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Edge magnitude based multilevel thresholding using Cuckoo search technique

Rutuparna Panda *, Sanjay Agrawal, Sudipta Bhuyan

Department of Electronics and Telecommunication Engineering, VSS University of Technology, Burla 768018, India

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ABSTRACT

Multilevel thresholding technique is popular and extensively used in the field of image processing. In this paper, a multilevel threshold selection is proposed based on edge magnitude of an image. The gray level co-occurrence matrix (second order statistics) of the image is used for obtaining multilevel thresholds by optimizing the edge magnitude using Cuckoo search technique. New theoretical formulation for objective functions is introduced. Key to our success is to exploit the correlation among gray levels in an image for improved thresholding performance. Apart from qualitative improvements the method also provides us optimal threshold values. Results are compared with histogram (first order statistics) based between-class variance method for multilevel thresholding. It is observed that the results of our proposed method are encouraging both qualitatively and quantitatively.

1. Introduction

Interpretation of any image requires the image to be properly segmented into meaningful regions. So multi level thresholding plays a very important role in image processing. One of the very basic, easy and efficient techniques used in image segmentation is gray level thresholding. It classifies the pixels of the image into classes based on their gray levels. But the main problem in thresholding is to choose a proper threshold value. Many types of statistical properties like maximum likelihood (Kurita, Otsu, & Abdelmalek, 1992), moment (Tsai, 1985), entropy (Kapur, Sahoo, & Wong, 1985), and between-class variance (Otsu, 1979) from image histogram have been used for choosing a threshold. Otsu (1979) considered the image histogram consisting of two Gaussian distribution representing the object and background. He then used the technique of maximizing the between-class variance for selecting a threshold. Kittler and Illingworth (1986) used the technique of selecting a threshold value that minimized the error in the Bayes sense. Pun (1980, 1981) used the maximum entropy as optimal criteria for thresholding. Sahoo, Soltani, Wong, and Chen (1988) presented a survey of thresholding techniques. Their study mainly focused on some automatic global thresholding methods using uniformity and shape measures. They stated that one of the drawbacks of point dependent thresholding technique is its dependence on first order statistics i.e. histogram of the image. But thresholding results can be improved if second order statistics i.e. co occurrence matrix of image can be used. Lee, Chung, and Park (1990) presented a comparative performance study of several global thresholding techniques for segmentation. They studied five global thresholding algorithms for segmentation. They observed that most algorithms are suitable for images with bimodal histograms only. They insisted for a more sophisticated and reliable technique to get a good threshold for segmentation. Sezgin and Sankur (2004) presented a survey over various thresholding techniques and their quantitative performance evaluation. They categorized the thresholding methods according to the information used such as histogram shape, entropy, object attributes, spatial correlation and local gray level surface. But they mainly focused on document image applications.

Chang, Du, Wang, Guo, and Thouin (2006) presented a survey and comparative analysis of entropy and relative entropy thresholding methods. They presented eight different entropy based information theoretic methods evaluated by shape and uniformity. But they observed that information conveyed by histogram is not sufficient to select a proper threshold value because it does not take into consideration image spatial correlation. It discards any correlation among gray levels due to which images with similar histogram may result in same threshold value. This has motivated us to use gray level co-occurrence matrix (GLCM) for selecting proper thresholds to capture transitions between gray levels. It can successfully describe and capture image correlation which is necessary to improve thresholding performance. Many studies are available in the literature where different properties of images have been derived from GLCM for obtaining an optimal threshold (Chanda & Majumder, 1988; Gonzalez & Woods, 1992; Li, Cheriet, & Ching Suen, 2005; Mokji & Abu Bakar, 2007). The co-occurrence

* Corresponding author. Tel.: +91 663 2430211; fax: +91 663 2430204.
E-mail addresses: r_ppanda@yahoo.co.in (R. Panda), agrawals_72@yahoo.com (S. Agrawal), sudiptabhuyan1@gmail.com (S. Bhuyan).

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matrix has been used for computing many types of entropies like local, global, joint and relative to select a proper threshold value (Pal & Pal, 1989; Clausi & Jernigan, 1998; Fritz, 2008). However, the edge information in the co-occurrence matrix has not been used effectively. So we are using this method where some statistical features are derived from the GLCM based on the edge information. The features are optimized using Cuckoo search technique and results are compared with that of histogram based between-class variance method. The reason for using Otsu's method in our paper is its establishment as one of the most successful technique in image thresholding. We are using a relatively new optimization method named Cuckoo search technique. In summary, we mainly focus on a comparative study between edge magnitude based multilevel thresholding vs. histogram based multilevel thresholding scheme.

The paper is organized as follows: Section 2 explains the idea of gray level co occurrence matrix. Section 3 describes the concept of Cuckoo search technique. Section 4 discusses the proposed technique. Results and discussions are presented in Section 5. Section 6 is the conclusion.

2. Gray level co-occurrence matrix

Gray level co-occurrence matrix (GLCM) plays an important role in image processing. The gray level co-occurrence matrix provides us an idea about how often different combinations of pixel intensity values occur in an image. Basically second order statistical features are obtained from GLCM. The frequency of appearance of one gray level in linear spatial relationship with another gray level within the same area is obtained from this matrix. Note that the co-occurrence matrix is computed based on relative distance between pixel pairs and their orientations. In GLCM, the number of rows and columns is equal to the number of gray levels. Interestingly, a matrix element $m\ (a,b|d,\theta)$ contains the second order statistical probability values for changes between gray levels a and b at a particular displacement d and at a particular angle θ. Let 'I' be an image with L gray levels in the range $0\ldots L-1$. Let $d=(a,b)$ denote an integer valued displacement vector, which specifies the relative position of the pixels at coordinates (x,y) and $(x+a,y+b)$. A gray level co-occurrence matrix M is a $L\times L$ matrix whose (i,j) element is the number of pairs of pixels of 'I' in relative position d such that the first pixel has gray level 'i' and the second pixel has gray level 'j'. So the matrix M involves counts of pairs of neighboring pixels. Simple relationships exist among certain pairs of the estimated probability distribution $p(d,\theta)$ as shown in Fig. 1. Note that the distance d is taken as 1 to simplify and reduce the computational complexity.

Let $p^T(d,\theta)$ denote the transpose of matrix $p(d,\theta)$.

Then $p(d,0^\circ)=p^T(d,180^\circ)$, $p(d,45^\circ)=p^T(d,225^\circ)$, $p(d,90^\circ)=p^T(d,270^\circ)$, $p(d,135^\circ)=p^T(d,315^\circ)$. Thus the computation of $p(d,180^\circ)$, $p(d,225^\circ)$, $p(d,270^\circ)$, $p(d,315^\circ)$ adds nothing significant to the GLCM. So M is formed for each of four quantized directions 0°, 45°, 90°, and 135° only. Then the final GLCM is calculated by taking their average [15]:

$$\mathrm{GLCM}=\frac{[M(d,0^\circ)+M(d,45^\circ)+M(d,90^\circ)+M(d,135^\circ)]}{4} \tag{1}$$

Thresholding an image by a single level threshold value 'T' divides the image co-occurrence matrix into four regions, *bb*, *bf*, *ff* and *fb* as shown in Fig. 2.

In region *bb* (background), the gray level transition within the background is represented. In region *ff* (foreground), the gray level transition within the foreground is represented. Region *bf* and *fb* represent joint transitions across boundaries between background and foreground. Thus, the method of threshold selection using

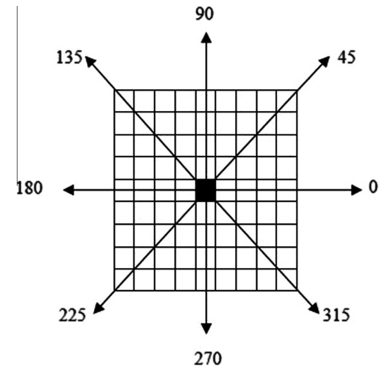

Fig. 1. Geometry for relationship among probability distribution $p\ (d,\theta)$.

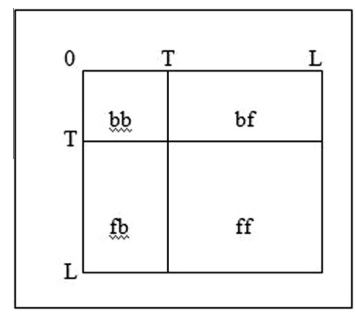

Fig. 2. Four regions of a co-occurrence matrix.

GLCM for single level thresholding can be grouped into two classes only i.e. local and joint regions. Many features can be extracted from the GLCM (Haralick, Shanmugam, & Dinstein, 1973; Haralick & Shapiro, 1992). But it has been described that six of them are more relevant (Otsu, 1979): contrast, correlation, energy, entropy, variance and inverse difference moment. All these features are computed on the basis of frequency of pixel pair. But another feature can be extracted from the GLCM on the basis of gray value difference of the pixel pair called edge magnitude 'q' (Mokji & Abu Bakar, 2007). The value of the edge magnitude is obtained from the position of the pixel pair in the GLCM. The edge magnitude increases diagonally and it is zero along the diagonal of the GLCM. Among the features given above, only the contrast computation carries the edge magnitude information. This information is then used for the thresholding process. For single level thresholding, the threshold 'T' is calculated as (Mokji & Abu Bakar, 2007):

$$T=\frac{1}{\eta}\sum_{m=0}^{L-1-q}\sum_{n=m+q}^{L-1}\left(\frac{m+n}{2}\right)\mathrm{GLCM}(m,n) \tag{2}$$

where

$$\eta=\sum_{m=0}^{L-1-q}\sum_{n=m+q}^{L-1}\mathrm{GLCM}(m,n) \tag{3}$$

The summation range computes the threshold in a specific area in the GLCM which is constrained by $n-m\geqslant q$. In the GLCM, the pixel pairs whose edge magnitude is greater than or equal to 'q' are involved in computation of threshold. η is defined as these total number of pixel pairs within the GLCM with edge magnitude greater than or equal to 'q'. Selection of 'q' is crucial for improving thresholding results, because an optimum 'q' value will get the computation area on the object's boundary. Further, the computation is restricted to upper triangle of the GLCM due to