Infrared Physics & Technology 66 (2014) 103–113

Contents lists available at ScienceDirect

Infrared Physics & Technology

journal homepage: www.elsevier.com/locate/infrared

Integration of local information-based transition region extraction and thresholding

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HIGHLIGHTS

- We present a simple but effective method of transition region extraction and thresholding.
- The integration of the weighted local entropy with the improved local grayscale difference accurately depicts characteristics of transition regions.
- The proposed method yields effective and efficient thresholding results.

ARTICLE INFO

Article history:
Received 31 December 2013
Available online 9 June 2014

Keywords:
Local entropy
Local grayscale difference
Segmentation
Transition region

ABSTRACT

Transition region-based thresholding method utilizes the pixel location and neighborhood information to segment an image into a number of interesting regions which have specific characteristics in recent years. In this paper, a novel transition region extraction and thresholding method is proposed, which is based on the integration of the weighted local entropy with the improved local grayscale difference. The integration of two modified local information can character the intrinsic quality of transition regions easily and effectively. For some synthetic and real images, the proposed method is quantitatively and qualitatively compared with other transition region-based thresholding methods such as local entropy method, gray level difference method, modified local entropy method, and as well gray-level histogram-based thresholding methods e.g. Otsu-based method and entropy-based method. The experimental results have confirmed the validity and efficiency of the proposed approach.

1. Introduction

Image segmentation, partitioning image data into interesting regions, is a vital step in image data analysis and compression [1,2]. Though there exist lots of different image segmentation methods, the most important image segmentation is thresholding method that serves a variety of applications, such as medical image analysis [3,4], character identification [5], and object recognition [6]. Thresholding methods usually use one or more the following information [7]: histogram shape-based method, clustering-based method, entropy-based method, object attribute-based method, spatial correlation-based method and local gray-level surface-based method.

Global thresholding methods which are easy to be implemented and also computationally less involved have been developed to segment images and recognize patterns, e.g. Otsu-based method [8], minimum error thresholding method [9], entropy-based method [10], Tsallis entropy-based method [11] and Parzen window-based method [12]. Otsu-based method is an excellent thresholding method by maximizing the variance between the objects and backgrounds in an image. Entropy-based method is effective for images with different signal-to-noise ratios and different objects. Parzen window-based method adopts the Parzen window technique to estimate the spatial probability distribution of gray-level image values [12]. Those methods are derived from the gray-level histogram of an image, which is adopted to approximate the unknown gray-level probability density function.

However, the above global thresholding methods are sensitive to noise and have the disadvantage of spatial uncertainty since they usually ignore the pixel location and their neighborhood information [13]. Thus, the utilization of the pixel location and neighborhood information should be helpful to overcome those disadvantages [14]. Transition region-based thresholding is a newly developed image binarization technique [14–17]. Transition region has both edge and region characteristics, and it is with certain pixel's width and non-zero cover area, locates between the object and the background, and covers around the object. It proves

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http://dx.doi.org/10.1016/j.infrared.2014.05.019
1350-4495/

that transition region-based thresholding is adaptive and automatic [16].

Some transition region-based thresholding methods have been proposed in recent years [15–19]. The most classical ones are gradient-based methods, such as average gradient-based method (AG-TRETM) and effective average gradient-based method (EAG-TRETM) [15]. However, the main disadvantage of those gradient-based methods is that they are more sensitive to noise [16]. Since the local entropy (LE) represents the change frequency of gray levels in a neighborhood window, LE-based transition region extraction and thresholding method (LE-TRETM) better captures the nature of transition regions than EAG-TRETM [11]. Nonetheless LE-TRETM still has two deficiencies: One is that it cannot extract transition regions effectively in images with Gaussian noise [18], the other is that it only considers the change frequency of gray levels, but neglecting the change extent of gray levels [17]. To eliminate the limitations of LE-TRETM, some methods including local fuzzy entropy method (LFE-TRETM) [18], gray level difference method (GLD-TRETM) [17], and modified local entropy method (MLE-TRETM) [19] are proposed. The indirect reflection for the degree of changes in LFE-TRETM is inadequate and instable, causing unsatisfactory effects [19]. GLD-TRETM neither represents the change frequency of gray levels in the neighborhood window, nor accurately captures the change extent of gray levels in the neighborhood window [14]. Thus, both the change frequency and the change extent of gray levels are taken into account in MLE-TRETM [19]. In addition, considering the absolute spatial difference, an image data field is developed by simulating a short-range nuclear force [14,20].

The existing transition region-based thresholding methods have both advantages and limitations. In order to improve the descriptor for transition regions, the relative grayscale differences as well as the spatial position differences between the central pixel and its neighborhood pixels should be taken into account [14,20]. Therefore, a novel integration of local information-based transition region extraction and thresholding (ILI-TRETM) method is developed in this paper, which overcomes the aforementioned drawbacks by analyzing the properties of transition regions. The proposed method integrates the weighted local entropy with the improved local grayscale difference, which depicts characteristics of transition regions more accurately. The proposed method is compared with LE-TRETM, GLD-TRETM, MLE-TRETM, Otsu-based method and Entropy-based method by testing on a variety of synthetic and real images. The experimental results demonstrate the effectiveness and efficiency of the proposed method.

The organization of the remainder of this paper is as follows: Section 2 reviews the properties of transition region, and ILI-TRETM is constructed in Section 3. The proposed method is tested and verified to be a useful thresholding method in Sections 4 and 5 summarizes the contributions of the paper and proposes an outlook to future work.

2. Transition region

Transition region-based thresholding method firstly measures changes in an image according to a given standard, secondly extracts transition regions through a suitable threshold, and finally decides an optimal threshold for segmentation based on the peak or mean of the transition region histogram [14]. Undoubtedly, the extraction of transition region has great an effect on the accuracy of optimal threshold and the quality of segmentation result.

Transition region locating between the object and the background has the following properties: (1) Since the edge is the boundary between the object and the background, the extracted transition regions should cover around the object [16]; (2) Whether for step edges or for non-step edges, there always exist transition regions near edges. Transition regions near step edges have at least one pixel's width [17]; (3) The gray levels in the transition region change frequently [19]. The change frequency of gray levels in the transition region brings abundant information for the transition region extraction and thresholding. Local entropy can measure the change frequency of gray levels, but can not reflect the change extent of gray levels. Though gradient can measure sudden changes of gray levels, transition regions in images especially medical images contain essentially more frequent changes than large sudden changes [16]. Gray level difference not only considers changes of gray levels in transition regions, but also represents the change extent of gray levels [17]. However, different pixels are given the same grayscale value, so the gray level differences between those pixels and the central pixel may be the same, while the change extent of gray levels is not always consistent [20].

For example, there are two local neighborhood windows in Fig. 1(a) and (b) (The number in both neighborhood windows denotes gray level of pixel), and their respective corresponding three-dimension graphs are shown in Fig. 1(c) and (d). According to the expressions of local entropy $Le(i, j)$ [16], local complexity $Lc(i, j)$, local variance $Lv(i, j)$, and fusion descriptor $S(i, j)$ [19] which are described as (The neighborhood window with the size of $m \times n$ is centered on point (i, j)):

$$Le(i,j) = E(\Omega) = -\sum_{k=0}^{L-1} p_k \cdot \log p_k \qquad Lc(i,j) = C(\Omega) = \sum_{k=0}^{L-1} \mathrm{sgn}(k),$$
$$Lv(i,j) = \sigma^2(\Omega) = \frac{1}{m \times n - 1} \sum_{x=1}^{m} \sum_{y=1}^{n} (f(x,y) - \bar{f})^2 \quad S(i,j) = \beta \times NLc(i,j) + (1-\beta) \times NLv(i,j), \tag{1}$$

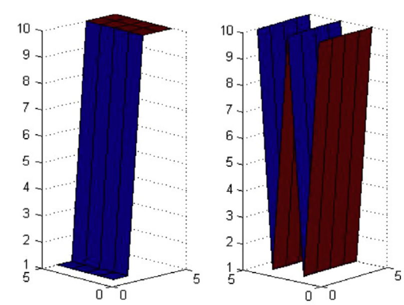
where p_k is the probability of gray level k appears in Ω ($k = 0,1,2,\ldots,L-1$), $f(x, y)$ is the gray value at pixel (x, y), $\bar{f}$ is the gray

1	1	10	10	10
1	1	10	10	10
1	1	10	10	10
1	1	10	10	10
1	1	10	10	10

(a)

10	10	10	10	10
1	1	1	1	1
10	10	10	10	10
1	1	1	1	1
10	10	10	10	10

(b)



(c) (d)

Fig. 1. Example of gray level changes in two neighborhood windows with the size of 5×5: (a) one example of gray level changes, (b) the other example of gray level changes, (c) three-dimension graph corresponding to (a), (d) three-dimension graph corresponding to (b).