A threshold segmentation method for non-uniform illumination image based on brightness equalization

To cite this article: Hui Guo *et al* 2019 *IOP Conf. Ser.: Mater. Sci. Eng.* **569** 052046

IOP Conf. Series: Materials Science and Engineering **569** (2019) 052046 doi:10.1088/1757-899X/569/5/052046

A threshold segmentation method for non-uniform illumination image based on brightness equalization

Hui Guo[1,2], Peng Chen[1,2], Shun Huang[1,2], Cong Hu[1,2], Lijun Zhang[1,2*]

[1]School of Automation, China University of Geosciences, Wuhan, 430074, China

[2]Hubei key laboratory of Advanced Control and Intelligent Automation for Complex System, Wuhan, 430074, China

lijunzh@cug.edu.cn

Abstract. In the process of image acquisition, non-uniform illumination images are common due to poor lighting, surface reflection, or a combination of these two factors. In order to improve the quality of image segmentation, an image threshold segmentation method is proposed for non-uniform illumination images. First, the brightness of different regions in the image is compensated to make the brightness background of the whole image consistent. Second, the gradation histogram of the processed image is obtained and simulated into Gaussian distribution curve, then the inflection points of the curve are calculated. Finally, the two inflection points are set as thresholds to segment the image after brightness equalization. This method eliminates the influence of non-uniform illumination to a certain extent and gets a better segmentation effect. Experiments were carried out on images containing several different types of non-uniform illumination. The results demonstrate that the proposed method outperforms the compared enhancement algorithms in threshold segmentation.

1. Introduction

Image segmentation is a classical problem in the field of image processing and analysis. Threshold segmentation is one of the earliest methods studied and used in image segmentation[1]. It has the advantages of obvious effect, easy implementation and good real-time performance. It is one of the most commonly used image segmentation methods in various image analysis, image recognition and machine vision systems[2]. The threshold-based segmentation methods has been widely used in industrial image defect extraction, infrared target detection, target recognition, document image segmentation, fingerprint recognition, fire detection and many other practical applications[3-4].

Due to the uncertainty of the background environment, non-uniform illumination sometimes appears in the image acquired by the camera, which makes the high light area, dark area and normal brightness area coexist in the image. To some extent, the non-uniform illumination will lead to the change of some features of the image, which reduces the accuracy of threshold segmentation and is not conducive to the subsequent image processing[7]. Therefore, it is of great significance to solve the problem of non-uniform illumination in images. There are currently two types of methods for threshold segmentation of non-uniform illumination images. One is the local threshold method, such as the *Sauvola* algorithm; the other is based on image enhancement method. The source image is processed by *Retinex* and homomorphic filtering method, and then the classical global threshold method is used for segmentation. A general *Retinex* algorithm for image processing will assume that the initial light changes slowly, which means that the light image is smooth. But this is not the case. At the edges of areas with large differences in brightness, the image is not smooth. So in this case, the *Retinex* enhancement algorithm will augment the image with a large area of difference in brightness, resulting in a halo[6]. The homomorphic filter belongs to the frequency domain processing method, which is used to adjust the grayscale range of the image, but it can't reduce the influence of convolution noise. The local threshold method has problems such as poor real-time performance and sensitivity to noise when dealing with non-uniform illumination images[5]. In view of the above problems, this paper proposes a threshold segmentation method for non-uniform illumination images based on brightness equalization. The method divides the background of the image and dynamically adjusts the brightness value of each sub-block, so that the background brightness of the adjusted image is approximately at the same level, and then the double threshold is selected for segmentation processing, and a better effect is obtained.

2. Proposed method

2.1. Brightness equalization

In a good image, background and target should be evenly distributed in the upper and lower parts of the image. If the illumination is uniform, the average of the four parts of the grayscale should be similar. On the contrary, the difference in the average grayscale of these four parts should be obvious. There is an $M \times N$ image with a grayscale of $(0,...,L)$, and the average brightness is:

$$L_1 = \frac{\sum_{i=0}^{M-1}\sum_{j=0}^{N-1} p(i,j)}{M \times N} \tag{1}$$

Where $p(i,j)$ is the luminance value of the pixel whose coordinate is (i,j) in the image. The image is divided by a sub-block of size $m \times n$, and the average brightness of sub-blocks can be expressed as:

$$L_2 = \frac{\sum_{i=0}^{m-1}\sum_{j=0}^{n-1} p(i,j)}{M \times N} \tag{2}$$

Then the difference between the mean value of the sub-block brightness and the mean value of the full picture is $\Delta L = L_2 - L_1$.Obviously, ΔL of the highlighted sub-block in the image is positive, and ΔL of the low-light sub-block is negative. The luminance of the sub-block in which ΔL is positive is weakened, and the luminance of the sub-block in which ΔL is negative is enhanced. The method in the paper does not directly add or subtract the same adjustment value to each sub-block, but interpolates the matrix of the sub-block according to the ΔL format of the block, by adopting the bicubic interpolation method. Extend it to the entire original image size so that the adjustment values between adjacent sub-blocks are smoother. Then subtract the extended ΔL matrix from the pixel value of the original image, and the brightness balance adjustment of the whole image can be realized.

The specific steps are as follows:

- Find the average grayscale value of I the source image.
- Divide the image into $M \times N$ blocks according to a certain size, find the average value of each block, and obtain the brightness matrix D of the sub-blocks.
- Subtracting the average grayscale of I the source image by the value of each element in the matrix D, the luminance difference matrix E of the sub-block is obtained.
- The bicubic interpolation is used to expand the matrix E into a brightness distribution matrix R of the same size as the source image.
- The luminance equalized image is obtained by subtracting the corresponding value in the matrix E from the luminance value of the pixel in the source image and performing smoothing processing.

IOP Conf. Series: Materials Science and Engineering **569** (2019) 052046 doi:10.1088/1757-899X/569/5/052046

2.2. Dual-threshold selection

After the brightness equalization process, the illumination background in the image tends to be consistent. Since the grayscale values of most pixels are relatively close, a distinct single peak effect appears in the grayscale histogram. According to this characteristic, we consider to simulate the single wave peak curve in grayscale histogram into Gaussian distribution curve, as shown in figure 1.

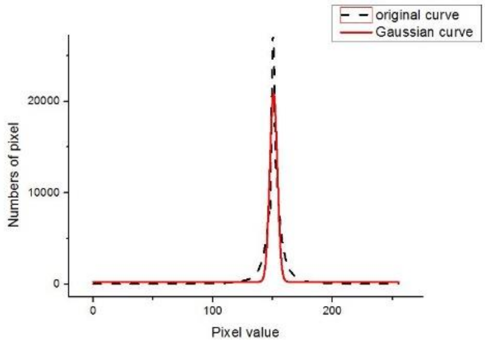


Figure 1. Result of curve fitting.

The fitted one-dimensional normal distribution probability density function is denoted as $f(x)$, as shown in the following equation:

$$f(x)=\frac{1}{(2\pi)^{1/2}\sigma}\exp\left(\frac{-(x-\mu)^2}{2\sigma^2}\right) \tag{3}$$

The variable x represents the grayscale, and $f(x)$ represents the number of pixels corresponding to the grayscale.

Therefore, on the fitted Gaussian distribution curve, if there is one pixel grayscale level, the number of pixel point changes greatly in its neighbourhood, and we can suspect that the pixel corresponding to this grayscale level is on the image contour. We can describe this feature by the derivative $f'(x)$. When $f'(x)$ takes the extreme value, the pixel corresponding to this grayscale level is most likely to be on the contour.

$$f'(x)=-\frac{1}{(2\pi)^{1/2}\sigma^3}(x-\mu)\exp\left(\frac{-(x-\mu)^2}{2\sigma^2}\right) \tag{4}$$

The condition that function $f'(x)$ takes the extreme value is $f''(x)=0$.

$$f''(x)=-\frac{1}{(2\pi)^{1/2}\sigma^3}(x-\mu)\exp\left(\frac{-(x-\mu)^2}{2\sigma^2}\right)(1+\frac{x-\mu}{\sigma})(1-\frac{x-\mu}{\sigma}) \tag{5}$$

Two solutions can be obtained by solving the above formula (5). At this point, $X_1=\mu-\sigma$ and $X_2=\mu+\sigma$.Taking into account the error of the fitted data, select T_1 and T_2 as the threshold of the segmentation: $T_1=\mu-2\sigma$, $T_2=\mu+2\sigma$.

The conversion function of the dual-threshold method can be expressed as:

$$g_{x,y}=\begin{cases}0 & f_{x,y}\le T_1,\ f_{x,y}>T_2\\ 255 & T_1< f_{x,y}\le T_2\end{cases} \tag{6}$$

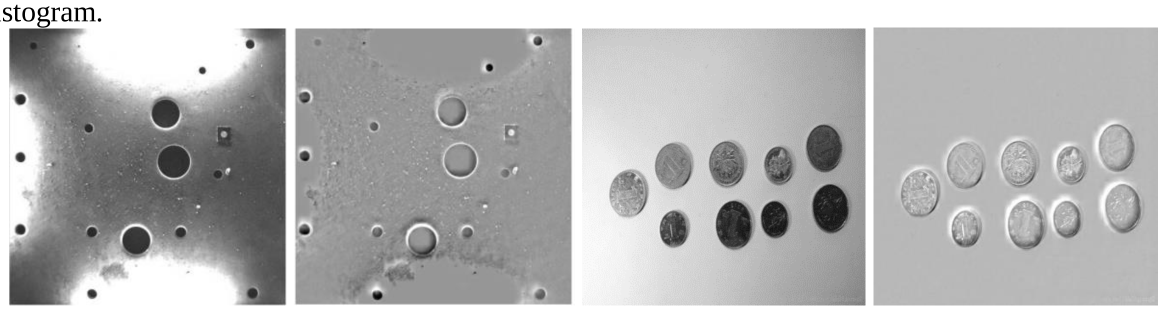
In the above formula, $f_{x,y}$ represents the grayscale value of the pixel point at image (x,y) before threshold segmentation, $g_{x,y}$ is the grayscale value of the corresponding pixel point after threshold segmentation.

IOP Conf. Series: Materials Science and Engineering **569** (2019) 052046 doi:10.1088/1757-899X/569/5/052046

3. Experimental Results and Analysis

3.1. Results after brightness equalization

It can be seen from figure 2 that the local area in the original image is obviously too bright, and the other areas are darker; the overall brightness of the image after the brightness equalization processing is relatively uniform. As can be seen from figure 3, there are obvious peaks in the processed grayscale histogram.



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

Figure 2. Results after brightness equalization. (a) Original image 1 (b) Image 1 processed by brightness equalization (c) Original image 2 (d) Image 2 processed by brightness equalization.

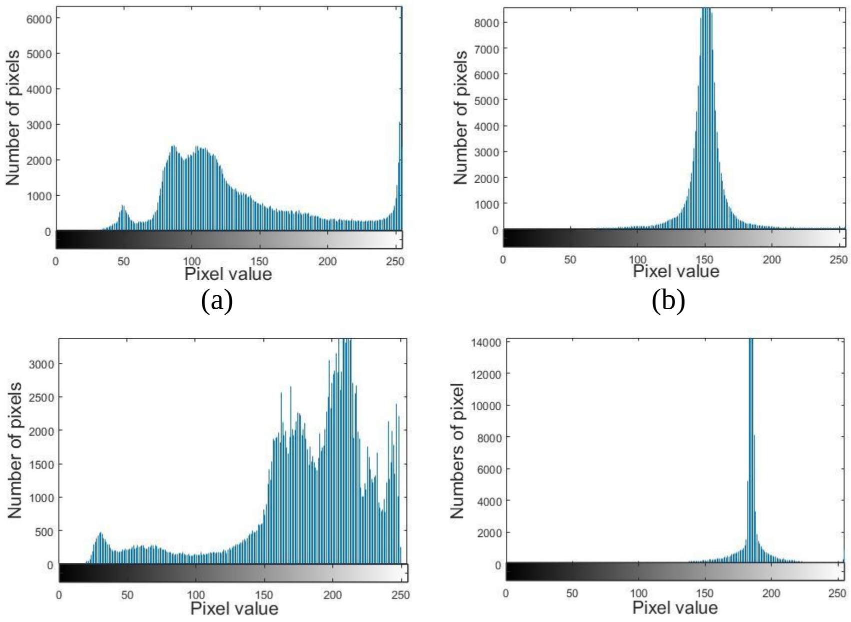


Figure 3. Grayscale histogram comparison (a) histogram of image 1
(b) Histogram processed by brightness equalization (c) histogram of image 2
(d) Histogram 2 processed by brightness equalization.

3.2 Threshold segmentation results

In order to verify the effectiveness of the proposed method, three non-uniform illumination images were selected for comparison experiments. The image data used in this paper were downloaded from the website established by the Department of Computer Science and Applied Mathematics of the Weizmann Institute of Science in Israel[10]. In this paper, two image enhancement methods and a local threshold method are selected for comparison, namely *Retinex* enhancement algorithm and homomorphic filtering method, and *Sauvola* algorithm. The original image is enhanced by these two methods, and then the processed image is subjected to threshold segmentation processing using the Otsu algorithm to obtain two binary images.

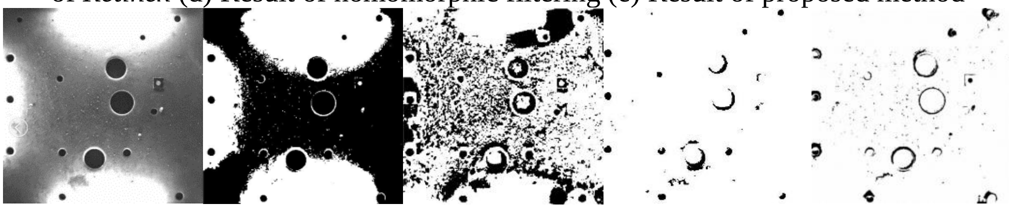
The experimental results are shown in the following three figures：

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

Figure 4. Results for image *computer*. (a) Original image (b) Result of *Sauvola* (c) Result of *Retinex* (d) Result of homomorphic filtering (e) Result of proposed method

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

Figure 5. Results for image *sonnet*. (a) Original image (b) Result of *Sauvola* (c) Result of *Retinex* (d) Result of homomorphic filtering (e) Result of proposed method



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

Figure 6. Results for image *circle*. (a) Original image (b) Result of *Sauvola* (c) Result of *Retinex* (d) Result of homomorphic filtering (e) Result of proposed method

It can be seen from the results in figure 4 that for images with non-uniform illumination, the method in this paper has better segmentation effect on images, higher information retention and less noise. In figure 5, the average grayscale value of the original image is high and the local illumination is strong. From the threshold segmentation effect of the four methods, the method in this paper is obviously superior to the other three image methods. The threshold segmentation effect in figure 6 shows that the *Sauvola* algorithm and the *Retinex* enhancement algorithm are relatively inferior. The homomorphic filter method and the proposed method are similar in effect, but the image details obtained by proposed method are more abundant.

3.3 Quantitative measurement results

In order to quantitatively compare the results of subsequent experiments, we use the recall rate, precision rate, F_measure and error rate to measure the effect of image segmentation[8-9]. In this paper, the recall rate refers to the ratio of the correct target point in the binary image to all target points in the original image.

Assuming that the target point set in the binary image is A, the target point set in the grayscale image is B, and the recall rate expression is:

$$P_R = \frac{A \cap B}{B} \times 100\% \tag{7}$$

Precision is the ratio of the correct target point in the binary image to all target points in the binary image. The exact expression is：

$$P_p = \frac{A \cap B}{A} \times 100\% \tag{8}$$

The F measure is represented by a combination of recall rate and precision rate:

$$F_{Measure} = \frac{P_R \times P_p}{\zeta P_R + (1-\zeta) R_p} \times 100\% \tag{9}$$

The error rate is used to detect the difference between the actual segmentation result and the ideal segmentation result relative to all pixels.

$$E_{Rate} = 1 - \frac{2(A \cap B)}{A+B} \times 100\% \tag{10}$$

Table 1. Comparison of binary image evaluation indexes

Image	Method	P_R	P_p	$F_{Measure}$	E_{Rate}
Computer	Sauvola	61.62%	99.93%	94.95%	24.14%
	Retinex	68.19%	99.94%	96.24%	18.93%
	Homo filter	83.79%	99.94%	98.38%	8.83%
	Proposed	89.92%	99.95%	99.42%	3.15%
Sonnet	Sauvola	73.33%	99.84%	97.08%	15.38%
	Retinex	51.74%	99.82%	92.84%	31.80%
	Homo filter	66.09%	99.48%	91.66%	20.96%
	Proposed	89.39%	99.54%	99.36%	7.25%
Circle	Sauvola	59.27%	99.72%	94.63%	25.56%
	Retinex	92.83%	99.94%	99.36%	3.71%
	Homo filter	86.26%	89.64%	88.96%	9.72%
	Proposed	98.31%	99.95%	99.85%	0.85%

It can be seen from Table 1 that in the overall data, the method of this method has better effect on image segmentation of non-uniform illumination, higher recall rate and lowest error rate, which is better than the other three methods.

4. Conclusion

Aiming at the problem of uneven illumination in the image, we propose a method of threshold segmentation based on luminance equalization. The method adopts the method of brightness equalization and double threshold segmentation to obtain a better binary image. The experimental results show that the proposed method has certain advantages compared with the other three methods.

References

[1] Wong, A., Sahoo, P. (1989) A gray-level threshold selection method based on maximum entropy principle. IEEE Transactions on Systems, Man and Cybernetics, 19(4): 866-871.
[2] Otsu, N. (2007) A Threshold Selection Method from Gray-Level Histograms. IEEE Transactions on Systems, Man, and Cybernetics. 9(1): 62-66.
[3] Chen, Q., Sun, Q., Heng, P. (2008) A double-threshold image binarization method based on edge detector. Pattern Recognition 41(4): 1254-1267.
[4] Zhang, Y., Lin, W., Li, Q. (2018) Multiple-Level Feature-Based Measure for Retargeted Image Quality. IEEE Transactions on Image Processing, 27(1): 451-463.
[5] Moser, G., Serpico, S. (2006) Generalized minimum-error thresholding for unsupervised change detection from SAR amplitude imagery. IEEE Transactions on Geoscience and Remote Sensing, 44(10): 2972-2982.

[6] Rommetveit, K., Kristrun, G., Jepsen, K. (2013) The Technolife project: An experimental approach to new ethical frameworks for emerging science and technology. International Journal of Sustainable Development, 16(1/2): 23-45.
[7] Yotsna, J., Chauhan, S., Sharma, E., (2016) Binarization techniques for degraded document images. In: International Conference on Reliability. London. pp. 105-109.
[8] Su, B., Tan, C., Lu, S. (2013) A Robust Document Image Binarization Technique for Degraded Document Images. IEEE Transactions on Image Processing, 172: 63–69.
[9] Gatos, B., Ntirogiannis,K., Pratikakis, I. (2009) Document image binarization contest. International Journal on Document Analysis and Recognition, 14(1): 35-44.
[10] Venu, N. (2014) Performance and evalution of Guassian kernals for FCM algorithm with mean filtering based denoising for MRI segmentation. In: 2014 International Conference on Communication and Signal Processing. New York. pp. 223-229.