Two-dimensional Otsu's Zigzag Thresholding Segmentation Method

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Research Article

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Posted Date: March 31st, 2023

DOI: https://doi.org/10.21203/rs.3.rs-2750189/v1

Additional Declarations: No competing interests reported.

Two-dimensional Otsu's Zigzag Thresholding Segmentation Method

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Abstract: In the two-dimensional histogram thresholding method, the segmentation accuracy could be degraded due to insufficient misclassification. An improved image segmentation method combining a priori knowledge of two-dimensional histogram and fully considering the influence of edges, the two-dimensional Otsu's zigzag thresholding segmentation method is proposed. We combine a priori information about the edge regions and noisy regions in a two-dimensional histogram, use a zigzag threshold as a segmentation criterion to correct the overall error classification and use small probability events to determine the line equations to achieve segmentation adaptively. Based on extensive experimentation, our method has been observed to significantly outperform comparable techniques.

Key Words: Image segmentation; Thresholding segmentation; Otsu; Two-dimensional histogram; Curve threshold

1. Introduction

Image segmentation is a fundamental and key technology in image processing and an important part of automatic target recognition [1]. Among the many segmentation methods, the thresholding method is one of the more widely used methods because of its simplicity, effectiveness, small computation, and stable performance [2]. Moreover, the thresholding method is particularly effective for image segmentation where there is a strong contrast between the object and the background. Global thresholding techniques are widely used among the thresholding methods because of their adaptive segmentation features and easy implementation [3]. The classical global thresholding methods mainly include the minimum error method [4], various entropic segmentation methods [5]-[8], the maximum correlation method [9], and the maximum inter-class variance method (also known as the Otsu method) [10]. The Otsu method is based on a one-dimensional greyscale histogram of the image. It uses an exhaustive search method to maximize the variance between classes to determine the optimal threshold [11]. Satisfactory results can be achieved on images with obvious bimodal gray distribution histogram [12]. However, when the signal-to-noise ratio of the image is low or the region of the target and background in the image is very different, Otsu will have the problem of the thresholding "offset" [13], and the spatial information of the image is not considered, so the presence of noise makes the segmentation effect poor. Liu et al. [14] proposed an Otsu method based on a two-dimensional (2D) grayscale histogram, and Fan et al [15] proposed a three-dimensional Otsu thresholding method. Among the three methods, the original Otsu method has lower computational complexity, but the segmentation results are not as good. The three-dimensional Otsu method is too computationally complex and therefore has some limitations in practical applications [16]. In contrast, 2D Otsu method has better segmentation results and its computational complexity is within an acceptable range.

2D Otsu takes into account not only the information of the pixel point itself but also the spatial information of pixel point and its neighborhood is also considered, which has excellent noise immunity and is suitable for the segmentation of low signal-to-noise ratio images [17]. However, the method assumes that the influence of edge region information on image segmentation can be ignored. This assumption makes the classical 2D Otsu method ineffective for segmenting images with rich edge information [18]. Therefore, subsequent researchers have given many improved methods: Liang et al. [19] introduced the idea of iterative segmentation based on the original 2D Otsu thresholding segmentation method, after obtaining the maximum inter-class variance threshold point for the whole image grayscale, the edge region continues to be segmented iteratively so that a series of threshold points are obtained, and a fold line threshold can be obtained by connecting each threshold point in turn, the advantages of this method are that line threshold replaces traditional point threshold and improves the accuracy of the segmentation, while the disadvantages are that there is region wrong classification and the number of iterations is artificially given based on experience, which reduces the adaptiveness. Zhao et al. [20] obtained the coordinates of the image edge points in the 2D histogram in order to obtain the correct region delineation results, and fitted these points with a curve, and then used the oblique division method to distinguish the target region from the background region, which corrected some of the edge regions to a certain extent, but the delineation of the noisy regions and edge regions was not fine enough, and the computational effort was large; later, Liang et al. [21] proposed a 2D Otsu fitting line thresholding method, fit the fold lines in the to a curve [19] , and the iteration stop condition is proposed for the probability of pixel points in the edge region and noisy region to meet the probability criterion of small probability events, this method does not make use of the a priori information of the 2D histogram, so it is not accurate enough to delineate the edges and noise regions in the image, and the accuracy of the fitting results is not high for complex images. Wu et al. [22][23] and others combined the a priori analysis of 2D histogram to give a 2D histogram oblique segmentation method and a fast algorithm. Furthermore, the 2D histogram oblique segmentation method is expanded to include straight lines with any angle between the normal line and the gray level axis, although it effectively improved the applicability of the method, in practical applications, the fixed case is usually used to achieve the segmentation. Moreover, the man-made determination of the angle makes the method less adaptive [24], and the method suffers from obvious partitioning errors, attributing part of the target noise to the background region and a small part of the background noise to the target region.

As can be seen, the existing methods generally suffer from pixel-incorrect classification and poor self-adaptation, which can seriously affect the segmentation accuracy of images and lead to inaccurate edge shapes and uneven distribution of internal pixels [25]. At the same time, this may affect any subsequent further processing of the image, including analysis, recognition, etc., thereby reducing the effectiveness of the process [26]. Therefore, this paper proposes zigzag thresholding segmentation method based on 2D Otsu, which makes full use of the further prior knowledge of the 2D histogram to obtain further refinement of the noise region, edge region, background region, target region, and to determine the division of corresponding regions, which can effectively of improving the segmentation capability of 2D Otsu and improving the accuracy of the segmentation. The image is segmented using the zigzag line. To improve the adaptive nature of this method and to effectively determine the dividing line between image edges and noise (the L3 and L4 line segments in Fig. 4), this paper uses the principle of small probability events and the dichotomy method to differentiate between image edges and noise by adjusting the parameters according to different scenes. The rest of the paper is organized as follows. Section 2 introduces the basic principles of traditional 2D Otsu method, and Section 3 describes the 2D Otsu curve thresholding method including the 2D histogram oblique segmentation method. Section 4 introduces the method used in this paper. Experiments are carried out on typical images and the results are analyzed as shown in Section 5, which verifies the effectiveness of our method, both quantitatively and qualitatively. Finally, Section 6 is the conclusion.

2. Traditional 2D Otsu method

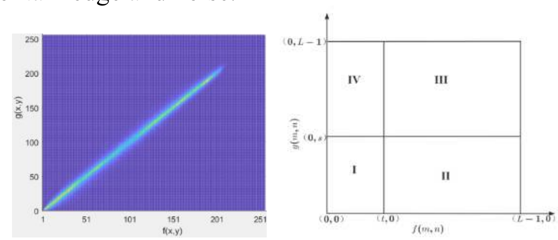
For an image with size of M by N, the gray value of a pixel (x, y) is denoted by $f(x, y)$. Let $g(x, y)$ denotes the local average gray value in a $k \times k$ neighborhood window, which are defined as follows:

$$g(x, y) = \frac{1}{k^2} \sum_{m=-k/2}^{k/2} \sum_{n=-k/2}^{k/2} f(x+m, y+n) \tag{1}$$

In general, $k = 3$,and $0 < x < M$, $0 < y < N$. The image gray level is L and the average gray level of its neighborhood is also L. Let C_{ij} be the frequency of pair (i, j), where $f(x, y) = i$ and $g(x, y) = j$, then the 2D joint probability density is as follows:

$$P_{ij} = \frac{C_{ij}}{MN}, \sum_{i=0}^{L-1} \sum_{j=0}^{L-1} P_{ij} = 1 \tag{2}$$

If we assume that the pair (t, s) is a thresholding vector to be used for threshold, the (t, s) divides 2D histogram into four quadrants. In Fig. 1(b), the two regions I and III on the diagonal contain information about the target and background, respectively, and the regions II and IV away from the diagonal contain edge and noise.



(a) 2D histogram probability distribution (b) 2D histogram region segmentation

Fig. 1 2D histogram and its partition

3. 2D Otsu curve thresholding method

The probability values of regions II and IV are considered to be approximately 0 in the traditional 2D Otsu method [27], this assumption allows the 2D Otsu method to ignore information about edge regions and noise, resulting in reduced adaptivity. For tasks requiring high accuracy image segmentation, ignoring edge and noise information significantly degrades the accuracy of the segmentation and is therefore not feasible. Fan et al. [28] proposed 2D Otsu curve thresholding method. In this method, if vector (t, s) is selected as the threshold, the 2D histogram can be divided into two parts, $C_0(t, s)$ and $C_1(t, s)$, by making a curve $r(i, j)$ over the point, which is denoted as background and target respectively. The 2D histogram of curve thresholding method is shown in Fig. 2.

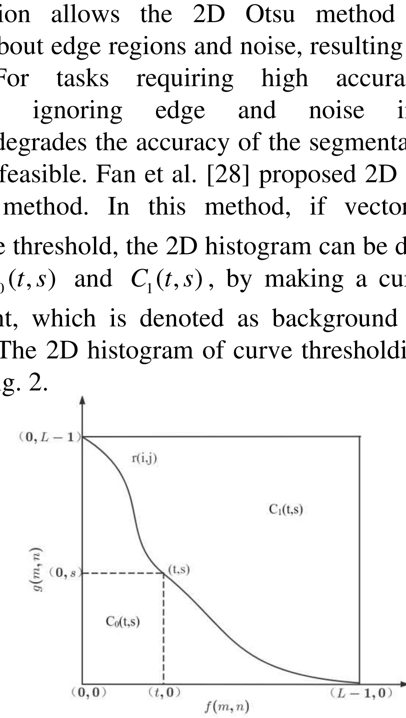


Fig. 2 The 2D histogram of curve thresholding method

In the curve thresholding method, the selection of the curve $r(i,j)$ is a key issue. For engineering ease, these methods are often implemented in such a way that the curve is converted to a straight line and passes through the threshold point (t,s). In this approach, the pixel points in regions I and III are already explicitly classified due to the presence of threshold points, while regions II and IV contain unclassified pixel points. Therefore, the points on the threshold curve are necessarily distributed in either region II or IV, and the optimal line threshold depends on the percentage of pixels in region II and IV in the different images [29]. Assuming that the final optimal line threshold is obtained as shown in Fig. 3, we refer to this type of optimal line thresholding method as "winged" line thresholding method.

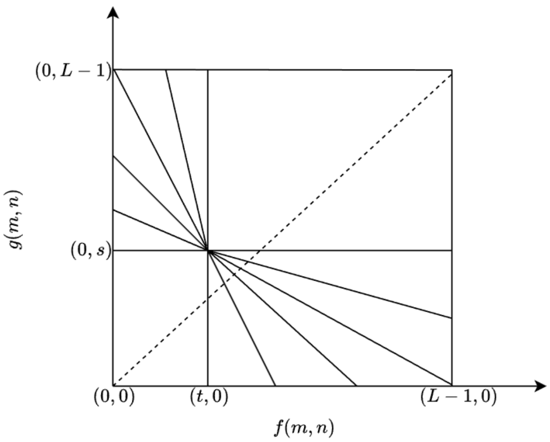


Fig. 3 Best line threshold histogram

However, the above method is very time consuming. Therefore Wu et al. [22] proposed a 2D histogram oblique segmentation method, which can be seen as a special case of the "winged" line threshold described above. This method uses a line $g=-f+T$ segment perpendicular to the main diagonal (T is the threshold, $0 \le T \le 2L$), to divide the histogram into two categories: target and background, and the image is divided according to the magnitude of the sum of the image gray value and the average gray value of its domain pixels, and the pixels are classified in the following way.

$$f_T(x,y)=\begin{cases}0, i+j \le T \\ L, i+j > T\end{cases} \tag{3}$$

where $f_T(x,y)$ indicates the segmented image. Compared to the traditional 2D Otsu method, the 2D histogram oblique segmentation method improves the accuracy of 2D thresholding by considering all regions when calculating threshold. Taking $0 < T \le L-1$ as an example, combined with the 2D histogram oblique segmentation in Fig. 4, the following specific sub-regions were misclassified: (1) the BN1 region, which belongs to the background noise but is divided into the target region; (2) the ON2 and ON3 regions, which belong to the target noise but are classified as the background region.

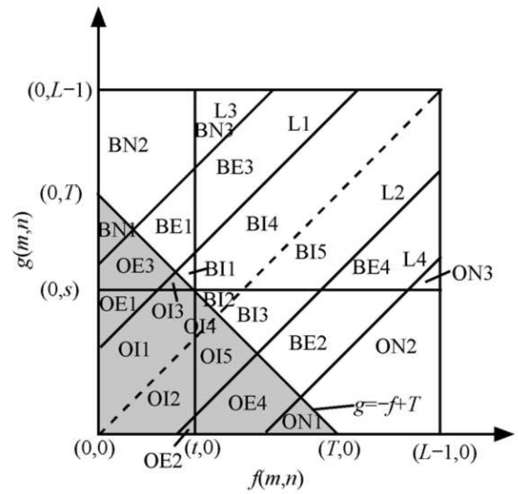


Fig. 4 2D histogram oblique segmentation method

The line $g=-f+T$ divides the 2D histogram into region I and region III corresponding to the target and background, and the probabilities of occurrence of the target and background are $\omega_0(T)$ and $\omega_1(T)$:

$$\begin{aligned}\omega_0(T) &= \sum_{(i,j)\in \mathrm{I}} p(i,j) \\ \omega_1(T) &= \sum_{(i,j)\in \mathrm{III}} p(i,j)\end{aligned} \tag{4}$$

Where,

$$\omega_0(T)+\omega_1(T)=1 \tag{5}$$

The mean vectors corresponding to the target and background are U_0 and U_1, and the expressions are:

$$U_0=(U_{00},U_{01})'=\left[\frac{\sum_{(i,j)\in \mathrm{I}} iP_{ij}}{\omega_0},\frac{\sum_{(i,j)\in \mathrm{I}} jP_{ij}}{\omega_0}\right]' \tag{6}$$

$$U_1=(U_{10},U_{11})'=\left[\frac{\sum_{(i,j)\in \mathrm{III}} iP_{ij}}{\omega_1},\frac{\sum_{(i,j)\in \mathrm{III}} jP_{ij}}{\omega_1}\right]' \tag{7}$$

The total mean vector on the 2D histogram is U_T:

$$U_T=(U_{T0},U_{T1})'=[\sum_{i=0}^{L-1}\sum_{j=0}^{L-1} iP_{ij},\sum_{i=0}^{L-1}\sum_{j=0}^{L-1} jP_{ij}]' \tag{8}$$

$$U_T=P_0U_0+P_1U_1 \tag{9}$$

Define the inter-class deviation matrix S_B as

$$\begin{aligned}S_B &= \omega_0[(U_0-U_T)(U_0-U_T)']+\omega_1[(U_1-U_T)(U_1-U_T)'] \\ &= \omega_0[\begin{matrix}(U_{00}-U_{T0})^2 & (U_{00}-U_{T0})(U_{01}-U_{T1}) \\ (U_{00}-U_{T0})(U_{01}-U_{T1}) & (U_{01}-U_{T1})^2\end{matrix}]+ \\ &\omega_1[\begin{matrix}(U_{10}-U_{T0})^2 & (U_{10}-U_{T0})(U_{11}-U_{T1}) \\ (U_{10}-U_{T0})(U_{11}-U_{T1}) & (U_{11}-U_{T1})^2\end{matrix}]\end{aligned} \tag{10}$$

Using traces of S_B as a measure of inter-class deviation:

$$\begin{aligned} trS_B &= \omega_0[(U_{00}-U_{T0})^2+(U_{01}-U_{T1})^2]+ \\ &\quad \omega_1[(U_{10}-U_{T0})^2+(U_{11}-U_{T1})^2] \\ &= \omega_0[(\frac{U_i}{\omega_0}-U_{T0})^2+(\frac{U_j}{\omega_0}-U_{T1})^2]+ \\ &\quad \omega_1[(\frac{U_{T0}-U_i}{\omega_1}-U_{T0})^2+(\frac{U_{T1}-U_j}{\omega_1}-U_{T1})^2] \\ &= \frac{(U_i-\omega_0U_{T0})^2+(U_j-\omega_0U_{T1})^2}{\omega_0}+ \\ &\quad \frac{(U_i-\omega_0U_{T0})^2+(U_j-\omega_0U_{T1})^2}{\omega_1} \\ &= \frac{(U_i-\omega_0U_{T0})^2+(U_j-\omega_0U_{T1})^2}{\omega_0(1-\omega_0)} \end{aligned} \tag{11}$$

Where, $U_i=\sum_{(i,j)\in \mathrm{I}} iP_{ij}, U_j=\sum_{(i,j)\in \mathrm{I}} jP_{ij}$ the optimal threshold is determined by the following equation

$$(t,s)=Arg\max_{\substack{0<t<L-1\\0<s<L-1}}\{trS_B(t,s)\} \tag{12}$$

By means of a line with $i+j=t+s$, the original image is segmented, so that the classification becomes:

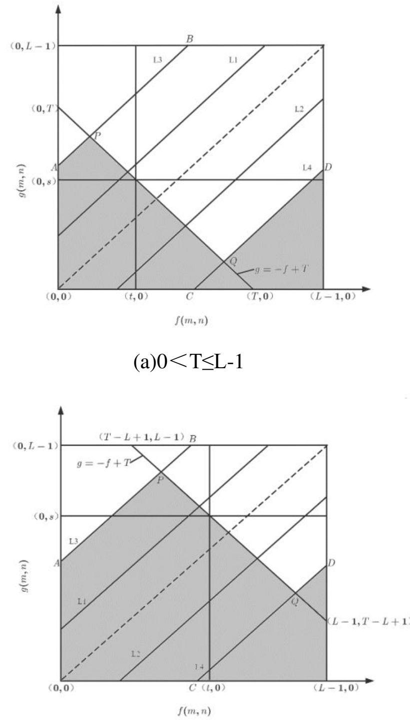
$$f_T(x,y)=\begin{cases}0, i+j\le t+s\\ L, i+j>t+s\end{cases} \tag{13}$$

This method of threshold selection based on straight lines is the 2D line thresholding type Otsu method.

4. 2D Zigzag thresholding segmentation method

4.1. Introduction to the method

The main objective of this paper is to improve the accuracy of image segmentation by accurately partitioning the regions of a 2D histogram. After giving a schematic description of the 2D histogram oblique segmentation method, this paper aims to improve the accuracy of image segmentation by correctly delineating the regions of the 2D histogram and accurately distinguishing the target and background region. In this paper, the three sub-regions of the 2D histogram oblique segmentation method are subdivided using a zigzag, which is composed of three segments (AP segment, PQ segment, and QD segment in Fig. 5). The advantages of the traditional method are fully utilized to form a terrific effective and accurate image segmentation technique. The proposed method has been evaluated through a series of experiments on various images and has been shown to have excellent accuracy and suitability than traditional methods. The specific line segment APQD is shown in the Fig. 5.



(a)0<T≤L-1

(b)L-1 < T≤2L-2

Fig. 5 2D Zigzag thresholding segmentation method

where the equations for L3 and L4 are:

$$\begin{cases} g_{L3}=f+N\\ g_{L4}=f-N\end{cases} \tag{14}$$

where N is the intercept of L3 and L4 from the coordinate axes, respectively. To determine the size of N, the standard requirement for the probability of a small probability event (called small probability setting value ε) is used in this paper, which is based on the literature [14]. It is determined by determining whether the ratio of pixels other than L3 and L4 to the entire image is less than ε, and if it is, segmentation is halted in order to determine the value of N, by applying the principle of small probability events, the method in this paper can select suitable ε values in different scenarios, effectively solving the problem of low universality of the method. Theoretically, N should be incremented from 0 to L-1, then the optimal solution can be obtained. However, in order to enhance this work uses the dichotomous approach to carry out accelerated segmentation [30], which is used to derive the equations for L3 and L4. The upper and lower bounds of the dichotomy can also be adjusted according to specific practical scenarios, further improving the applicability of our method. Thus, the following can be used to obtain the three equations AP, PQ, and QD:

$$\begin{aligned} &AP: g_{AP}=f+N,(0<i\le\frac{T-N}{2}) \\ &PQ: g_{PQ}=-f+T,(\frac{T-N}{2}<i\le\frac{T+N}{2}) \\ &QD: g_{QD}=f-N,(\frac{T+N}{2}<i\le L-1) \end{aligned} \tag{15}$$

4.2. Algorithm flow

Algorithm ：2D Zigzag thresholding segmentation method

input：A single image.

output：Otsu segmentation result image.

1：Make a judgment on the image, if the image is in color, then grayscale it, if it is a grayscale image then proceed directly to the next step.

2：Calculate the neighborhood average gray value of the image and combine the image gray values to form a 2D histogram of the image.

3：Using the original 2D Otsu method, threshold points are obtained.

4：Using the 2D histogram oblique segmentation method, obtain line threshold, L3 and L4 parallel to the main diagonal.

5：Determine whether the sum of the ratio of pixels outside L3 and L4 to the whole image pixels is less than ε. If it is less, stop the process and determine the value of N, using the binary search method in the process of determination to improve the processing speed of the program.

6：Determine the equation of the zigzag and use it to calculate the threshold value of the line.

7：Binary the image according to the segmentation criteria to achieve segmentation.

The flow chart of the method is as follows.

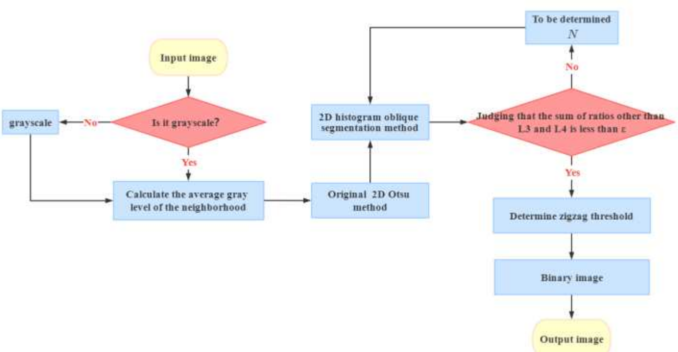
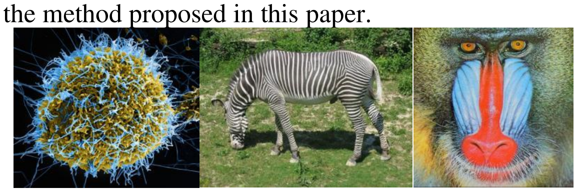


Fig. 6 Algorithm flow chart

5. Experimental results and analysis

The experimental hardware configuration is a PC with AMD Raidon 5 5600H, RadeonGraphics @3.30GHz 16GB RAM, and the software uses MATLAB R2018a for the experiments. This chapter evaluates the method in terms of subjective visual and objective image quality indicators, verifies the feasibility of the method in this paper through experiments, and shows that this method can improve segmentation accuracy and universality through a comparison of methods. The experimental method include the original 2D Otsu method [14], the 2D histogram oblique segmentation method [22], the 2D Otsu's broken-line thresholding segmentation method [19], and the method proposed in this paper.



(a) virus (b) zebra (c) baboon

(d) street (e) road (f) snow

Fig. 7 Input images

The percentage of pixels in regions II and IV of the six images, expressed as $[n(\mathrm{II})/N]$ and $[n(\mathrm{IV})/N]$, respectively, was calculated from the six images (Fig. 7), as shown in Table 1; the percentage of pixels in regions II and IV of the whole image, expressed as $[n(\mathrm{II、IV})/N]$. where n is the number of pixels in the region and N is the number of pixels in the whole image.

Table 1 Pixel proportion of unclassified regions in image histogram

name	$[n(\mathrm{II})/N]/\%$	$[n(\mathrm{IV})/N]/\%$	$[n(\mathrm{II、IV})/N]/\%$
virus	3.13%	0.93%	4.06%
zebra	27.40%	1.44%	28.84%
baboon	14.78%	1.14%	15.92%
street	24.69%	1.16%	25.85%
road	19.24%	1.09%	20.34%
snow	29.38%	0.85%	30.23%

Table 1 shows that the proportion of pixels in regions II and IV is well above the negligible threshold. Therefore, treatment of these regions was considered necessary. Furthermore, the results obtained from regions II and IV become critical if precise edge handling is required. While our method performs similarly to other methods when the total number of pixels in these regions is low, but improves significantly when the total pixel count is high.

To make the segmentation result more intuitive, the pixels in regions II and IV are colored in this paper. By making the pixels in region II red and region IV blue, the edges of the image and the noisy regions can be seen visually.

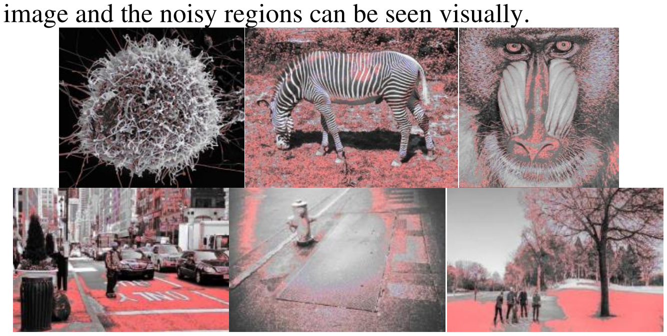


Fig. 8 Marking of pixels in regions II and IV

In probability theory, events with probabilities between 0.01~0.05 are usually referred to as small probability events. Therefore, in this study, we have selected 0.01, 0.02 and 0.05 as experimental parameters ε, aiming to showcase the advantage of tunable parameters of the proposed method. In addition, we also include the cases with parameters 0.1 and 0.2 to further evaluate the robustness and adaptability of the method in this paper. Through the comparative analysis of the experimental results, we can have a more comprehensive understanding of the performance of the method under different parameter settings, which can provide valuable reference for further optimization and promotion of this method. Table 2 shows the runtime of the six images, where the runtime is the average of five experiments.

Fig. 9 Experimental results of different small probability settings

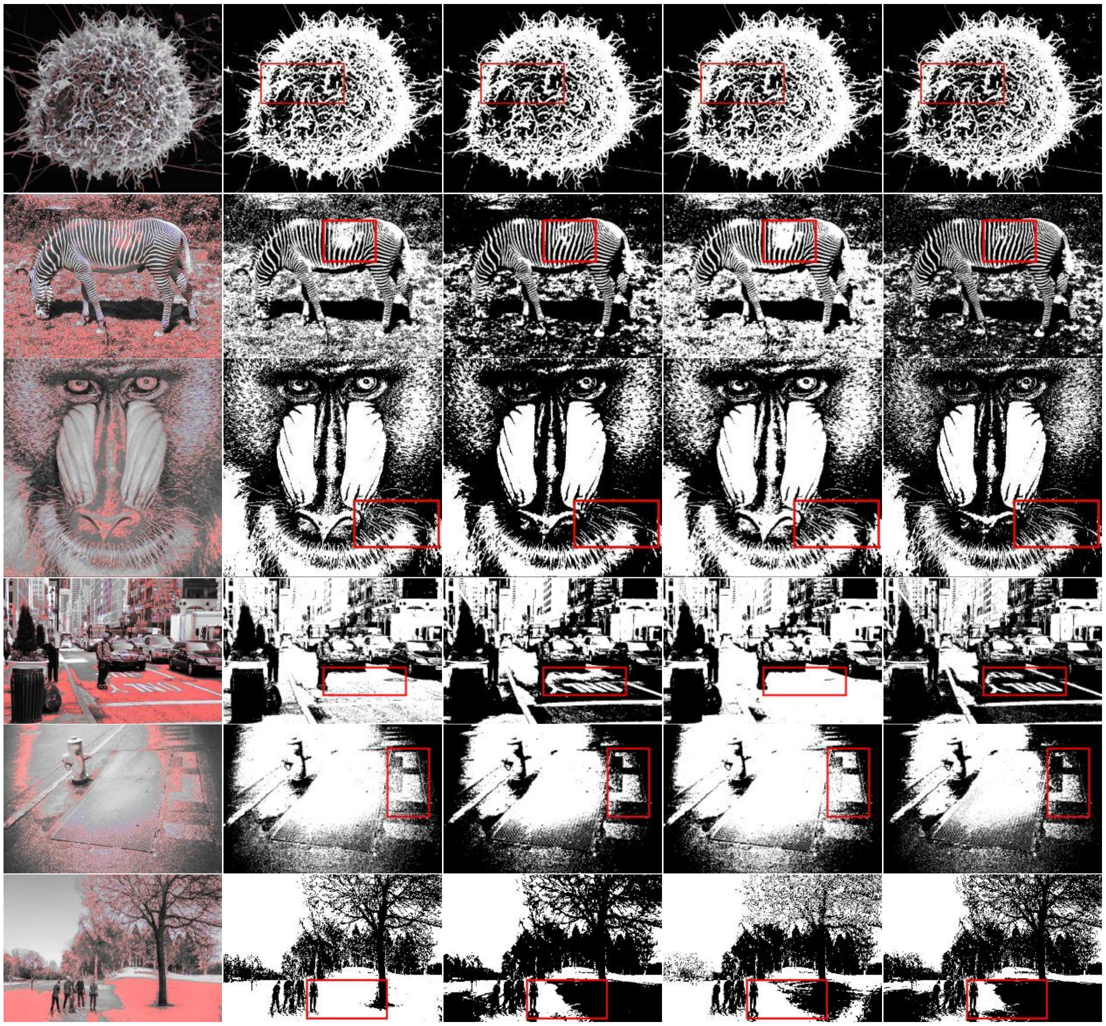
According to the data in Table 2, the running time of the method in this paper is influenced by the parameter ε. When ε takes a value of 0.01, the processing time of the program is significantly shorter or comparable to the processing time of the other parameters. As can be seen in the experimental results in Fig. 9, as the value of ε increases, the number of noise points in the processed image also increases, thus affecting the visual effect of the image. Therefore, the method in this paper can choose different ε values according to different needs in practical applications, which shows the excellent adaptive performance of the method in this paper. In addition, our method has obvious advantages for high-precision image segmentation, which can improve the accuracy of image segmentation and shorten the running time of the program.

Table 2 Comparison of effects of different small probability setting values ε

ε	Running time/s					
	virus	zebra	baboon	street	road	snow
ε =0.01	0.12	0.08	0.04	0.06	0.07	0.09
ε =0.02	0.13	0.06	0.04	0.07	0.07	0.06
ε =0.05	0.13	0.07	0.05	0.07	0.08	0.07
ε =0.1	0.15	0.08	0.05	0.09	0.11	0.08
ε =0.2	0.13	0.08	0.08	0.08	0.11	0.08

5.1. Splitting performance experiments

The experimental results are given for the six images (Fig. 7) to verify the feasibility of the method in this paper. The experimental images are: virus, zebra, street, snow, road and baboon.

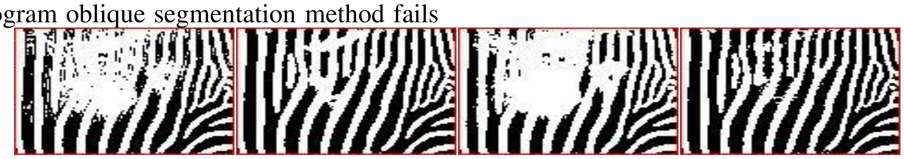


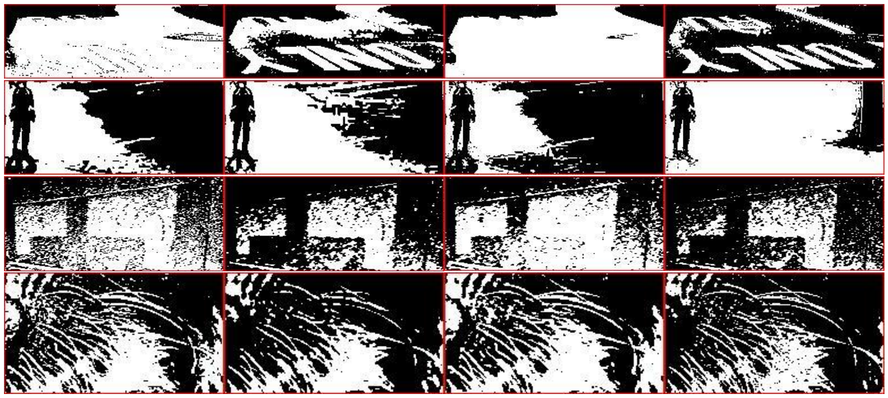
grayscale images (a) (b) (c) (d)

Fig. 10 Experimental results of different method (from left to right are: grayscale images; (a)original 2D Otsu method; (b)2D histogram oblique segmentation method; (c)2D Otsu's broken-line thresholding segmentation method; (d) proposed)

5.2. Experimental analyses

In the zebra, street, snow, and road, which are typical cases with more noise points, the 2D Otsu's broken-line thresholding segmentation method and 2D histogram oblique segmentation method have a much better processing effect than original 2D Otsu method, but insufficient segmentation of details. The results show that our method performs similarly to other segmentation methods for images segmentation that contain less noise and edge information, such as in virus. In the zebra, the zebra stripes are accurately processed by our method, while all other methods have a serious wrong classification. The proposed in this paper shows its advantages in the street. As can be seen from the figure, the original 2D Otsu method and the 2D Otsu's broken-line thresholding segmentation method are both poor at segmenting the ground text, and the 2D histogram oblique segmentation method fails to clearly segment the text on the ground. In contrast, the method proposed in this paper can clearly segment the text regions. For the snow, our method performs better than other methods. In terms of snow shadows and human shadows, our method is detailed and can distinguish these influences, resulting in significantly accurate segmentation image. In the road, the other three methods cannot segment the road surface, but the method in this paper can accurately segment the distribution of the road floor. For the segmentation of the baboon's eye, the segmentation results of the original 2D Otsu method are reasonable. However, the processing of the baboon's beard in this paper is more refined than the other four methods. To see the segmentation of the details more clearly, we zoomed in on a part of the image, as shown in the Fig. 11.





(a) (b) (c) (d)

Fig. 11 Selected images of detail display (from left to right are: (a)original 2D Otsu method; (b)2D histogram oblique segmentation method; (c)2D Otsu's broken-line thresholding segmentation method; (d) proposed)

5.3. Segmentation quality assessment

Subjective methods of evaluating the quality of image segmentation are highly subjective and have limitations in the uniform evaluation of different image segmentation results. Objective evaluation of image segmentation quality is necessary and meaningful [31]. In this paper, the maximum correlation criterion (MCC) is used as the evaluation function of the image segmentation method [21]. This criterion was proposed by Yen et al. [32] based on the maximum entropy criterion, and evaluates the effect of the segmentation method by calculating the positive correlation between the total number of correlations and the segmentation quality. And it was extended to 2D by Chen et al. [33]. Table 3 shows the quantitative evaluation of the segmentation effects of the four methods. The results show that the method in this paper is consistent subjectively and objectively, and has good performance in terms of visual effects and correlation number indicators.

Table 3 Quantitative evaluation of segmentation results of different methods

Images	Original 2D Otsu method	2D histogram oblique segmentation method	2D Otsu's broken-line thresholding segmentation method	Proposed
virus	12.22	12.24	10.84	12.26
zebra	11.67	11.66	10.51	11.69
baboon	15.39	15.30	13.62	15.32
street	16.87	17.07	15.02	17.27
road	14.49	11.92	10.46	11.94
snow	15.79	16.31	13.92	16.48

6. Conclusion

This paper finds that 2D Otsu thresholding segmentation method suffers from pixel classification errors and poor applicability in practical applications. To address these problems, this paper proposed 2D Otsu's zigzag thresholding segmentation method. By experimentally shows that edges and noisy regions cannot be ignored in their entirety, otherwise they will lead to a significant reduction in segmentation accuracy. To solve this problem, this paper uses the original 2D Otsu method for 2D histogram segmentation, which can appropriately ignore edge information or noise regions when the proportion of these regions can be regarded as small probability events, thus solving the problem that the classical 2D Otsu method assumes unreasonable premises. This paper makes use of the priori information in 2D histogram to improve the existing 2D histogram oblique segmentation method and solve the problem of apparent wrong classification that exists. At the same time, this paper takes full account of the influence of edge information or noisy regions on the segmentation of greyscale images, and effectively improves the accuracy of segmentation by correcting the problem of incorrect pixel classification. It can be seen through the experiments that our method has an excellent segmentation effect on images with rich edge information after correcting the misclassified regions in the 2D histogram oblique segmentation method. To solve the problem of poor adaptability, this paper effectively improves the adaptive ability of the method by adjusting the small probability event parameter ε and the application of the dichotomous method. This method can make the image segmentation great accurate, the self-adaptability strong, the edge shape accurate, and the internal pixel distribution uniform. However, the processing time is longer than that of original 2D Otsu method and other improved algorithms, making the method in this paper limited in application scenarios.

Declarations

Ethical Approval We used all publicly available datasets, and previous authors have had ethical approval.

Competing interests No potential conflict of interest was reported by the authors

Authors' contributions Yahui Chen and Yitao Liang initially perceived and designed the study. Yahui Chen conducted the experimental research. Yahui Chen and Yitao Liang conducted the theoretical research. All authors analyzed the data and wrote the manuscript.

Funding This work was supported by a grant from National Natural Science Foundation of China (31171775), Key Science and Research Program of the Education Department of Henan Province (17A510008), and Key Project of Innovation Fund of Henan University of Technology(2020ZKCJ02).

Data availability statement Data in this paper is available at the link https:https://cocodataset.org/#home given in paper.

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