Optics & Laser Technology 62 (2014) 1–11

Contents lists available at ScienceDirect

Optics & Laser Technology

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

Image data field-based framework for image thresholding

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ARTICLE INFO

Article history:
Received 4 November 2013
Received in revised form
26 January 2014
Accepted 9 February 2014
Available online 3 March 2014

Keywords:
Data field
Image thresholding
Image transformation

ABSTRACT

Thresholding is a popular image segmentation method that converts a gray level image into a binary image. In this paper, we propose an image data field-based framework for image thresholding, and improve four selected methods under the proposed framework, which involves three major steps, generating the image data field, implementing image transformation with potential-weighted sum, and then determining the binary threshold for the transformed image by applying the conventional approaches. Image data field keeps the balance between spatial and grayscale information in local neighbourhood by potential calculation, and keeps the balance between the local information and the global trend by image data field generator. Compared with the original algorithms on a variety of synthetic and real images, with or without noise, the experimental results suggest that the presented method is accurate, noise-robust, efficient and scalable.

1. Introduction

Thresholding is one of the most simple and important methods for image segmentation [1], and has served a variety of applications [2], such as object recognition, image analysis and scene interpretation. Over the years, a lot of image thresholding approaches have been proposed, and a number of performance evaluation metrics for thresholding have been developed. A recent survey over thresholding methods and their applications is provided in [3].

According to the time complexity, the existing image thresholding methods can be classified into two categories, that is, pixel-level and grayscale-level. The pixel-level methods process the image in a pixel-by-pixel manner and usually require the time linear correlated with the number of pixels, including Gaussian mixture model-based method [4], fuzzy c-means method [5], local entropy-based transition region extraction and thresholding (LE for short) [6] and gray level difference-based thresholding (GLD) [7]. While the grayscale-level methods are based on the histogram or a certain function and to search the optimum grayscale threshold one-by-one, and then the time cost is linear correlated with the grayscale level, such as Otsu [8] and Kittler [9], as well as some recent methods, standard deviation-based statistical thresholding (SDT) [10] and variational minimax optimization-based method (VMM) [11].

However, most of existing methods only partially use the features extracted from images, and do not or little consider any spatial context information. Therefore, these methods make themselves very sensitive to noise, and then usually cannot get satisfactory results sometimes.

More recently, some physical world-inspired methods have been surfaced, including the gravitational approaches in [12,13], which have a good performance for edge detection, and shown their advantages. In order to mitigate the defect of the existing methods and meanwhile promote the image segmentation performance, we propose an image data field-based framework for image thresholding, and improve four selected methods under the new framework. Our method is also as physical world-inspired ones, and satisfies the *ARES* property, but what it meant is not the ancient Greek god, and it stands for *a*ccurate, *r*obust, *e*fficient and *s*calable: (1) the proposed framework is more *accurate*, since it can keep the balance between spatial and grayscale information in local neighbourhood by potential calculation, and keep the balance between the local information and the global trend by image data field generator, and we will analyze this property in the next section. (2) The method is more *robust* to noise, the following experimental results indicate this point. (3) The presented framework is *efficient*, the additional time cost is linearly related with the number of pixels. (4) The proposal is *scalable*, both the selected and some other traditional methods can be easily generalized under this framework to improve the segmentation performance.

The rest of the paper is organized as following: Section 2 proposes a novel image data field-based framework for image thresholding, and an introductory explanation of data field is also presented. Then, Section 3 provides the improvement for four

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http://dx.doi.org/10.1016/j.optlastec.2014.02.004
0030-3992

selected methods under the new framework, and the algorithm analysis is as well presented, such as parameter setup and computational complexity. Section 4 shows the experimental results and discussion. Finally, the conclusion is drawn in Section 5.

2. Image data field-based framework

2.1. Data field

Data field is proposed by Li [14] in recent years, and has been of particular interest to researchers. Its main idea is originated from physical field. In nuclear field, nuclear force binds protons and neutrons together to form the nucleus of an atom. Data field provides an analogy with the mechanism of the nuclear field theory. Given a data space, data field describes the complex correlation among data objects, where there are some effects and interactions in an unknown way, and expresses the power of an item in the universe of discourse by a potential function as the physical field does.

Data field is introduced into various applications [15], and also has been successfully used in image segmentation [16–18]. There are two general categories of data field, static and dynamic one, and we use the former in the paper. The static data field is corresponding to the stable active field in theoretical physics. Inspired by preliminary work [17], we introduce the static data field and conduct a general framework for image thresholding.

2.2. Image data field

Suppose $\Omega = \{p = (x_p, y_p) | x_p \in [1, h], y_p \in [1, w]\}$ is a finite space consisting of two-dimensional pixels, $f : \Omega \rightarrow [0, L-1]$ is a mapping, $f(p)$ denotes the grayscale value of the pixel p, and then an image is a pair $I = (\Omega, f)$, where h, w, and L are the height, width, and gray level of the image respectively.

According to data field, each pixel $p \in \Omega$ is a particle with mass, and the grayscale change interactions (attraction or repulsion) between each other form an image data field on Ω. Assuming two pixels $p, q \in \Omega$, let $\varphi(p,q)$ be the potential at any pixel p produced by q, and then it can be computed by

$$\varphi(p,q) = \exp\left(-\frac{|f(p)-f(q)|}{\sigma_m^2}\right) \exp\left(-\left(\frac{\max(|x_p - x_q|, |y_p - y_q|)}{\sigma_d}\right)^2\right), \tag{1}$$

where $m(p,q) = \exp(-(|f(p)-f(q)|)/\sigma_m^2)$ is the strength of interaction, and can be as the mass of data object. $d(p,q) = \exp(-(\max(|x_p - x_q|, |y_p - y_q|)/\sigma_d)^2)$ is the distance of interaction, as well as the spatial weight. σ_m and σ_d denote the influential factor related with interaction mass and distance respectively. It should be noted that considering the time complex and the efficiency, the different distances for $m(p,q), d(p,q)$ are used.

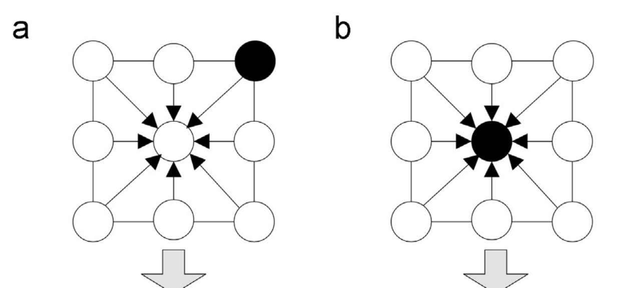
To obtain the precise potential value of any pixel under these circumstances, all interactions from pixels should be concerned. Thus, the potential of any pixel p in the data space is the sum of all data on radiation

$$\varphi(p) = \sum_{q \in \Omega} \varphi(p,q), \tag{2}$$

where $\varphi(p,q)$ is calculated by Eq. (1).

Therefore, Eq. (1) is crucial to the potential distribution of an image data field. In Eq. (1), we consider a few groups of parameters, including $\sigma_m = 1, 3, 5, 7, 9, 11$ and $\sigma_d = 1, 3, 5, 7, 9, 11$, and then investigate the change tendencies of mass $m(p,q)$ and spatial weight $d(p,q)$ respectively. Fig. 1 shows the corresponding results, and both of the curves produce similar attenuation with the various parameters. That is, just for the same $d(p,q)$, the potential value of image data field with smaller σ_m tends to attenuate more rapidly, and vice versa. The too large influential factors are insignificant when involving image data field. Of course, the exponent of variable in $d(p,q)$ is 2, thus $d(p,q)$ attenuates more sharply than $m(p,q)$.

Additionally, the expression of $d(p,q)$ is more like the Gaussian distribution, and then satisfies *three sigma rule*. The influential range of any pixel in image data field is rather finite, shorter than $3\sigma_d/\sqrt{2}$. Beyond this distance, pixels are almost not influenced by a specified pixel, and the potential values become zero. For example, given $\sigma_d = 11$, the magnitude of $d(p,q)$ is negligible when the distance between p and q is greater than 20. As can be



0.9608	0.9608	0.1300
0.9608	1.0000	0.9608
0.9608	0.9608	0.9608

0.1300	0.1300	0.1300
0.1300	1.0000	0.1300
0.1300	0.1300	0.1300

Fig. 2. Two sample neighbourhoods and corresponding potential values.

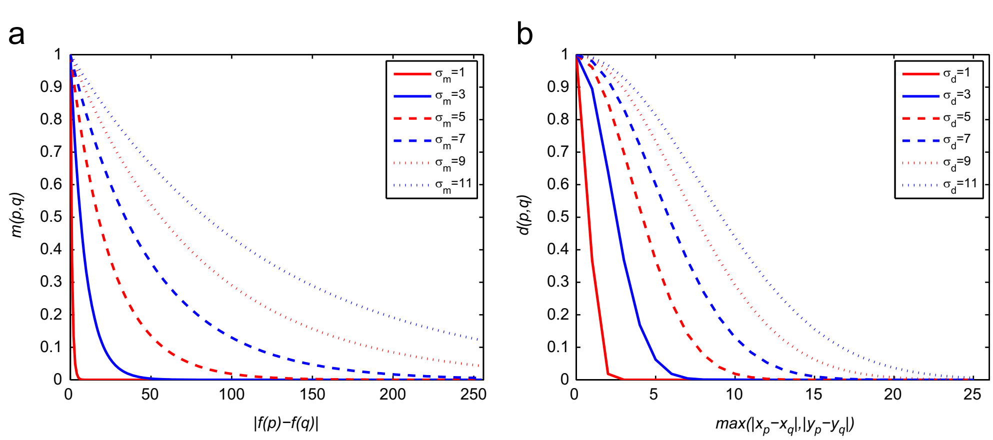


Fig. 1. The magnitude varied with parameters: (a) the mass–change curve and (b) the change curve of spatial weight.