Research and analysis of threshold segmentation algorithms in image processing

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Abstract. Image segmentation is one of the most difficult and important tasks in digital image processing. The accuracy and effect of segmentation determine the final success or failure of the calculation and analysis process. Therefore, analysis and improvement on basic image segmentation algorithms should be paid attention to in a quite wide range of applications. This paper mainly introduces and studies the principle and characteristics of threshold segmentation algorithm, and analyses the application scenarios of global threshold segmentation and adaptive local threshold segmentation related algorithms, which has certain reference significance for digital image processing related research.

1. Introduction
When a person observes a scene, the process of segmenting the scene in the visual system is essential. This process is very effective, so that what people see is not a complex scene, but a collection of objects. The process is described by digital image processing, that is, dividing the image into several specific regions with unique properties, each region representing a set of pixels and each set representing an object[1]. The technology for completing the process is usually called image segmentation, which is a key step from image processing to image analysis.

The existing image segmentation methods are mainly divided into the following categories: threshold-based segmentation methods, region-based segmentation methods, edge-based segmentation methods, and specific theory-based segmentation methods. This paper mainly focuses on the cabinet value segmentation technology, which is a region-based and simple shape extraction technology through gray value information[2]. Because of its simple implementation, small computation and stable performance, it has become the most basic and widely used segmentation technology in image segmentation. Usually the output image after threshold segmentation has only two gray values: 255 and 0, so the threshold segmentation process is also often called image binarization process. The threshold segmentation process can be regarded as the process of separating foreground from background. Threshold segmentation mainly extracts foreground based on gray value information, so it is especially useful for segmentation of images with strong contrast between foreground objects and background[3]. For threshold segmentation of images with very low contrast, it is necessary to enhance the contrast of the images first, and then perform threshold processing. This paper mainly introduces and analyzes two commonly used threshold segmentation techniques—global threshold segmentation and adaptive local threshold segmentation.
2. Global threshold segmentation

Global threshold segmentation refers to setting the pixels whose gray value is greater than the threshold value (\( \text{thresh} \)) as white and the pixels less than or equal to the threshold value as black. Or conversely, the pixels larger than the threshold value are set to black and the pixels smaller than or equal to the threshold value are set to white. The difference between the two is that the two are different in presentation form.

Assuming that the input image is \( I \), the height is \( H \) and the width is \( W \), and that \( I(r,c) \) represents the gray value of column \( c \) and row \( r \) of \( I \), \( 0 \leq r < H, 0 \leq c < W \), the output image after global threshold processing is \( O \), \( O(r,c) \) represents the gray value of column \( c \) and row \( r \) of \( O \), then:

\[
O(r,c) = \begin{cases} 
255, & I(r,c) > \text{thresh} \\
0, & I(r,c) \leq \text{thresh}
\end{cases}
\]

2.1. Entropy algorithm

The concept of information entropy originates from information theory[4]. It is assumed that the source symbol \( u \) has \( N \) values, which are recorded as follows:

\[ u_1, u_2, u_3, \cdots, u_N \]

And the probability of the occurrence of each source symbol is recorded as:

\[ p_1, p_2, p_3, \cdots, p_N \]

Then the information entropy of the source symbol is recorded as:

\[
\text{entropy}(u) = - \sum_{i=1}^{N} p_i \log p_i
\]

The image can also be regarded as a kind of information source[5]. Assuming that the input image is \( I \) and \( \text{normHist}_i \) represents the normalized gray histogram of the image, the 8-bit image can be regarded as a source consisting of 256 gray-scale symbols, and the probability of each symbol appearing is \( \text{normHist}_i(k) \), of which \( 0 \leq k \leq 255 \).

The steps for calculating threshold using entropy are as follows.

Step 1: Calculate the cumulative probability histogram of \( I \), also known as zero-order cumulative moments, and record it as:

\[
cumuHist(k) = \sum_{i=0}^{k} \text{normHist}_i(t), \quad k \in [0, 255]
\]

Step 2: Calculate the entropy of each gray level and mark it as:

\[
\text{entropy}(t) = - \sum \text{normHist}I(k) \log(\text{normHist}I(k)), \quad 0 \leq t \leq 255
\]

Step 3: Calculate the \( t \) value that maximizes \( f(t) = f_1(t) + f_2(t) \), which is the threshold value obtained, as \( \text{thresh} = \arg \max(f(t)) \), where:

\[
f_1(t) = \frac{\log(\text{cumuHist}(t))}{\log(\text{cumuHist}(255))} \log(\max\{\text{cumuHist}(0), \text{cumuHist}(1), \cdots, \text{cumuHist}(t)\})
\]

\[
f_2(t) = (1 - \frac{\text{entropy}(t)}{\text{entropy}(255)}) \log(1 - \text{cumuHist}(t)) \log(\max\{\text{cumuHist}(t + 1), \text{cumuHist}(t + 2), \cdots, \text{cumuHist}(255)\})
\]
2.2. Otsu threshold processing

When thresholding an image, the selected thresholds should maximize the difference between the average gray level of the foreground area, the average gray level of the background area and the average gray level of the whole image, which is expressed by the variance of the region. Otsu[6] proposes the maximum variance method, which is derived from the principle of discriminant analysis least square method. The calculation process is simple, and it is a commonly used stable threshold segmentation algorithm.

Assuming that the input image is \( I \), the height is \( H \) and the width is \( W \), the \( \text{histogram}_i \) represents the normalized gray histogram of the image, and the \( \text{histogram}_i(k) \) represents the ratio of the number of pixels whose gray value equals \( k \) in the image, where \( k \in [0, 255] \), the detailed steps of the algorithm are as follows:

Step 1: calculate the zero-order cumulative moments (or cumulative histograms) of the gray histogram.

\[
\text{zeroCumuMoment}(k) = \sum_{i=0}^{k} \text{histogram}_i(i), \ k \in [0, 255]
\]

Step 2: calculate the first-order cumulative moments of gray histogram.

\[
\text{oneCumuMoment}(k) = \sum_{i=0}^{k} (i \times \text{histogram}_i(i)), \ k \in [0, 255]
\]

Step 3: Calculate the mean of gray level of image \( I \), which is the first-order cumulative distance when \( k = 255 \), as:

\[
\text{mean} = \text{oneCumuMoment}(255)
\]

Step 4: When calculating each gray level as a threshold, the average gray level of foreground area, the average gray level of background area and the variance of the average gray level of the whole image are calculated. The following measures are used to measure the variance:

\[
\sigma^2(k) = \frac{(\text{mean} \times \text{zeroCumuMoment}(k) - \text{oneCumuMoment}(k))^2}{\text{zeroCumuMoment}(k) \times (1 - \text{zeroCumuMoment}(k))}, \ k \in [0, 255]
\]

Step 5: Find the maximum \( \sigma^2(k) \) mentioned above, and the corresponding \( k \) is the threshold of Ostu automatic selection, that is:

\[
\text{thresh} = \arg_{k \in [0, 255]} \max(\sigma^2(k))
\]

2.3. Implementation and analysis of algorithms

For the two algorithms of global threshold segmentation, entropy algorithm and Otsu threshold processing, this paper is implemented under Python language development platform, and 200 pictures are randomly selected. The typical experimental results are shown in Figure 1. It can be seen from the figure that the Otsu threshold processing results are better than the entropy threshold method, which can completely segment the foreground and background and distinguish the target objects in the figure. For the method of calculating threshold using the concept of entropy, there are some variations, such as those proposed by researchers Johannsen[7], Portes de Albuquerque[8], but the effect has not been significantly improved.
3. Adaptive threshold segmentation

3.1. Problem analysis
In the case of uneven illumination or uneven distribution of gray values, if global threshold segmentation is used, the segmentation result is often not ideal. For example, if two images with uneven illumination are processed, the effect is shown in Figure 2. Obviously, the result is only to segment the areas with strong illumination, while the shadows or areas with weak illumination are not. Not separated. Since the global threshold is not appropriate, the thought strategy is to set a corresponding threshold for the gray value of each position, and the setting of this position threshold also has an inevitable relationship with its neighborhood.
3.2. Calculation method
When smoothing the image, the average value smoothing, Gaussian smoothing and median value smoothing use different rules to calculate the gray level "average value" in the neighborhood centered on the current pixel, so the output result after smoothing can be used as the reference value for setting the threshold value for each pixel. As mentioned in Reference 7, the result after average value filtering is multiplied by a certain scale coefficient as the final threshold matrix.

In adaptive threshold processing, the size of the smoothing operator determines the size of the segmented object. If the filter size is too small, the estimated local threshold will not be ideal. According to experience, the width of the smoothing operator must be greater than the width of the object to be identified. The larger the size of the smoothing operator, the better the smoothed result can be used as a reference for the threshold value of each pixel. Of course, it cannot be infinite.

Suppose the input image is $I$, the height is $H$ and the width is $W$, and the size of the smoothing operator is $H \times W$, where $W$ and $H$ are odd numbers. The steps of the adaptive threshold segmentation algorithm are as follows.

Step 1: The image is smoothed and the smoothing result is recorded as $f_{\text{smooth}}(I)$, where $f_{\text{smooth}}$ can represent mean smoothing, Gauss smoothing and median smoothing.

Step 2: Adaptive threshold matrix $\text{Thresh} = (1 - \text{ratio}) \times f_{\text{smooth}}(I)$, usually $\text{ratio} = 0.15$.

Step 3: Threshold segmentation using local threshold segmentation rules.

3.3. Analysis of Adaptive Threshold Segmentation
The effect of adaptive threshold segmentation on the two original images in Figure 2 is shown in Figure 3, where the adaptive threshold is a mean smoothing operator using 3x3, 7x7, 11x11 and 31x31 respectively. It can be seen from the effect that the effect obtained when the size of smoothing operator is small is not ideal, but with the increase of the size, the foreground objects segmented by adaptive threshold become more and more complete. Compared with the effect segmented by other threshold algorithms, it can be seen that the adaptive threshold overcomes the uneven illumination.
Figure 3. The effect of adaptive threshold segmentation under different smoothing coefficients.

4. Conclusions
For the field of digital image processing, this paper analyzes the effect of image processing in global threshold segmentation, which shows that Otsu threshold processing is obviously better than entropy algorithm. And for the uneven illumination in the image, this paper studies the adaptive threshold segmentation algorithm. By selecting different mean smoothing operators, the image threshold segmentation will be affected, which has certain reference significance for the relevant research of digital image processing.

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