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Data field-based transition region extraction and thresholding

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ABSTRACT

Thresholding is a popular image segmentation method that converts a gray level image into a binary image. In this paper, we propose a data field-based method for transition region extraction and thresholding, which involves three major steps, including generating the image data field, deriving the transition region by comparing the potential values, and calculating the threshold from the transition region. Image data field can effectively represent the spatial interactions of neighborhood pixels, and its potential value is a more robust measurement for the gray level change. In addition, we introduce a fully automatic scheme for parameters selection. The approach is validated both quantitatively and qualitatively. Compared with existing relative methods on a variety of synthetic and real images, with or without noisy, the experimental results suggest that the presented method is efficient and effective.

1. Introduction

Great interest has been shown in image segmentation, which serves a variety of applications, such as image classification [1], iris segmentation and recognition [2–4], and salient object extraction [5]. A number of image segmentation approaches have been proposed, which have proven successful in many applications, but none of them is generally applicable to all images and different algorithms are usually not equally suitable for any given particular application. In spite of several decades of investigation, image segmentation remains a challenging research topic.

Thresholding is one of the most important and effective techniques for image segmentation, and plays a key role when segmenting images with distinctive gray levels corresponding to object and background [6]. Many techniques and performance evaluation metrics for thresholding have been developed over the years. Comprehensive overviews and comparative studies of image thresholding can be found in the literature [7–10]. Sezgin et al. [10] provide a recent version, in which the Otsu method [11], the Kapur method [12] and Minimum Error Thresholding (MET) [13] are taken as state-of-art algorithms. But great efforts should be made in selecting a threshold in order to ensure quality and rapidity. Thresholding is sensitive to noise and has the disadvantage of spatial uncertainty since pixel location and neighboring information usually are ignored by thresholding methods [14]. Thus, utilizing knowledge on some other fields to overcome the existing drawbacks should be helpful. For example, some innovative methods for image segmentation have surfaced, which are inspired by the physical world. Sun et al. [15] introduce a low-level edge detection algorithm based on the law of gravitation. The algorithm assumes that each pixel is as a celestial body with a mass represented by its grayscale intensity, and each celestial body exerts forces onto its neighboring pixels and in return suffers forces from neighboring pixels, which are calculated by the law of gravity. Lopez-Molina et al. [16] calculate the gravitational forces using the triangular norm (t-norms) instead of the product operation in [15], and then present an extension study of t-conorms as substitutes of t-norms for the generalized gravitational approach to edge detection [17]. Similarly, Wang et al. [18] present an approach for edge detection based on the theory of electrostatic fields. However, none of them focus on image thresholding.

Recently, transition region-based image thresholding has received some attentions [19–25]. It is an intermediate approach between edge detection and region extraction, since transition regions have both edge and region characteristics. Transition regions, which are with certain pixel width and non-zero cover area, locate between the object and the background, and cover around the objects. The main idea of transition region-based image thresholding is that the method measures changes in an image according to a specific criterion, then extracts the transition regions by choosing an appropriate threshold, and finally sets a threshold for segmentation corresponding to the peak or mean of the transition region histogram. Liu et al. [23] review the transition region-based methods and points out that the quality

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of transition region extraction directly influences the accuracy of optimal threshold and the quality of segmentation result.

In the existing transition region-based methods, gradient-based methods are the most classical, such as the effective average gradient-based (EAG) method [19], which is a historical standard. Non-gradient based methods include the local entropy (LE) method [22] and the gray level difference (GLD) method [25]. The GLD method generates a gray level difference image with a predefined neighborhood, and extracts transition regions by appropriate thresholding. The final segmentation threshold is determined using the mean grayscale value of pixels in the transition region. Li et al. [25] analyze the advantage of gray level difference to determine transition region, and exhibits better performance in experimental results as compared to EAG and LE. However, there are some drawbacks of the GLD method, and the results are unsatisfactory or even questionable in some cases. Firstly, GLD fails at representing gray level changes in the neighborhood, since the measurement proposed by Li et al. [25] cannot reflect the difference between the gray level of central pixel and that of each neighboring pixel. Second, GLD cannot accurately capture the extent of gray level changes in the neighborhood. Given different pixels with the same grayscale value, the gray level difference between these pixels and the central pixel may be exactly the same, while the extent of gray level change is not always consistent. The absolute spatial difference should be taken into account, but the GLD method is neglect of this. We believe that an improved descriptor for transition region is necessary.

This paper proposes image data field to represent local gray level changes in the neighborhoods of transition regions, and provides a novel approach for transition region-based image thresholding. An image data field is developed by simulating a short-range nuclear force. The main ideas are: (1) each image pixel is a data particle with mass, and has interactions with neighboring pixels; (2) the potential sum at any pixel is calculated by obeying the law of short-range nuclear force field; (3) transition regions are extracted by an appropriate potential threshold; (4) the final segmentation threshold is determined using the mean grayscale value of pixels in transition region. Compared with two relative methods (LE and GLD) and three classical methods (the Otsu method, the Kapur method and MET), the performance of the proposed method is demonstrated on a variety of images, with or without noise. Experimental results show the effectiveness and the efficiency of the proposed method.

The rest of the paper is organized as follows: Section 2 proposes a novel algorithm for image thresholding, and the algorithm analysis is also presented, such as parameter setup and computational complexity. Section 3 shows experimental results and provides some discussions. Finally, conclusions are drawn in Section 4.

2. The image data field-based method

Li [26] thinks of each data object as a particle with mass related to data space, and uses data fields to describe the complex correlation among data objects, where there are some effects and interactions in an unknown way. We introduce data field and conduct a novel mechanism for transition region extraction. Similar to that by Sun, Lopez-Molina, and Wang et al. [15,16,18], the mechanism encourages the homogeneous pixels to cluster, and then separates the transitional pixels from homogeneous regions. This idea enables us to make an analogy with the mechanism of the nuclear field theory. In nuclear field, nuclear force binds protons and neutrons together to form the nucleus of an atom. Similarly, we take each pixel as a particle with mass, which relates to the grayscale difference in a certain neighborhood. Each pixel receives and exerts an attraction or repulsion from other pixels, and the magnitude of attraction or repulsion is determined by the corresponding potential value, the better the potential value, the higher the magnitude of repulsion. We refer to this mechanism as image data field, and take the corresponding potential value as an indication of gray level changes to extract transition regions.

2.1. Data field

It is clear that data field [26] is the key technique. Given a data object x in data space Ω, let $\varphi_x(y)$ be the potential at any position $y \in \Omega$ produced by x, then $\varphi_x(y)$ can be computed by anyone of the following equation:

$$\varphi_x y = m_x \times \exp(-(\|x-y\|/\sigma)^k) \tag{1}$$

$$\varphi_x(y) = G \times m_x/(1+(\|x-y\|/\sigma)^k) \tag{2}$$

$$\varphi_x(y) = m_x/(4\pi\varepsilon_0 \times (1+(\|x-y\|/\sigma)^k)) \tag{3}$$

where $\|x-y\|$ is the distance between x and y, the strength of interaction $m_x \geq 0$ can be regarded as mass or charge of data objects, a natural number k is the distance index, and $\sigma \in (0,+\infty)$ is the influential factor that indicates the range of interaction. Additionally, the distance is usually measured by Euclidean, Manhattan or Chebyshev metric. In this paper, we choose the Chebyshev distance for $\|x-y\|$.

Eqs. (1)–(3) are three common choices of the above potential function. Eq. (1) imitates nuclear field with Gaussian potential, while Eqs. (2) and (3) imitate gravitational field and electrostatic field respectively, where G and ε_0 are the constants depended on the law of gravitation and the Coulomb law. Mathematically considered, therefore, the latter two seem essentially the same, and we only compare Eqs. (1) and (3) in the next subsection. In addition, we need to state that, there are several alternative formulae for $\varphi_x(y)$, such as electromagnetic field, temperature field or nuclear field with exponential potential.

In general, there is more than one object in data space. To obtain the precise potential value of any position under these circumstances, all interactions from data objects should be concerned. Given a data set $D=\{x_1,x_2,\ldots,x_n\}$, because of overlap, the potential of any position y in the data space is the sum of all data radiation,

$$\varphi(y) = \sum_{i=1}^{n} \varphi_{x_i}(y) \tag{4}$$

where $\varphi_{x_i}(y)$ is calculated by one of Eqs. (1)–(3).

2.2. Image data field

Suppose $P=\{p=(p_x,p_y)\,|\,p_x \in [0,w-1] \wedge p_y \in [0,h-1] \wedge p_x,p_y \in Z\}$ is a finite space consisting of two-dimensional pixels, $f: P \rightarrow [0,L-1]$ is a mapping, and then an image is a pair $I=\langle P,f \rangle$, where Z denotes set of integers, and h, w, and L are the height, width, and grayscale level of the image respectively. Inspired by data field, each pixel $p \in P$ is a particle with mass, and the grayscale change interactions (attraction or repulsion) between each other form an image data field on P.

Because of several alternative formulae for $\varphi_x(y)$, we need to choose an appropriate one for image segmentation. Nuclear force field corresponding to Eq. (1) is a short-range interaction in the physical world [27], and conversely, gravitational field corresponding to Eq. (2) is a long-range interaction. Field intensity of the former attenuates rapidly with the increment of interaction distance. To verify how the field forms with a given σ affect the potential attenuation, we fix $m_x=1,k=2$ in Eqs. (1) and (2), and