

An Image Segmentation Algorithm in Image Processing Based on Threshold Segmentation

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Abstract

Image segmentation is a key technology in image processing, and threshold segmentation is one of the methods used frequently. Aimed at that only one threshold or several thresholds are set in traditional threshold-based segmentation algorithm, it is difficult to extract the complex information in an image, a new segmentation algorithm that each pixel in the image has its own threshold is proposed. In this algorithm, the threshold of a pixel in an image is estimated by calculating the mean of the grayscale values of its neighbor pixels, and the square variance of the grayscale values of the neighbor pixels are also calculated as an additional judge condition, so that the result of the proposed algorithm is the edge of the image. In fact the proposed algorithm is equal to an edge detector in image processing. Experimental results demonstrate that the proposed algorithm could produce precise image edge, while it is reasonable to estimate the threshold of a pixel through the statistical information of its neighbor pixels.

1. Introduction

In classical threshold image segmentation [1] [2], an image is usually segmented and simply sorted to object and background by setting a threshold. If there are two peaks in the histogram of an image, it is easy to get good result by threshold segmentation. But if there is complex information in the image, the threshold algorithm is not suitable definitely. There have been several upgraded algorithms based on threshold segmentation which give the optimum threshold, such as Otsu algorithm [3], 2-D Otsu algorithm [4]-[7], and so on [8]-[11]. Among them, Otsu algorithm provides a way to set a self-adaptive threshold; nevertheless, it has a limitation that it gives only one threshold, which is difficult to extract all the useful information in the image. A new

segmentation algorithm is proposed that each pixel in the image has its own threshold by calculating the statistical information of the grayscale values of its neighborhood pixels. An additional judge condition is given that it is possible to get the edge of the image as the result of the proposed algorithm.

2. The proposed algorithm

2.1 Pre-processing

Usually, it is believed that the grayscale values of the object in an image are lower than the grayscale values of the background. In this paper, it is assumed that the pixels in an image ranked top 10% in grayscale values have little influence in the result of the proposed segmentation algorithm.

A threshold can be set by analyzing the histogram of an image. If the distribution function $f(z)$ of the histogram is assumed to be continuous, then a threshold T will be calculated by Eq. 1.

$$\int_T^{255} f(z)dz = \text{sum} / 10 \quad (1)$$

Sum is the total number of the pixels in the image. All the pixels with their grayscale values higher than T will be set to white (255). Then grayscale stretch is necessary that the smoother the histogram spreads, the more entropy we can extract. It would be accomplished according to Eq. 2.

$$G_{str} = \frac{G - G_{min}}{T - G_{min}} \times 255 \quad (2)$$

In the above equation, G_{min} means the grayscale value of the pixel that is the darkest one in the image. If the grayscale value of a pixel in the image is G , it becomes G_{str} after the grayscale stretch.

2.2 Threshold segmentation

A square-shaped operator (which is called structural operator below in this paper) whose size

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may be 3×3 , 5×5 or 7×7 pixels would be used to calculate the statistical information of every single pixel in an image. There may be several objects in an image. When the image is divided into hundreds of blocks by the operator, the information in each block becomes much fewer.

It is assumed that there are two grayscale regions in each block at most: object and background. If the size of the structural operator is small enough, the assumption is reasonable, and the experiment will give the proof.

In this paper, the thresholds of the pixels in an image are estimated in following method [12]:

Suppose that an image contains only two principal grayscale regions and let z denote grayscale values. These values are often viewed as random quantities, and their histogram may be considered as an estimate of their probability density function (PDF), $p(z)$. This overall density function is the sum or mixture of two densities, one for the bright and the other for the dark regions in the image. The mixture probability density function describing the overall grayscale variation in the image is

$$p(z) = P_1 p_1(z) + P_2 p_2(z) \quad (3)$$

Here P_1 and P_2 are the probabilities of occurrences of the two classes of pixels; that is, P_1 is the probability (a number) that a random pixel with value z is an object pixel. Similarly, P_2 is the probability that the pixel is a background pixel. It is assumed that any given pixel belongs either to an object or to the background, so that

$$P_1 + P_2 = 1 \quad (4)$$

An image is segmented by classifying as background pixels with grayscale values greater than a threshold T , all other pixels are called object pixels. The main objective is to select the value T that minimizes the average error in making the decision that a given pixel belongs to an object or to the background. $P_1(z)$ and $P_2(z)$ are the PDF of the object and the background respectively. The probability of erroneously classifying a background point as an object point is

$$E_1(T) = \int_{-\infty}^T p_2(z) dz \quad (5)$$

Similarly, the probability of erroneously classifying an object point as a background point is

$$E_2(T) = \int_T^{\infty} p_1(z) dz \quad (6)$$

Then the overall probability of error is

$$E(T) = P_2 E_1(T) + P_1 E_2(T) \quad (7)$$

To find the threshold value for which the error $E(T)$ is minimal that requires differentiating $E(T)$ with respect to T (using Leibniz's rule) and equating the result to 0. The result is

$$P_1 p_1(T) = P_2 p_2(T) \quad (8)$$

Obtaining an analytical expression for T requires to know the equations for the two PDFs. Estimating these densities in practice is not always feasible, and an approach used often is to employ densities whose parameters are reasonably simple to obtain. One of the principal densities used in this manner is the Gaussian density. In this case,

$$p(z) = \frac{P_1}{\sqrt{2\pi}\sigma_1} e^{-\frac{(z-\mu_1)^2}{2\sigma_1^2}} + \frac{P_2}{\sqrt{2\pi}\sigma_2} e^{-\frac{(z-\mu_2)^2}{2\sigma_2^2}} \quad (9)$$

Where μ_1 and σ_1^2 are the mean and variance of the Gaussian density of the object pixels, and μ_2 and σ_2^2 are the mean and variance of the Gaussian density of the background pixels. Substituting Eq. 8 into Eq. 9, then we can get the following quadratic equation and also the solution of threshold T ,

$$AT^2 + BT + C = 0 \quad (10)$$

where

$$A = \sigma_1^2 - \sigma_2^2$$

$$B = 2(\mu_1 \sigma_2^2 - \mu_2 \sigma_1^2)$$

$$C = \mu_1 \sigma_2^2 - \mu_2 \sigma_1^2 + 4\sigma_1^2 \sigma_2^2 \ln(\sigma_2 P_1 / \sigma_1 P_2) \quad (11)$$

If the variances are equal, $\sigma^2 = \sigma_1^2 = \sigma_2^2$, then,

$$T = \frac{\mu_1 + \mu_2}{2} + \frac{\sigma^2}{\mu_1 - \mu_2} \ln\left(\frac{P_1}{P_2}\right) \quad (12)$$

If $P_1 = P_2$, the optimal threshold is the average of the means.

The above analysis is also available in the small blocks in an image. So in this paper, the threshold of a pixel can be estimated by calculating the mean of the grayscale values of its neighbor pixels instead of the mean of μ_1 and μ_2 .

$$T_{ij} = \frac{1}{(2m+1)(2n+1)} \sum_{x=-m}^m \sum_{y=-n}^n z(i+x, j+y) \quad (13)$$

In Eq. 13, $z(i,j)$ is the grayscale value of the pixel which is located in (i,j) . And m and n are all natural numbers. If $z(i,j)$ is lower than T_{ij} , it is supposed that the pixel belongs to the object, else it belongs to the background. Actually if there is a small deviation in the estimation of the threshold T_{ij} , the result of the segmentation algorithm would not change much. And the experiment will give the proof.

If there is a block in an image that the object and the background exist in the same time, the variance of the grayscale values of the pixels in this block is definitely greater than the variance in a block that contains only the object or only the background. If the variance of the grayscale values of pixels in a block as show in Eq. 14 is considered, then the edge in this block can be obtained.

$$\sigma_{ij}^2 = \frac{1}{(2m+1)(2n+1)} \sum_{x=-m}^m \sum_{y=-n}^n (z(i+x, j+y) - T_{ij})^2 \quad (14)$$

If the grayscale value of a pixel is lower than its threshold, while the variance of the grayscale values of the pixels in its neighbors is higher than the given value Delta, this pixel is defined as the boundary, and its grayscale value is evaluated as 0, else it is defined as the background and its grayscale value becomes 255. As to decreasing the complexity of the proposed algorithm, the variance of the grayscale values of the pixels in this block can be replaced by the grayscale values difference between the brightest pixel and the darkest pixel in this block.

3. Experimental results

To verify the efficiency of the proposed algorithm, the video sequence of “Claire” is selected to do the experiment. The experiment is proceeded in a PC (CPU: Inter Core2 E6300, 1.86GHz, RAM: 2G, DDR2). The algorithm is implemented in VC++ 6.0. The 3rd frame in this video is picked as in random, and the image is resized to 256×256 pixels. The result of the segmentation is shown in Fig. 1.

3.1 Comparison of the segmentation results between the proposed algorithm and Canny operator

Fig. 1 (a) is the original image, to make a comparison, this image is segmented by Canny operator [13][14].

Fig. 1 (b) is the result of Canny operator with default parameter (0.4, 0.4, 0.8, which are the standard deviation of Gaussian filter, the ratio of the upper threshold and the lower threshold, and the proportion of the pixels with their grayscale values greater than the upper threshold to the total pixels in an image).

Obviously, there is mis-segmentation in the result for the influence of the noise in the background. During dozens of experiments in Canny operator, we pick a result with rather good effect (0.9, 0.8, 0.8), which is shown in Fig. 1 (c). Fig. 1 (d) is the result of the proposed algorithm, and the size of the structural operator is 3×3 pixels.

From Fig. 1, it is obvious to get better result by the proposed algorithm than by Canny operator, as the influence of the noise is restrained, meanwhile it is easy to get a segmentation result with higher precision.

3.2 The relationship between the size of the structural operator and the result of the proposed algorithm

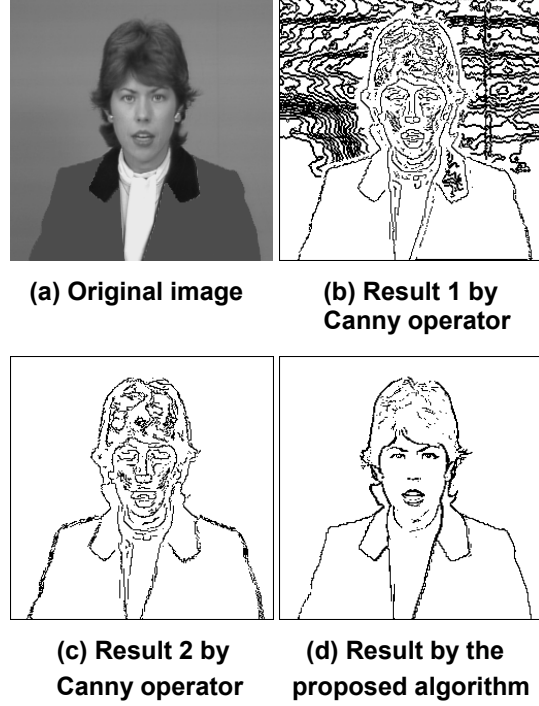


Fig. 1 Comparison of the segmentation results between the proposed algorithm and Canny operator.

The relationship between the size of the structural operator and the segmentation result is researched. In Fig. 2, (a), (b), (c) and (d) are the segmentation results by the proposed algorithm, and the sizes of the structural operators are 3×3 , 7×7 , 11×11 and 15×15 pixels, respectively. From Fig. 2, it is concluded that the larger size of the structural operator is, the longer time it takes to run the proposed algorithm, and the thicker edge of the image is.

The relationship between the size of the structural operator and the running time is shown in Fig. 3.

Suppose an image whose size is $W \times H$ pixels, where W and H are the number of columns and rows of the image respectively. In this experiment, if the size of the structural operator is $K \times K$ pixels, and the increase of the size of the structural operator is 2 pixels, the increase of the computing complexity of the proposed algorithm is

$$\Delta F_1 = 4 \times (K+1) \times W \times H \quad (15)$$

To reduce the difficult of the proposed algorithm, the pixels far from the center of the image won't be handled, and only the $[W-(K-1)] \times [H-(K-1)]$ pixels in the center are involved in the calculation. If the increase of the size of the structural operator is 2 pixels, the increase of the computing complexity is

$$\Delta F_2 = A \times W \times H + B \times (W + H) + C \quad (16)$$

Where

$$\begin{aligned}
A &= 4 \times K \\
B &= 6K^2 + 8K + 4 \\
C &= 3K^4 + 8K^3 + 12K^2 + 12K + 4
\end{aligned} \tag{17}$$

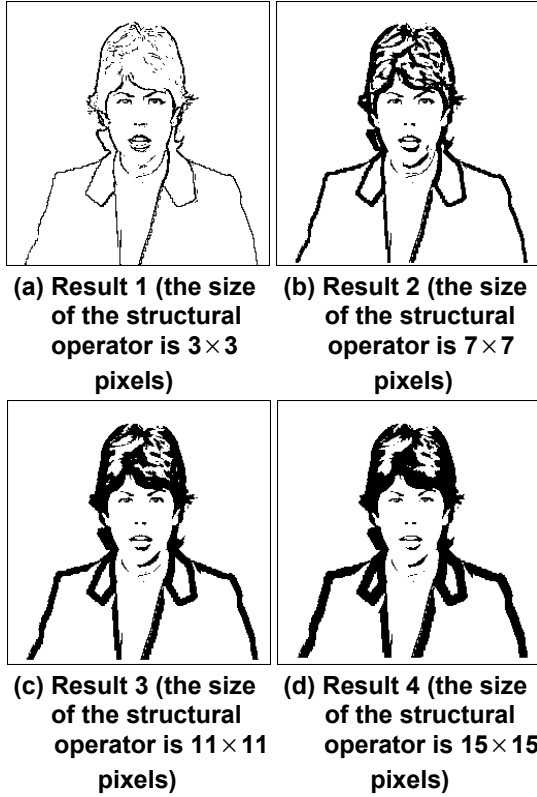


Fig. 2 Experimental results with different sizes of structural operators

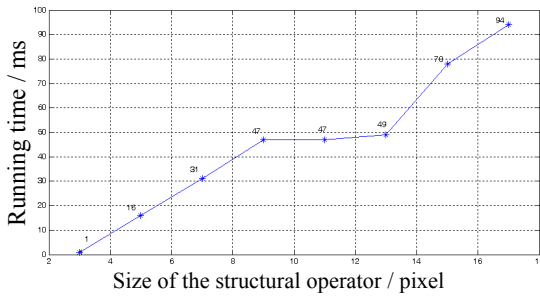


Fig. 3 The relationship between the size of the structural operator and the running time

When the size of the structural operator is becoming larger, the change tendency of the segmentation results is that: the edge is growing towards the inside of the image. It is easy to obtain the boundary of the image via analyzing the grayscale values of the pixels in the selected window. Fig. 4 (b) shows that there are two regions separated by the red line, the left belongs to the background and the right belongs to the object. Two pixels

whose grayscale values are both 76 and are picked from this window. The pixel located in (35, 48) is named as pixel A that is labeled in a rectangle, while the pixel located in (36, 45) is named as pixel B that is labeled in a circle.

The mean of the grayscale values of the pixels around the pixel A is 86.3, which is higher than 76. And the difference of the grayscale values between the brightest pixel and the darkest pixel is 32, which is high enough to fulfill the qualification. So pixel A is considered as an object pixel.



(a) 10×10 pixels window picked from the original image

V/H	30	31	32	33	34	35	36	37	38	39
51	109	110	109	109	110	112	92	76	76	76
50	107	109	109	108	110	98	77	76	76	76
49	108	109	109	109	108	100	77	76	76	76
48	108	108	109	110	100	76	76	76	76	76
47	109	109	109	110	88	76	76	76	76	76
46	109	107	109	103	78	76	76	76	76	76
45	109	108	110	89	77	76	76	76	76	76
44	108	109	108	90	76	76	76	76	76	76
43	107	109	97	76	76	76	76	76	76	76
42	107	108	98	76	76	76	76	76	76	76

(b) Grayscale values of the pixels in the picked window

Fig. 4 Analysis of the 10×10 pixels picked window in the original image

But the grayscale values in the 3×3 pixels neighborhood area around pixel B are all 76, which definitely doesn't meet the qualification. So when the size of the structural operator is 3×3 pixels, pixel B is not considered as an object pixel. If the interesting area is the 7×7 pixels neighborhood area around pixel B, the result is different. The mean of the grayscale values of the pixels in this area is 79.4, which is higher than 76, while the grayscale values

difference between the brightest pixel and the darkest pixel is 34, so the two qualifications are both fulfilled. So pixel B is considered as an object pixel at this time. But no matter what the size of the structural operator is, the pixels on the left of the red line in Fig. 4 (b) won't be judged as object pixels. It is concluded that when the size of the structural is growing larger, the extracted boundary is growing thicker, and the direction it grows is from the bright area to the dark area.

In this paper, although it takes less time to run the algorithm with smaller structural operator, it doesn't assure that the edge obtained is continuous. Meanwhile the larger structural operator is chosen, the more time is needed, and the edge is growing thicker, but the continuity is better. So there is always one side of the boundary (inboard or outboard) is exactly the precise edge of the original image. When the continuous contour of an image is required, it is better to choose larger structural operator.

3.3 Estimate bias of the threshold and its influence

It is assumed that the threshold of the pixel $G(i,j)$ is $\text{Threshold}(i,j)$, which should be equal to the mean $\text{Mean}(i,j)$ of grayscale values of the pixels in the 3×3 neighborhood area of pixel $G(i,j)$. If $\text{Threshold}(i,j)$ varies in a range near $\text{Mean}(i,j)$, the result is shown in Fig. 5.

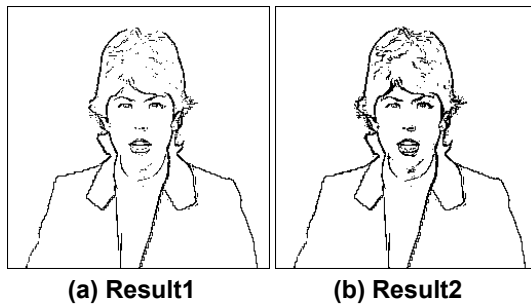


Fig. 5 Results with the threshold varies in a range

In Fig. 5, (a) is the result in which $\text{Threshold}(i,j) = \text{Mean}(i,j) - 5$, and (b) is the result in which $\text{Threshold}(i,j) = \text{Mean}(i,j) + 5$. It is apparent that there are no obvious differences between the two images. So the estimate of the threshold of pixel $G(i,j)$ can be changed in a range near $\text{Mean}(i,j)$.

3.4 Results of the proposed algorithm with other standard images

It can obtain good results to segment other standard images by the proposed algorithm.

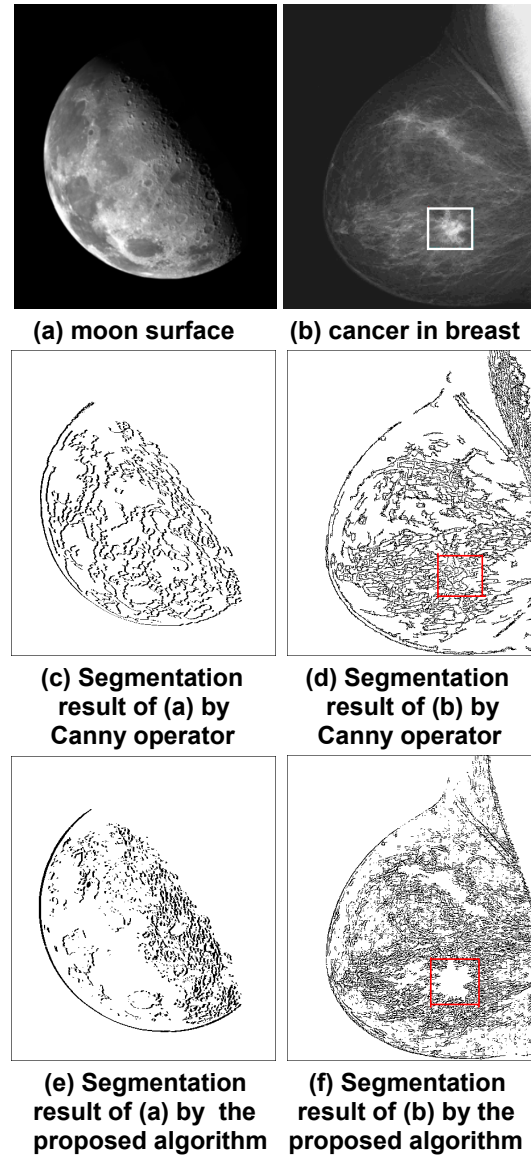


Fig. 6 Comparison of the segmentation results between the proposed algorithm and Canny operator

In Fig. 6, (a) and (b) and picked from [12], (c) and (d) are the segmentation results of (a) and (b) by Canny operator respectively, which are rather good results after testing many times. While (e) and (f) are the segmentation results of (a) and (b) by the proposed algorithm respectively, and the size of the structural element is 3×3 pixels. It is apparent to obtain more accurate segmentation results by the proposed algorithm than by Canny operator. In detail, (e) can reflect the geographical information better than (c). Meanwhile there is a cancer in (b), which can be detected in (f) in evidence. But in (d), it is impossible to distinguish the cancer from other parts of the breast in (b).

4. Conclusion

In this paper, an edge detection and image segmentation algorithm in image processing based on threshold segmentation is proposed. In this algorithm, each pixel in an image has its own threshold, which is estimated by calculating the statistical information of its neighborhood pixels. Experimental results show that it is apparent to obtain better results by the proposed algorithm than by Canny operator. In the proposed algorithm, it takes little time to get a precise result when small size structural operator is selected. And the continuous contour of an image is easy to obtain when the large size structural operator is selected. The proposed algorithm also has an obvious advantage in noise restraining, which is a good edge-detecting and image segmentation algorithm with wide applicability.

5. References

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