Image Segmentation by Edge Pixel Classification with Maximum Entropy

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Abstract

Image segmentation is a process to classify image pixels into different classes according to some pre-defined criterion. In this paper, an entropy-based image segmentation method is proposed to segment a gray-scale image. The method starts with an arbitrary template. An index called Gray-scale Image Entropy (GIE) is employed to measure the degree of resemblance between the template and the true scene that gives rise to the gray-scale image. The classification status of the edge pixels in the template is modified in a way to maximize the GIE. By repeatedly processing all the edge pixels until a termination condition is met, the template would be changed to a configuration that closely resembles the true scene. This optimum template (in an entropy sense) is taken to be the desired segmented image. Investigation results from simulation study and the segmentation of practical images demonstrate the feasibility of the proposed method.

1. Introduction

Many image processing tasks require to know the meaning (e.g. object or background) of the image pixels. Image segmentation is an important process to furnish such information to many image processing applications such as pattern recognition and object identification [1]. Throughout the years, image segmentation has been tackled in different approaches. The most popular method to perform image segmentation is thresholding - due to its simplicity, high speed of operation, and ease of implementation. Various thresholding methods have been studied intensively and [2-4]. A disadvantage of thresholding is that its performance is limited since image pixels with the same gray-level value will invariably be segmented into the same class. In this way, information about the spatial configuration of the image has not bee utilized and hence the image segmentation result will always have room for improvement. To overcome this shortcoming, the spatial structure of the image has to be taken into account when image segmentation is to be performed. One way to achieve this is to formulate a template and then modify the template until it becomes the optimum segmented image according to some index that measures the goodness of a segmented image. A suitable index that can "guide" the modification of the template is a crucial element in formulating image segmentation under this principle. The entropy measure has been employed for this purpose with various degrees of success [7-9]. The index *Gray-scale Image Entropy* (GIE) has been derived to indicate how good an image represents the *true scene* that gives rise to the gray-scale image in an imaging process [10,11]. With an observed gray-scale image, the true scene is usually unknown. In this case the GIE can be calculated by taking the template *in lieu* of the true scene. The resultant GIE value would then measure the how well the template approximates the true scene. The greater the GIE value the better the approximation. In this paper, an image segmentation method that consists of three steps is proposed and studied. Step 1 is the formation of an arbitrary template. Step 2 is the modification of the template in an iterative manner while being "guided" by the GIE index. Step 3 is the determination of the termination condition to obtain the final segmented image. By this method, the template that best approximates the true scene would be obtained as the optimum segmented image, with optimality to be interpreted in an entropy sense.

2. Gray-Scale Image Entropy (GIE)

An imaging process captures an image about an underlying true scene. The image segmentation task is to produce a segmented image to approximate the true scene as closely as possible. In some previous studies, the measure Gray-scale Image Entropy (GIE) is defined to measure the amount of information contained in a gray-scale image with respect to a true scene [12]. This is an index to measure whether a gray-scale image is good for the purpose of image segmentation. For instance, if a clear and sharp image with good contrast is taken of a true scene, such an image will be a very good image for the purpose of image segmentation. The GIE value is formulated as the reduction of uncertainty about pixels classification as a result of observing the gray-scale image. The definition of GIE is:

$$GIE = H(f) - \sum_{j=0}^{J-1} \alpha_j H(f_j) \qquad (1)$$

$$H(f) = -\sum_{g=0}^{L-1} f(g) \log f(g) \qquad (2)$$

$$H(f_j) = -\sum_{g=0}^{L-1} f_j(g) \log f_j(g) \qquad (3)$$

Where g is the gray-level value, L is the number of different gray-level values in a digital image, $f_j(g)$ is the probability density function (pdf) of the j^{th} sub-image, α_j is the relative size of the j^{th} sub-image, J is the total number of sub-images in the gray-scale image (including objects and background).

To calculate GIE According to equations (1-3), both the gray-scale image and the true scene need to be known. However, in most image segmentation tasks, the true scene is not known otherwise the segmented image could have been obtained immediately. To calculate the GIE, a *postulated scene* can be used in place of the true scene. Such a postulated scene is called a *template*. The resultant GIE value would then indicate whether the template resembles closely the true scene – the greater the GIE value the better the degree of resemblance.

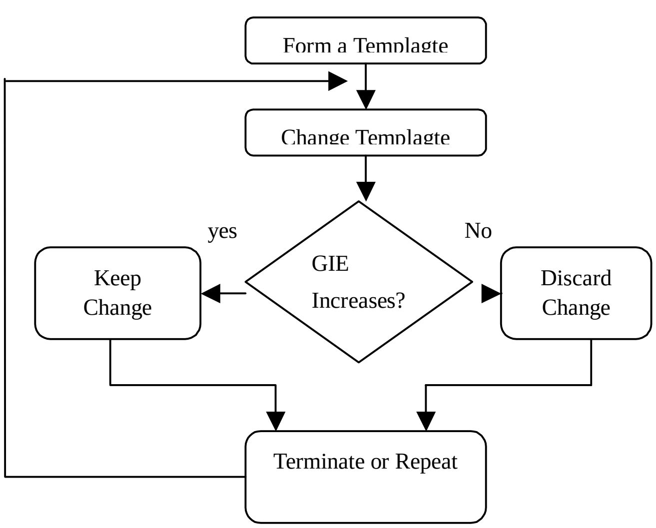


Fig. 1 Flowchart for Image Segmentation

With this general principle, an image segmentation method is devised. The first step is to formulate an arbitrary template. The second step is to modify the template in a way to increase the GIE. The third step is to determine when to stop. The general operation can be illustrated in the flowchart as shown in Figure 1. A crucial element in the flowchart is the way to modify the template. Obviously the performance of the segmentation method would rely on how the template is modified. If a well-designed way is used, the segmentation result will gradually approach the optimum segmentation result. In the following section, we will describe a way to modify the template.

3. Image Segmentation by Shrinking and Growing with Maximum Entropy (SGME)

Given a gray-scale image, an arbitrary template is constructed as an initial approximation to the underlying true scene. As a kind of *a priori* information about the true scene, we assume that the true scene, and hence the template, consists of an object in a background.

For those object pixels in the template, if they lie at the boundary of the object, they are called “object edge” pixels. For each object edge pixel, its classification status is tentatively changed from object to background. With such a change, a new template is formed and hence a new GIE value could be calculated. If the new GIE value is greater than the GIE value before the change in pixel classification is effected, the change will be kept; otherwise the change will not be kept and the pixel classification will be kept as the original status. The object edge pixels are processed one by one along the object boundary. After the complete boundary has been proposed, this amounts to one round of iteration. The object edge pixels are processed repeatedly until no pixel classification change has been effected within one round of iteration, or a pre-defined number of iterations have been executed. The operation in this step effectively “shrink” the template object to match it with the true scene object. An example is shown in Figure 2 to illustrate a typical result of this step.

From Figure 2, it can be seen that small holes have been created as a result of shrinking the template object. One approach to removing these small holes is to apply “majority 2-D filtering” to the processed template. In this method, a block of 3 by 3 pixels is considered. The classification status of the entire block of pixels will be changed to the classification that most pixels belong to. An example of the processing result is shown in Figure 3.

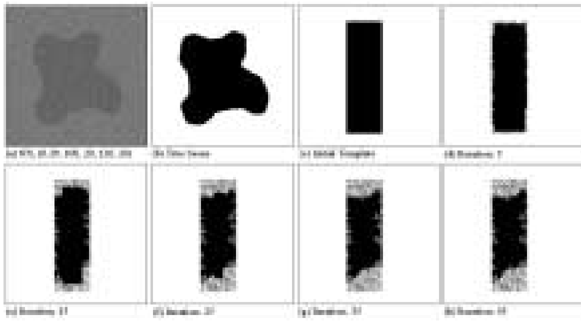


Fig.2 “Shrinking” the template object

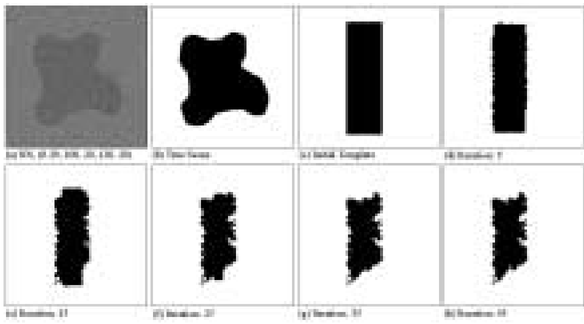


Fig.3 Object shrinking with majority filtering

After the template object has been “shrunk”, the next step is to “grow” it. For those background pixels that lie at the boundary of the object, they are called “background edge” pixels. Each background edge pixel is tentatively classified as an object pixel. If the resultant GIE value increases, such a classification is to be effected; otherwise the classification status of the background edge pixel will remain unchanged. This operation effectively “grows” the template object to match it with the true scene object. An example to illustrate the effect is shown in Figure 3.

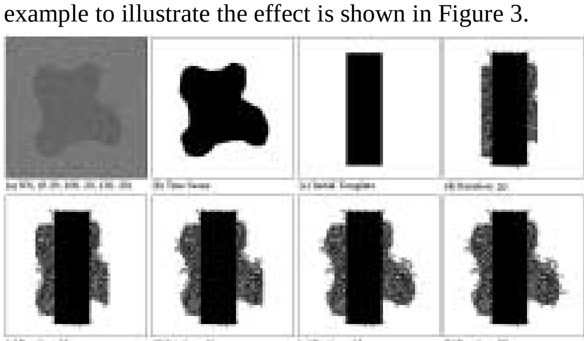


Fig. 3 “Growing” the template object

With “shrinking” and “growing”, the template object will gradually approximate the true scene object better and better under the guidance of the GIE measure. This method is called SGME. In another simulation study, the segmented image obtained by the SGME method is shown in Figure 4. The segmented image is compared to the true scene (this is available in a simulation study) and the error map is plotted. From this comparison, it can be seen that the image segmentation result is quite close to the true scene, with segmentation mainly distributed around the object boundary.

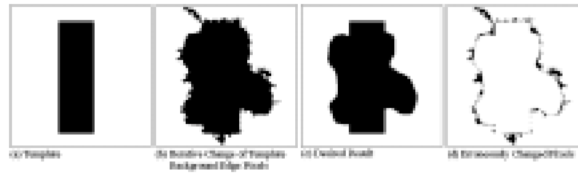


Fig. 4 Segmentation results compared to true scene

To investigate whether the order of applying “shrinking” and “growing” would affect the image segmentation result, Figure 5 shows the segmentation results when the “shrinking” operation is applied first, and Figure 6 shows the segmentation results when the “growing” operation is applied first. It can be seen that the order of application of the two processes, namely shrinking and growing, does indeed affect the segmentation result, but only to a minor degree.

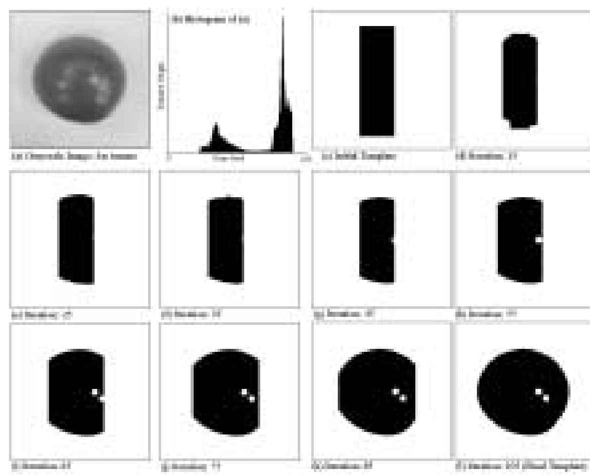
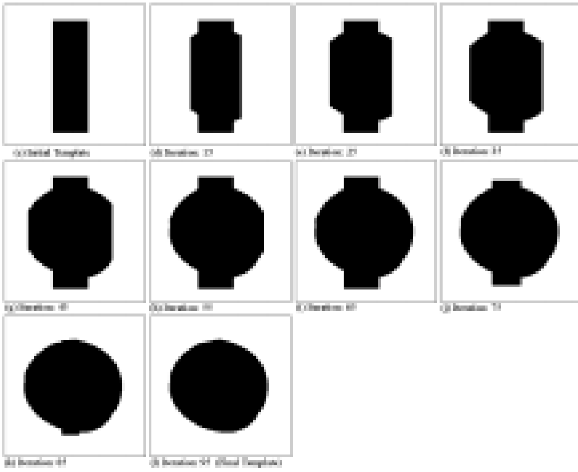


Fig. 5 Shrinking first

4. Simulation study

The performance of the proposed SGME image segmentation method is compared to two well-known image segmentation methods, namely Otsu’s segmentation method (denoted as OTSU) [3] and Kittler and Illingworth’s minimum error method (denoted as KIT86) [4] in a simulation study.

In this study, gray-scale images are synthesized according to an underlying true scene that consists of a circular object in a background. The probability density function of the gray-level values is assumed to be Gaussian for both the object and background pixels. A series of synthetic images are generated and then segmented by the three chosen segmentation methods. The segmented image is compared to the true scene and the number of error pixels is counted. An ensemble average of the number of error pixels is calculated for the entire set of images for each segmentation method. Their performance is compared in a table.



Fig, 6 Growing first

To generate the series of the synthetic images, the mean gray-level value of background pixels ranges from 51 to 105 with a step size of 6. The mean gray-level value of object is set to 257-mean gray-level value of the background pixels. Standard deviation of the gray-level values takes on values of 20, 30 and 40. The size of circular object relative to the image size varies from 0.1 to 0.5 with a step size of 0.1. As a result, 450 synthetic images have been generated. The overall average performance for each segmentation method is tabulated in Table 1 below.

Table 1 Experimental Results

Method	Average number of error pixels	Percentage of error pixels
SGME	173	0.26%
OTSU	6085	9.3 %
KIT86	7449	11.4 %

These simulation results show that the SGME image segmentation method can produce more accurate segmented images when compared to conventional thresholding method such as Otsu's and Kittler's methods.

5. Conclusion

In this paper, a new image segmentation method known as SGME has been proposed. In this method, an arbitrary template is postulated to approximate the true scene. By shrinking and growing the template object in an iterative manner, a segmented image that closely resembles the true scene in an entropy sense is obtained. Simulation results show that when compared to conventional thresholding methods, the SGME segmentation method is capable of obtaining more accurate segmented images.

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