of image histogram. O'Gorman (1994) proposes a binarization and multithresholding approach by applying a measure of both global and local information and choosing the threshold levels with connectivity preservation criterion. Jiang and Mojon (2003) propose a general framework of adaptive local thresholding based on a verification-based multithreshold probing scheme.

In certain cases, however, the existence of some undesired disturbance in thresholding may generate false result by using the existing methods. One of the primary disturbance sources is from uneven lighting, which often exists in the capturing of an image, especially during field operation. The main causes for uneven lighting are: (1) the light may not be always stable, (2) the object is so large such that it creates an uneven distribution of the light, and (3) the scene is unable to be optically isolated from shadows of other objects. One possible solution to this problem is to partition the whole image into certain small windows, and then use those existing methods to threshold each small window. This process is called thresholding in partitioned windows. Theoretically, the smaller the window size is, the better the result will be. However, when the window size becomes too small, it can produce the problem of homogenous windows, i.e., windows contain only background or object pixels. As a consequence, black areas called ghost objects will occur after thresholding. Therefore, there is a need to develop a new technique for automatically selecting window size in order to obtain optimal result.

In this paper, a new method of thresholding in partitioned windows is proposed. The technique is based on the pyramid data structure manipulation, and the window size is adaptively selected according to Lorentz information measure (Chang, 1989). The advantages of the technique are: (1) disturbance of uneven lighting is effectively eliminated by thresholding in partitioned windows, (2) no ghost object will occur by the adaptive selection of the window size, and (3) it can be easily combined with the existing thresholding techniques. Since multilevel thresholding is an extension of bilevel one and Otsu's approach is considered to be the classical method for bilevel thresholding, the technique is only applied to Otsu's. It can also be easily extended to other bilevel and multilevel thresholding methods. Experimental results show that uneven lighting gray level images can be thresholded accurately and effectively by using the new technique while Otsu's method cannot.

2. Lorentz information measure

For a given m gray level image $f(x,y)$, the amount of information contained is defined as picture (image) information measure (PIM) which indicates the least gray level variation when converting $f(x,y)$ to a constant gray level image, and is expressed by

$$\mathrm{PIM}(f) = \sum_{i=0}^{m-1} h(i) - \max_i h(i) \tag{1}$$

where $h:\{0,1,\ldots,m-1\}\to N$ is the gray level histogram of $f(x,y)$, and where $h(i)$ represents the gray level histogram of $f(x,y)$. It can be easily seen that PIM(f) = 0, only if $f(x,y)$ is a constant gray level image (i.e., $f(x,y)$ is a constant), and PIM(f) = max, while the gray level histogram $h(i)$ of $f(x,y)$ is uniformly distributed (i.e., $h(i)$ is a constant). Therefore, it can be concluded that, when $f(x,y)$ has the least information, PIM(f) has its minimum value; and when $f(x,y)$ has the most information, PIM(f) has its maximum value.

Assuming that total number of pixels of an image $f(x,y)$ is $N(f)$, the normalized PIM (NPIM) can be determined by

$$\mathrm{NPIM}(f)=\mathrm{PIM}(f)/N(f) \tag{2}$$

Defining the probability p_i as $h(i)/N(f)$, Eq. (2) can also be expressed as

$$\mathrm{NPIM}(f)=1-\max_i p_i,\quad 0\leqslant i\leqslant m-1 \tag{3}$$

Another usual definition, a generalized PIM, denoted as PIM_k, will be used to obtain the Lorentz information measure, and is given as

$$\mathrm{PIM}_k(f)=\sum_{i=0}^{m-1}h(i)-\sum_{i\in\theta(k)}h(i),\quad 0\leqslant k\leqslant m \tag{4}$$

where k is the number of k highest values of $h(i)$, and $\theta(k)=\{k$ highest values of $h(i)\}$. It indicates the minimum variation number that converts an image to the image with k gray levels. Correspondingly, normalized PIM_k, denoted as NPIM_k, is obtained by

$$\mathrm{NPIM}_k(f)=1-\sum_{i\in p(k)}p_i,\quad 0\leqslant k\leqslant m \tag{5}$$

where $p(k)=\{$the k maximum numbers of $p_i\}$.

From Eq. (5), it can be seen that

$$\begin{aligned}0&=\mathrm{NPIM}_m(f)\leqslant\mathrm{NPIM}_{m-1}(f)\\&\leqslant\ldots\leqslant\mathrm{NPIM}_1(f)\leqslant\mathrm{NPIM}_0(f)=1\end{aligned} \tag{6}$$

Let $S_k=\mathrm{NPIM}_{m-k}(f)$, $0\leqslant k\leqslant m$, then

$$\begin{aligned}S_0&=0\\S_m&=1\\S_k&=\sum_{i=0}^{k-1}p_i\end{aligned} \tag{7}$$

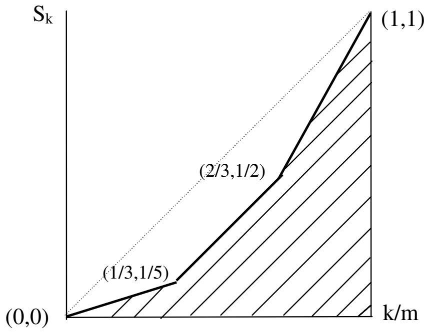

Fig. 1. Example of a Lorentz information curve (m = 3).

By connecting the points $(k/m,S_k)$, $k=0,1,\ldots,m$, a broken line which is called Lorentz information curve can be obtained. Fig. 1 shows an example of a Lorentz information curve with $m=3$, in which the histogram is $h:\{N/5,3N/10,N/2\}$ with N being the total number of pixels in an image. It can be seen that, once the gray level histogram of an image is generated, its Lorentz information curve will be uniquely determined, and vice verse.

We define area below the Lorentz information curve (area of the oblique lines in Fig. 1) as the Lorentz information measure LIM($p_0,p_1,\ldots,p_{m-1}$). When the gray level histogram of image is uniformly distributed, i.e., PIM(f) = max, its Lorentz information curve becomes a line from $(0,0)$ to $(1,1)$ (dashed line in Fig. 1). Otherwise, it will be the convex broken line below the dashed line (solid line in Fig. 1).

To summarize: as LIM($p_0,p_1,\ldots,p_{m-1}$) increases, the image contains more information; as LIM($p_0,p_1,\ldots,p_{m-1}$) decreases, the image has less information, and vice verse.

3. Thresholding by Otsu's method

For a gray level image $f(x,y)$, bilevel thresholding is to transform $f(x,y)$ to binary image $g(x,y)$ by a threshold T which can be expressed as

$$g(x,y)=\begin{cases}0 & \text{if } f(x,y)\leqslant T\\ 1 & \text{if } f(x,y)>T\end{cases}$$

In the mean time, multilevel thresholding can be considered as an extension of bilevel thresholding in which a gray level image $f(x,y)$ is transformed to a multilevel image $g(x,y)$, by several thresholds $T_1, T_2, \ldots, T_m$, as

$$g(x,y) = \begin{cases} 0 & \text{if } f(x,y) \leqslant T_1 \\ 1 & \text{if } T_1 < f(x,y) \leqslant T_2 \\ \vdots & \\ m & \text{if } f(x,y) > T_m \end{cases}$$

To emphasize the partitioned windows technique, only Otsu's thresholding method is considered among many other techniques. This method can be stated as follows:

For a given image $f(x,y)$ with m gray levels $0, 1, \ldots, m-1$, let the threshold be j, where $0 \leqslant j \leqslant m-1$. Then, all pixels in image $f(x,y)$ can be divided into two groups: group A with gray level values of pixels less than or equal to j; and group B with values greater than j. Also, let $(\omega_1(j), M_1(j)), (\omega_2(j), M_2(j))$ be the number of pixels and the average gray level value in group A and group B, respectively. Then

$$\omega_1(j) = \sum_{i=0}^{j} n_i, \quad 0 \leqslant j \leqslant m-1 \tag{8}$$

$$M_1(j) = \frac{\sum_{i=0}^{j}(i \cdot n_i)}{\omega_1(j)}, \quad 0 \leqslant j \leqslant m-1 \tag{9}$$

$$\omega_2(j) = \sum_{i=j+1}^{m-1} n_i, \quad 0 \leqslant j \leqslant m-1 \tag{10}$$

$$M_2(j) = \frac{\sum_{i=j+1}^{m-1}(i \cdot n_i)}{\omega_2(j)}, \quad 0 \leqslant j \leqslant m-1 \tag{11}$$

where n_i is the number of pixels with gray level value i.

Expressing the average gray level value M_T of all the pixels in image $f(x,y)$ as

$$M_T = \frac{\omega_1(j)M_1(j) + \omega_2(j)M_2(j)}{\omega_1(j) + \omega_2(j)}, \quad 0 \leqslant j \leqslant m-1 \tag{12}$$

the variance between the two groups, denoted as $\sigma_B^2(j)$, is

$$\begin{aligned} \sigma_B^2(j) &= \omega_1(j)(M_1(j) - M_T)^2 + \omega_2(j)(M_2(j) - M_T)^2 \\ &= \frac{\omega_1(j)\omega_2(j)(M_1(j) - M_2(j))^2}{\omega_1(j) + \omega_2(j)} \end{aligned} \tag{13}$$

For j ranging from 0 to $m-1$, calculate each $\sigma_B^2(j)$ using Eq. (13), and the value j corresponding to the greatest $\sigma_B^2(j)$ is the resulting threshold T.

4. Thresholding in partitioned windows

The criteria of adaptive window size selection are to calculate $\text{LIM}(p_0, p_1, \ldots, p_{m-1})$ in each window to decide whether the window contains both object and background. If yes, Otsu's method can be directly applied for thresholding. Otherwise, continuously adjust the window size according to a given pyramid data structure until it meets the requirement.

Suppose the size of an image $f(x,y)$ is $M \times N$. Divide the image $f(x,y)$ into small windows whose size is $a \times b$ (a and b can be set by the user according to their practical situation), and let $M = ma$, $N = nb$ as show in Fig. 2. Label each window as window 1, window 2, ..., window mn.

Now consider each window as a pixel and its $\text{LIM}(p_0, p_1, \ldots, p_{m-1})$ as its gray level value. Then a feature image $f'(x,y)$ = window 1, window 2, ..., window mn is formed. Calculate a threshold T' for $f'(x,y)$ by Otsu's threshold method, and threshold those pixels in each window of $f(x,y)$ whose $\text{LIM}(p_0, p_1, \ldots, p_{m-1})$ is greater that T'. For the remaining windows whose pixels have not been thresholded, do as follow.

Without loss of generality, assume that $\text{LIM}(p_0, p_1, \ldots, p_{m-1})$ of window k, $1 \leqslant k \leqslant mn$, is less than or equal to T'. Now enlarge window k to window K as shown in Fig. 3. Here window K contains window k, window $k+1$, window $k+m$, window $k+m+1$. Similarly, a new feature image $f'(x,y)$ = {window 1, window 2, ..., window mn, window K} is formed and a new threshold is calculated. If the $\text{LIM}(p_0, p_1, \ldots, p_{m-1})$ of window K is greater than this new threshold, it will be thresholded by Otsu's method. Otherwise window K will be enlarged until it is threshold. However, the worse case is that window K will be enlarged to the whole image size and thresholded by the

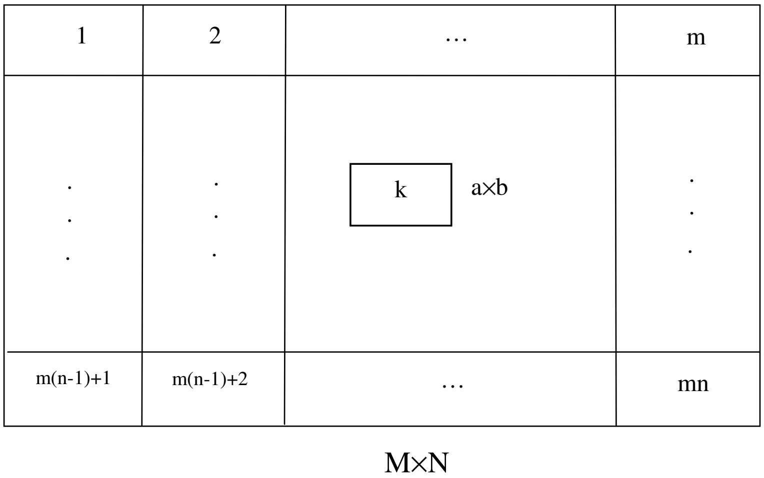

Fig. 2. Feature image $f'(x,y) = \{\text{window } 1, \text{window } 2, \ldots, \text{window } mn\}$.

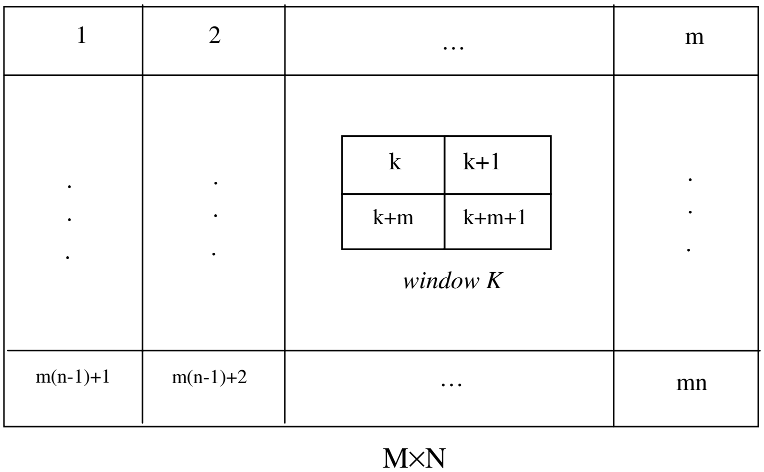

Fig. 3. Feature image $f'(x,y) = \{\text{window } 1, \text{window } 2, \ldots, \text{window } mn, \text{window } K\}$.

threshold calculated according to Otsu's method applying to the whole image.

Summarizing the above development, a detailed algorithm for the technique of thresholding with adaptive window size selection is provided as follows:

Algorithm.

Step 1. Start with partitioned windows each having size of $a \times b$, where a and b are the length and width, respectively.

Step 2. Compute $\mathrm{LIM}(p_0, p_1, \ldots, p_{m-1})$ for each window by Eqs. (1)–(7).

Step 3. Form a feature image $f'(x,y)$ by considering each window as its pixel and $\mathrm{LIM}(p_0, p_1, \ldots, p_{m-1})$ as its gray level value, respectively.

Step 4. Use Eqs. (8)–(13) to calculate threshold T' of $f'(x,y)$.

Step 5. Check the pixels in $f'(x,y)$ whether their gray level values are greater than T'. If yes, go to Step 6. Otherwise, go to Step 8.

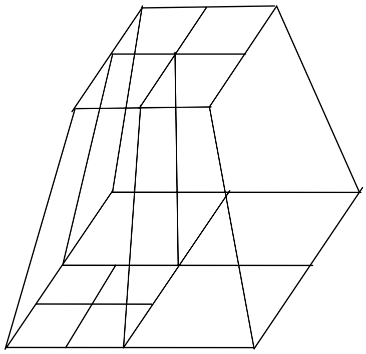

Fig. 4. Pyramid data structure.

Step 6. Threshold those pixels in each window of $f(x, y)$ which have not been thresholded before.

Step 7. Check if the whole image $f(x, y)$ has been thresholded. If yes, go to Step 10. Otherwise, go to Step 8.

Step 8. Check whether there exists any pixel in $f'(x, y)$ with gray level value less than or equal to T'. If yes, go to Step 9. Otherwise, go to Step 10.

Step 9. Let $a = 2a$, $b = 2b$ according to the pyramid data structure as shown in Fig. 4. If a and b equal to the image length and width, calculate the threshold T_{image} of the whole image $f(x, y)$ using Eqs. (8)–(13) and threshold those windows that have not been thresholded in $f(x, y)$ by T_{image}. Otherwise, regard it as a new window and go to Step 2.

Step 10. End.

5. Experimental results

Our proposed thresholding technique by adaptive window size selection has been tested by two uneven lighting images: a contour map image and a document image. In order to have some comparative results with other existing techniques, thresholding by applying Otsu's method alone and thresholding in partitioned windows with fixed window size have also been implemented. The reason for selecting contour map and document as testing images is that the objects in these images include thin lines and the background has large homogenous areas. Under uneven lighting conditions, improper thresholding may easily result in broken lines due to the thinness of contours or strokes, and large black regions because of homogenous areas. Therefore, they are specific cases for uneven lighting image thresholding.

The experimental results are demonstrated in Figs. 5 and 6. In either figure, (a) is the original uneven lighting image with the size of 256×256, where in Fig. 5(a) the left-up portion is darker while right-down portion is lighter, and in Fig. 6(a) the right portion is darker while left portion is lighter; (b) shows the thresholding result by using Otsu's method alone to the whole image; (c) is the thresholding outcome by the way of thresholding in partitioned windows with fixed window size of 32×32 in Fig. 5 and 64×64 in Fig. 6; and (d) provides the thresholding result by using our technique proposed in this paper. From the figures, we can see that:

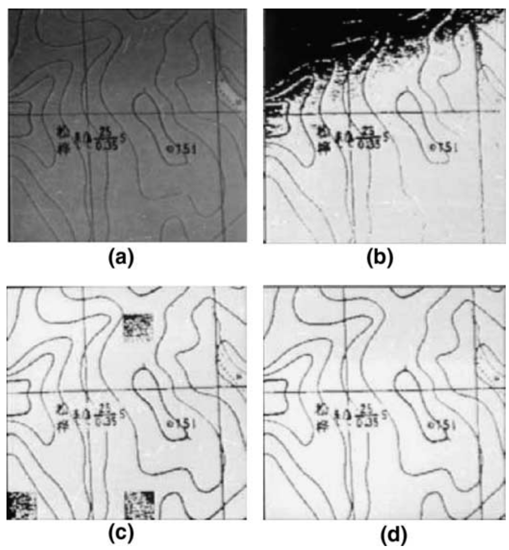

Fig. 5. Thresholding of uneven lighting contour map image: (a) original uneven lighting contour map image; (b) thresholding result by Otsu's method alone; (c) thresholding result by fixed window size selection; (d) thresholding result by adaptive window size selection.

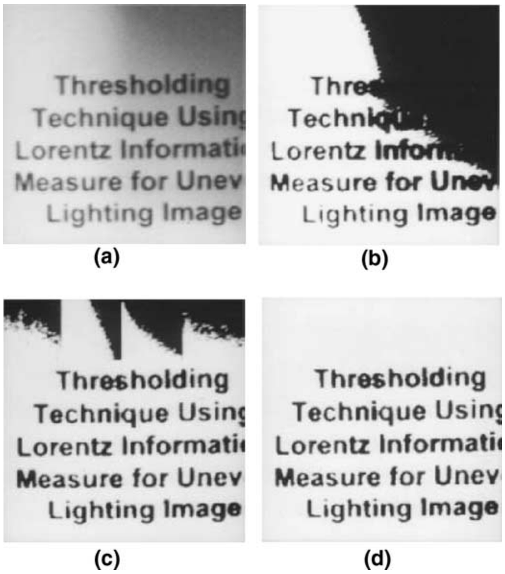

Fig. 6. Thresholding of uneven lighting document image: (a) original uneven lighting document image; (b) thresholding result by Otsu's method alone; (c) thresholding result by fixed window size selection; (d) thresholding result by adaptive window size selection.

(1) Using Otsu's method alone to the uneven lighting images can not obtain correct thresholding result. It can be easily seen that large black areas have been formed in the left-up and right portions in Figs. 5(b) and 6(b), respectively. Also broken contours have been appeared in the right-down portion in Fig. 5(b). All these defects are due to the fact that only one threshold is selected for the whole image.
(2) The way of thresholding in partitioned windows with fixed window size will, to some extent, improve the thresholding result for the uneven lighting images. It solves the problems arisen in Figs. 5(b) and 6(b), such as the appearance of broken contours and large black areas, but improper selection of window size still yet provides false thresholding result. As shown in Figs. 5(c) and 6(c), ghost objects have been appeared after thresholding since the window size is selected fixedly and not large enough.
(3) Our technique of thresholding in partitioned windows with adaptive window size selection can provide accurate result for the uneven lighting image. As shown in Figs. 5(d) and 6(d), since the window size can be adjusted automatically by using Lorentz information measure so that both objects and background will be contained in each window, the uneven lighting disturbance (which cannot be solved by Otsu's method) and ghost objects (which cannot be solved by thresholding in partitioned windows with fixed window size) are eliminated.

From the above discussions, we can conclude that, for uneven lighting image thresholding, our technique of thresholding in partitioned windows with adaptive window size selection is superior to other existing thresholding methods, such as Otsu's one which is considered to be one of the most powerful, although our technique may consume more time to implement since more calculation is needed for adaptive window size selection.

6. Conclusion

In this paper, a new method for thresholding in partitioned windows to solve the problem of uneven lighting without any ghost object has been proposed. The technique is based on pyramid data structure manipulation with window size adaptively selected according to Lorentz information measure. Experimental results show that uneven lighting gray level images can be thresholded accurately and effectively by using the new technique while Otsu's method cannot. The extension of the technique to multilevel thresholding is currently under investigation and will be reported later.

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