An Improved Image Segmentation Algorithm Based on MET Method

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Abstract

Image segmentation is a basic component of many computer vision systems and pattern recognition. Thresholding is a simple but effective method to separate objects from the background. A commonly used method, Kittler and Illingworth's minimum error thresholding (MET), improves the image segmentation effect obviously. It's simpler and easier to implement. However, it fails in the presence of skew and heavy-tailed class-conditional distributions or if the histogram is unimodal or close to unimodal. The Fisher information (FI) measure is an important concept in statistical estimation theory and information theory. Employing the FI measure, an improved threshold image segmentation algorithm FI-based extension of MET is developed. Comparing with the MET method, the improved method in general can achieve more robust performance when the data for either class is skew and heavy-tailed.

Keywords: *Image segmentation; Image thresholding; Minimum error thresholding (MET); Fisher information; Information theory.*

1. Introduction

The segmentation of images into homogeneous regions is an important area of research in computer vision. Image thresholding, which is a popular technique for image segmentation, is also regarded as an analytic image representation method [1]. This technique plays an important role in many of the tasks that are required for pattern recognition, computer vision, and video retrieval [2]. Image thresholding is computationally simpler than other existing algorithms, such as boundary detection or region dependent techniques [3-6]. Its aim is to find an appropriate threshold for separating the object of interest from the background. The output of a thresholding process is a binary image in which all of the pixels with gray levels higher than the determined threshold are classified as object and the remaining of pixels are assigned to background, or vice versa. This technique can be used in a variety of applications, including biomedical image analysis, handwritten character identification, automatic target recognition and change detection; see, for example [7-9].

Comprehensive overviews and comparative studies of image thresholding can be found in [10-14], for example. Many, and the most-widely used, approaches to image thresholding are based on analysis of the histogram of intensities in an image, searching for an optimal threshold t* to divide the image into two parts, C1 with intensities lower than t* and C2 for the remainder. Among these approaches, one of the most popular is Kittler and Illingworth's minimum-error-thresholding (MET) method [15]. The MET method is ranked as the best in a comprehensive survey of image thresholding conducted by Sezgin and Sankur [13]. In image thresholding, the determination of an optimal threshold is often based on the estimation measures of the location and the spreading of the intensities of the object and background. As with many other approaches, MET method use the sample mean and the sample standard deviation when estimating a location and spreading, respectively. As expected if the background and foreground are well separated in terms of grey levels, MET method may work well. Unfortunately, this assumption not true in many practical applications [14]. Particularly, MET method subject to a limitation of being unable to obtain satisfactory results when the distribution of the object is skew or heavy-tailed, or when there are outliers in the sample from the object.

Much effort has been focused recently upon an Information measure, to be denoted here Fisher's information measure, that was advanced by Fisher in 1925 [16]. The FI is a measure of the fluctuations in the observations. In a sense, the FI of an image specifies the

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quality of the image. The images contain a certain amount of FI by which the highest precision, that is, the lowest variance, with which the structure parameters from these images can be estimated is established. This lower bound on the variance of any unbiased estimator of a parameter is called the Cramér-Rao lower bound (CRLB) [16]. The CRLB is not related to a particular estimation method. It depends on the statistical properties of the observations, the measurement points, and in most cases, the hypothetical true values of the parameters. Therefore, in attempt to overcome the weakness of the MET method, we suggest to use The FI measure as the estimator of dispersion. So, in order to select a t* that is more robust to the presence of skew and heavy-tailed distributions for object (background) than the selected by the MET method, we propose in section 2 Fisher information-based approach to image thresholding. It is an extension of the MET method; the proposed method is based on the use of the FI measure. Like the original version, the new approach remain methodologically simple and computationally efficient. Tests against a variety of images, including some nondestructive testing (NDT) images, show that the proposed method can achieve more robust performance when the data for either class is skew and heavy-tailed. The remainder of this paper organized as follows: The proposed threshold algorithm is presented in section 2, the experimental results are presented in section 3 and the conclusions are presented in section 4.2.

2. The proposed threshold algorithm

In this section, a brief review of some FI concepts and global information measures of dispersion are given. The proposed thresholding objective function and the corresponding algorithm are then proposed.

2.1 FI measure for translation families

The concept of the FI measure was introduced by R. A. Fisher [16]. The FI measure has a great utility in physics as well. FI essentially describes the amount of information data provide about an unknown parameter. It has applications both in finding the variance of an estimator through the Cramer–Rao inequality and in the asymptotic behavior of maximum likelihood estimates [16]. Let X be a random variable, and let $f(x;\theta)$ be the probability density (mass) function for some model of the data that have parameter θ. The FI measure is given by the following [16, 17].

$$F(\theta)=\int\left(\frac{d\log f(x;\theta)}{d\theta}\right)^2 f(x;\theta)dx$$

$$=-\int\frac{d^2\log f(x;\theta)}{d\theta^2}f(x;\theta)dx. \tag{1}$$

The special case of translation families deserves special mention. These are mono parametric families of distribution of the form $f(x-\theta)$ which are known up to the shift parameter θ All members of the family possess identical shape, and here FI measure adopts the appearance

$$F=\int\left(\frac{d\log f}{dx}\right)^2 f\,dx=-\int\frac{d^2\log f}{dx^2}f\,dx. \tag{2}$$

This form of Fisher information measure constitute the main ingredient of a powerful variational principal devised by Frieden [18], that gives rise to a substantial portion of the physics. In the consideration that follow we shall restrict ourselves to the form (2) of FI measure.

2.2 FI measure versus variance

If X is a discrete random variable that takes on a finite or accountably infinite number N of values that are characterized by the probability density $p_i, i\in\mathbf{N}$ where p_i is the probability of x_i and $x_i\in(a,b)\subseteq\Re,$ is assumed to be normalized to unity so that $\sum_{i=1}^{N}p_i=1$. In this case, X can be specified by a probability vector, $P=\{p_1,p_2,\ldots,p_N\}$. Its distribution over the interval (a; b) can be studied by using the following complementary spreading and information measures: the variance and the FI measure [18]. The variance of the random variable X is given by the following.

$$V(X)=\sum_i(x_i-E(X))^2p(x_i), \tag{3}$$

where $E(X)$ denotes the expected value of X. The FI measure [18, 16, 19] of X is defined by the following.

$$F(X)=\sum_i\frac{(p(x_{i+1})-p(x_i))^2}{p(x_i)}, \tag{4}$$

which follows from a suitable discretization of Eq. (2).
These two quantities, which have a qualitatively different character, quantitatively measure the spreading of the random variable X in different and complementary ways. The variance, which is commonly known to measure the distribution of the probability mass around the centroid, is a global measure. It gives a large weight to the tails of the density, this strong dependence of the variance on the tails is not relevant, of course, when the tails fall of exponentially, which is the case for Gaussian or quasi-Gaussian distributions. In contrast to the variance, the FI is

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very sensitive to the difference in the density at adjacent points of the variable. Indeed, when the density $p(x_n)$ undergoes a rearrangement of points x_n, although the shape of the density can change drastically the local slope values $p(x_{n+1}) - p(x_n)$ change drastically and thus, the sum in Eq. (4), which defines the FI, will also change substantially [18, 19]. For different applications of FI measure we refer the reader to the books by Frieden [18, 20].

2.3 The MET method and its FI-based extension

2.3.1 The MET method

Let I denote a gray-scale image with L gray levels $[0,1,\ldots,L-1]$. The number of pixels with gray level i is denoted by n_i and the total number of pixels is denoted by $N = n_0 + n_1 + \ldots. + n_{L-1}$. The probability of gray level i appearing in the image is defined as the following:

$$p_i = \frac{n_i}{N}, \quad p_i \geq 0, \quad \sum_{i=0}^{L-1} p_i = 1.$$

Suppose that the pixels in the image are divided into two classes A and B by a gray level cutoff t. A is the set of pixels with levels $[0,1,\ldots,t]$, and the remaining pixels belong to B. A and B usually correspond to the object class and the background class, or vice versa. Then the probabilities of the two classes are given by the following.

$$P_A = \frac{p_1}{w_1}, \frac{p_2}{w_1}, \ldots., \frac{p_t}{w_1},$$

$$P_B = \frac{p_{t+1}}{w_2}, \frac{p_{t+2}}{w_2}, \ldots., \frac{p_{L-1}}{w_2},$$

where

$$w_1(t) = \sum_{i=0}^{t} p_i, \quad w_2(t) = 1 - w_1(t).$$

The mean gray levels of the two classes can be defined as follows

$$m_1(t) = \sum_{i=0}^{t} \frac{ip_i}{w_1},$$

$$m_2(t) = \sum_{i=t+1}^{L-1} \frac{ip_i}{w_2},$$

and the corresponding class variances are given by the following:

$$\sigma_1 = \sum_{i=0}^{t} \frac{(i-m_1)^2 p_i}{w_1},$$

$$\sigma_2 = \sum_{i=t+1}^{L-1} \frac{(i-m_2)^2 p_i}{w_2}.$$

The MET method criterion defined as [15]

$$\lambda(t) = w_1(t)\log\frac{\sigma_1(t)}{w_1(t)} + w_2(t)\log\frac{\sigma_2}{w_2(t)},$$

MET method selects a threshold t* that minimizes $\lambda(t)$ which is the following:

$$t_M^* = \arg_{1\leq t\leq L} \min\{\lambda(t)\}. \tag{5}$$

2.3.2 FI-based extension

As mentioned in section 1, we envisage that the use of the FI instead of the dispersion may provide a t that is more robust to the presence of skew and heavy-tailed distributions for object (background) than those selected by the MET method. The FI based extension of MET method, derived as the following:
By using Eq. (4) and the definition of $P_A(t)$ and $P_B(t)$ the priori FI for each distribution may defined as

$$F_A(t) = \frac{1}{w_1}\sum_{i=1}^{t} \frac{(p(x_{i+1}) - p(x_i))^2}{p(x_i)},$$

$$F_B(t) = \frac{1}{w_2}\sum_{i=t+1}^{L} \frac{(p(x_{i+1}) - p(x_i))^2}{p(x_i)}.$$

The Fisher information $F(t)$ is parametrically dependent on the threshold value t for the foreground and the background. We define the FI based extension of MET method as the following.

$$\lambda(t) = w_1(t)\log\frac{F_A(t)}{w_1(t)} + w_2(t)\log\frac{F_B(t)}{w_2(t)}, \tag{6}$$

where the FI based extension of MET method selects a threshold t* that maximizes $\lambda(t)$ as follows:

$$t_M^* = \arg_{1\leq t\leq L} \max\{\lambda(t)\}. \tag{7}$$

2.4 Algorithm

The proposed algorithm is a simple and effective thresholding method. This technique defines a FI based extension of MET method that is based on the FI corresponding to two thresholded classes and determines the optimal threshold by maximizing the criterion. The following steps describe the proposed algorithm for image segmentation:

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1. Let *max=0* be the optimal threshold, and let *max* I be the maximum value of the objective function.
2. For t =1 to Maximum of gray intensities
3. Compute the function objective value that corresponds to the gray level t

If $\lambda(t)$ > max,

Then max = $\lambda(t)$, Topt = t.

end

Take Topt as the optimal threshold for segmenting the image.

3. Experimental results

To compare the MET method and it's FI based extension, we apply it to a variety of images including, a nondestructive-testing (NDT) images, text images and general real-world images. All of the images used are 256×256 and have 8-bit (i.e. 256 gray levels) types.

3.1. Experiments on NDT and text images

The first set of experiments is related to the problem of the analysis of NDT and text images. NDT means to detect an object and quantify its possible defects without harmful effects on it by special equipments and methods [22].
In this study, two real images are used in the experiments to assess the performance of the proposed method. The first image is NDT image employed in a recent work of Li et al. [22]. It represents a light microscopy image of a material structure. Light microscopy is frequently used for inspecting the microstructures of materials to derive information about their properties such as the porosity, the particle sizes, the distribution uniformity, etc. The second image is a lenience plate image. Accurate segmentation of text in a plate lenience image plays a crucial role in a lenience plate recognition system. Obviously, the histogram of this gray level data is non-Gaussian in nature. Fig. 1 and Fig. 2 show that, in both 'material image' and 'text image', the two classes are distinct in size, intensity range and skewness. The results of thresholds, indicate that the MET method has serious under-segmentation for text image and conversely for material image. The performance of the FI-based extension of MET method is superior to that of the original MET method.

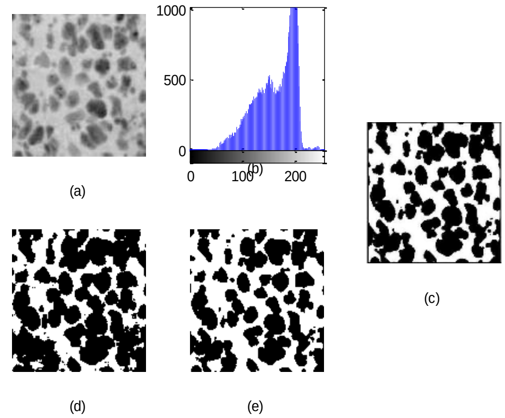

Fig.1. Thresholding results of material image: (a) original, (b) histogram, (c) ground truth image, (d) MET method (t = 187)) and (e) the FI-based MET method (t =171).

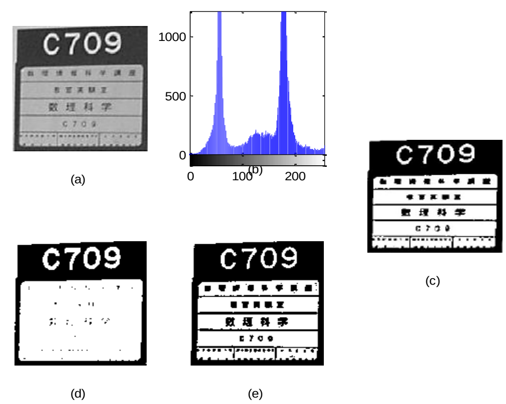

Fig.2. Thresholding results of lenience plate image: (a) original, (b) histogram, (c) ground truth image, (d) MET method (t = 83) and (e) the FI-based MET method (t =162).

3.2. Experiments on real-world images

In this section, a variety of real-world images is used for assessing the relative performance. Four sample images are used, namely Lymp, Grapes, Peppers and Lena. These images are of more complex structures than the images in NDT and Text. In Lymp image the minority class (object, which is for the dark and approximately elliptical cells) has more skewed and widely-ranging intensities for example. The quality of the results is compared only by visual perception. Figures 3, 4, 5 and 6 displayed the segmentation results of the MET method and its FI based extension. From these figures, it can be easily observed that the segmentation images of the four test images, based on FI-based extension MET method perform more robustly than the original method.

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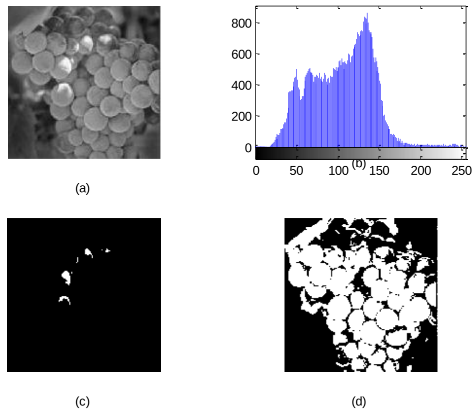

Fig.3. Thresholding results on the Grapes image: (a) original, (b) histogram, (c) MET method (t =219), (d) the FI-based MET method (t =109).

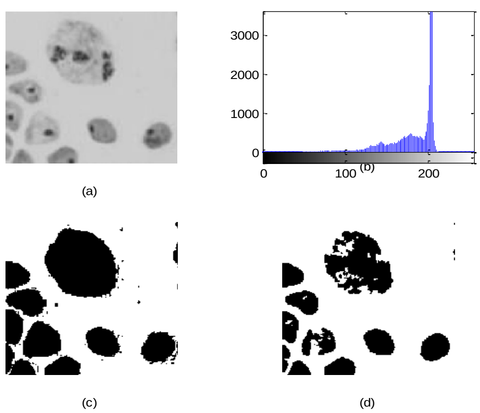

Fig.4. Thresholding results of the Lymp image: (a) original, (b) histogram, (c) MET method (t = 200) and (d) the FI-based MET method (t =182).

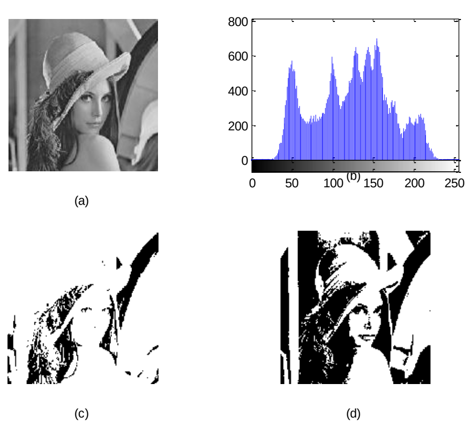

Fig.5. Thresholding results of the Lena image: (a) original, (b) histogram, (c) MET method (t = 28) and (d) the FI-based MET method (t =129).

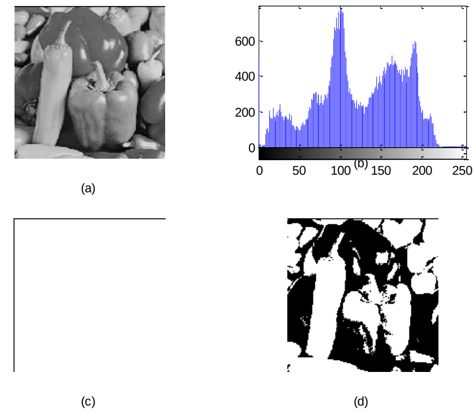

Fig 6. Thresholding results of the Peppers image: (a) original, (b) histogram, (c) MET method (t = 4), (d) the FI-based MET method (t =121).

4. Conclusions

The FI is a measure of the fluctuations in the observations. In a sense, the FI of an image specifies the quality of the image. In this paper, we proposed FI-based approach to image thresholding, to extend Kittler and Illingworth's MET method. The extension preserve the methodological simplicity and computational efficiency of the original method. In order to verify the effectiveness of the segmentation process using the proposed method, a set of images of different kinds were tested. The experimental results showed that the proposed method can in general achieve more robust performance for skew and heavy-tailed data.

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