Research on Barcode Image Binarization in Barcode Positioning System

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Abstract
Aiming at the disadvantages of the traditional positioning technology, barcode positioning system is introduced in this paper. Based on Otsu method, a novel barcode image binarization is put forward by comparing varieties of image binarization methods domestically and abroad. Moreover, we have a systematic research on histogram and binarization mechanism, and also give the calculation of histogram and derive a formula of Otsu method. Finally, the histogram and binarization of one-dimensional barcode image are realized with the specific examples. After experiments for scanned barcode image, the result has demonstrated effectiveness of the method.
Keywords: *binarization, histogram, Otsu method, barcode positioning.*

1. Introduction

At present, the common positioning methods of the transportation system are in two ways: One is positioning with laser or ultrasonic [1], whose advantage is that positioning accuracy and speed, but it only works on a straight line; and the other is positioning with the rotary encoder, whose advantage is can be positioned in the curve direction, but its accuracy is poor, and has the cumulative error. In view of these phenomena, the introduction of barcode positioning system can perfectly resolve the above problems. The barcode positioning system is a new measurement and positioning system, which is evolved from the large-scale logistics transportation system, is a breakthrough of the traditional positioning technology, and represents the development direction of positioning technology in the modern large-scale transportation system.
In this paper, the improved binarization based on Otsu method is put forward and applied to barcode positioning system according to its own characteristic of laser scanned barcode image. Finally, the histogram and binarization of one-dimensional barcode image are realized with the specific examples in Matlab programming environment, which has an excellent practical value.

2. Basic principles of barcode positioning system

The barcode positioning system is composed of the barcode reader and the barcode tape, etc. It works with the barcode reader installed on the robot, and the barcode tape installed on a walking track. When the robot is walking on the track, the barcode reader scans the current barcode constantly, and outputs the robot's current location information through the built-in decoder.
The schematic diagram of the barcode positioning system is as shown in Fig. 1. This system is mainly composed of the barcode tape, the barcode reader and the controller. The barcode tape has printed a number of fixed-length barcodes with certain rules. The barcode reader consists of scanning system, signal shaping system and decoder. Laser emitted from the light source scans the barcode, diffuse-reflected light from the barcode is absorbed by the photoelectric converter, and the reflected light signal is converted into the corresponding electrical signal. The electrical signal is converted into digital signal after signal shaping. The decoder distinguishes the number of bars and spaces by measuring the number of digital signal 0/1, and distinguishes the width of bars and spaces by measuring the duration of digital signal 0/1. According to the encoding rules, the signal combination of the bars and spaces is converted into location data. Finally, the decoded location data are sent to the controller through the interface.

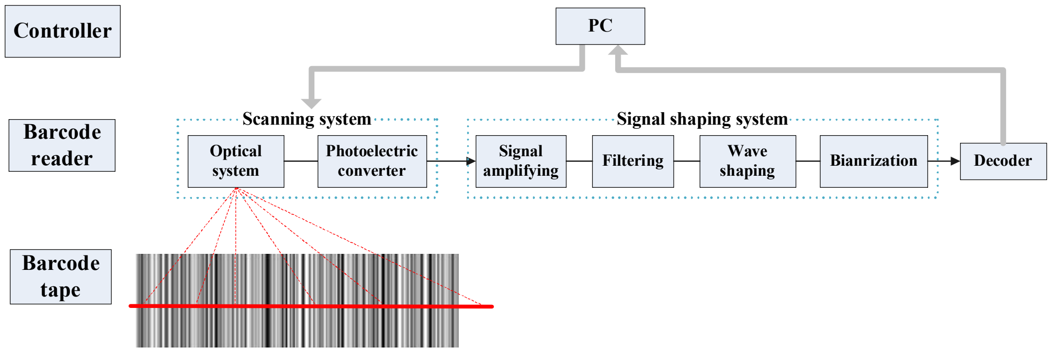

Fig. 1 The schematic diagram

3. The binarization of barcode image

In the process of barcode scanning, the light and distance would have great changes every time, so the barcode image (also referred to as digital signal) after signal shaping is binarization processed with a dynamic threshold method.

3.1 Histogram

3.1.1 The concept of histogram

In the view of probability, if the pixel intensity (gray level) is regarded as a random variable, then the percentage that the pixel number of a certain gray level accounts the total pixel number reflects the statistical characteristics of one image, which can be described as Probability Density Function (PDF) and be defined as gray histogram. Gray histogram is a function of gray level, which indicates the pixel number of a certain gray level and reflects the frequency of every gray level.

Let r represent the pixel gray level. Normalizing the pixel gray level, then the value of r will be restricted to the range $[0,1]$, where $r=0$ represents black and $r=1$ represents white. For a given image, it is random to take every gray level in $[0,1]$. In other words, the gray level is a random variable. In the discrete form, r_i denotes the discrete gray level and $P_r(r_i)$ denotes the Probability Density Function. In order to simplify the discussion, the gray level histogram is normalized and regarded as a probability distribution:

$$P_r(r_i)=\frac{n_i}{n} \qquad (0\le r_i\le 1 \quad i=0,1,2,\cdots,l-1) \qquad (1)$$

Where n_i denotes the pixel number at r_i, n denotes the total pixel number, n_i/n denotes the frequency of the gray level, l denotes the total number of gray level. After that, make a diagram in the rectangular coordinate system for the relationship of r_i and $P(r_i)$, you get the histogram.

Suppose that the gray level of the continuous image can be changed smoothly from the center of higher gray level to the edge of lower gray level. Now select a gray level D_1, and define a contour that connects all the points of the gray level D_1. The contour forms a closed curve which surrounded by the gray level that greater than or equal to D_1. And then define another contour with greater gray level D_2 .As shown in Fig.2, A_1 and A_2 are the areas surrounded by the contour of gray level D_1 and D_2, respectively. $A(D)$ is the threshold area function, which represents the area surrounded by the gray level D. Then the image histogram can be defined as

$$H(D)=\lim_{\Delta D\to 0}\frac{A(D)-A(D+\Delta D)}{D-(D+\Delta D)}=\lim_{\Delta D\to 0}\frac{A(D)-A(D+\Delta D)}{-\Delta D}=-\frac{d}{dD}A(D) \qquad (2)$$

Therefore, the histogram of a continuous image is the negative of its threshold area function derivative. And the symbol of negative is due to that the threshold area decreases with D increases.

For the discrete function, set ΔD be 1, then

$$H(D)=A(D)-A(D+1) \qquad (3)$$

For the digital image, the area of gray level D is the pixel number of the gray level that greater than or equal to D.

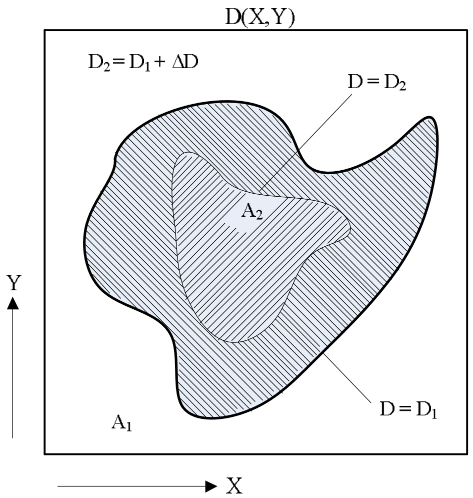

Fig. 2 The histogram definition of a continuous image

3.1.2 The characteristics of histogram

The characteristics of histogram are as follows [11]:

(1) The histogram is the statistic of every gray level, which reflects the occurrence number or frequency rather than the location of a certain gray level. In other words, it contains only the probability of a gray level but loses its location information in the image.

(2) Any image can identify its corresponding histogram uniquely. However, different images may have the same histogram. That is, the relationship between one image and its histogram is many-to-one mapping relationship.

(3) The histogram is obtained with the pixel statistic of the same gray level, so the histogram of every sub-area is equivalent to the histogram of the whole image.

(4) Normalizing the gray histogram and the area function, we get the Probability Density Function (PDF) and Cumulative Distribution Function (CDF). For $H(D)=-\frac{d}{d/D}A(D)$, let p be used to replace D and the equation be integrated from D to ∞, namely $\int_D^{\infty} H(p)dp=A(0)$. $A(\infty)=0$, so that $\int_D^{\infty} H(p)=A(D)$. If put $D=0$, then $\int_D^{\infty} H(p)dp=A(0)$ means the image area. For the discrete image, $\sum_{D=0}^{255} H(D)=NL\times NS$. If the image has the qualities of uniform gray-level, the great contrast between objective and background, and a contour that connects all the points of the gray level D_1, then $\int_{D_1}^{\infty} H(D)dD$ means the area.

3.1.3 The calculation of histogram

Let the pixels of a given image be represented in L gray levels ($L=256$, that is 8-bit gray level), then the histogram $pBuffer[0,L,L-1]$ of the gray image ($M\times N$) can be available with the following algorithm [9]:

Step1. Initialization: $pBuffer[i]=0 \quad (i=0,L,L-1)$;

Step2. Statistic: $pBuffer[f(x,y)]{+}{+} \quad (x=0,L,M-1;\ y=0,L,N-1)$;

Step3. Normalization: $pBuffer[f(x,y)]/=M\times N$.

Among them, the normalization of histogram is optional, you could neglect this operation if special process is needless.

3.2 OTSU

After the foregoing process of barcode image, we may select a simply global threshold method for binarization. Because of simple computation and well adaptation, the Otsu method becomes one of the most popular methods of threshold selection. This paper chooses the Otsu method for image binarization.

The Otsu method is an adaptive threshold method, which is OTSU for short, is also known as the maximum between-class variance method. It dichotomizes the image into two parts of the background and objective according to the gray level of the image. The greater the between-class variance between the two parts, the greater the difference of the two parts. When parts of the objective are wrongly divided into the background or parts of the background are wrongly divided into the objective, it will lead to the difference smaller [4]. Therefore, the segmentation that makes the between-class variance maximum means that the error dividing probability is the minimum.

Realizing processes are as follows:

(1) Gray-level classification: Suppose that we dichotomize the pixels into two classes C_0 and C_1 by a threshold at level t ; C_0 denotes pixels with levels $(0,1,2,K,t)$ and C_1 denotes pixels with levels $(t+1,t+2,K,255)$, that is $C_0=(0,1,2,K,t)$ and $C_1=(t+1,t+2,K,255)$.

(2)The probabilities of class occurrence and the class mean levels, respectively, are given be

$$\begin{cases} \omega_0=p_r(C_0)=\sum_{i=0}^{t} p_i \\ \omega_1=p_r(C_1)=\sum_{i=t+1}^{255} p_i=1-\omega_0 \end{cases} \tag{4}$$

and

$$\begin{cases} \mu_0=\sum_{i=0}^{t} i.p_i \big/ \omega_0 = u(t) \big/ \omega_0 \\ \mu_1=\sum_{i=t+1}^{255} i.p_i \big/ \omega_1 = \left[u_T-u(t)\right] \big/ 1-\omega_0 \end{cases} \tag{5}$$

Where $u(t) = \sum_{i=0}^{t} i \cdot p_i$, $u_T = \sum_{i=0}^{255} i \cdot p_i$.

(3) The class variances are given by

$$\begin{cases} \sigma_0^2 = \sum_{i=0}^{t} \left[(i-\mu_0)^2 \cdot p_i / \omega_0 \right] \\ \sigma_1^2 = \sum_{i=t+1}^{255} \left[(i-\mu_1)^2 \cdot p_i / \omega_1 \right] \end{cases} \tag{6}$$

(4) In order to evaluate the "goodness" of threshold (at level t), we shall introduce the following discriminant criterion measures used in the discriminant analysis:

$$\begin{cases} \sigma_W^2 = \omega_0 \cdot \sigma_0^2 + \omega_1 \cdot \sigma_1^2 \\ \sigma_B^2 = \omega_0 (\mu_0 - u_T)^2 + \omega_1 (\mu_1 - u_T)^2 = \omega_0 \cdot \omega_1 (\mu_1 - \mu_0)^2 \\ \sigma_T^2 = \sigma_B^2 + \sigma_W^2 \end{cases} \tag{7}$$

Among them, σ_W^2 , σ_B^2 and σ_T^2 are the with-in class variance, the between-class variance, and the total variance of levels, respectively.

(5) The optimal threshold: Now our problem is reduced to an optimization problem to search for a threshold that maximizes the following function

$$\eta(t) = \sigma_B^2 \Big/ \sigma_W^2 \tag{8}$$

That is, t^* is the optimal threshold when $\max_{0 \le t \le 255} \eta(t) = \max(t^*)$.

This standpoint is motivated by a conjecture that well-thresholded classes would be separated in gray levels, and conversely, a threshold giving the best separation of classes in gray levels would be the best threshold [3].

4. Experimental results

To verify the rationality of the method, we compare the performance of the proposed method with traditional method, such as [3] (referred to as Otsu N) and [5] (referred to as L. L. Li). As shown in Fig.3 and Table 1, the histogram and binarization of one-dimensional barcode image are realized with the specific examples in Matlab programming environment, and the result with threshold of Otsu is near to the result with manual threshold (the optimal threshold). a) is the original barcode image, b) is the histogram of image, c) is the result with manual threshold, d) is the result with default threshold, e) is the result with threshold of Otsu method.

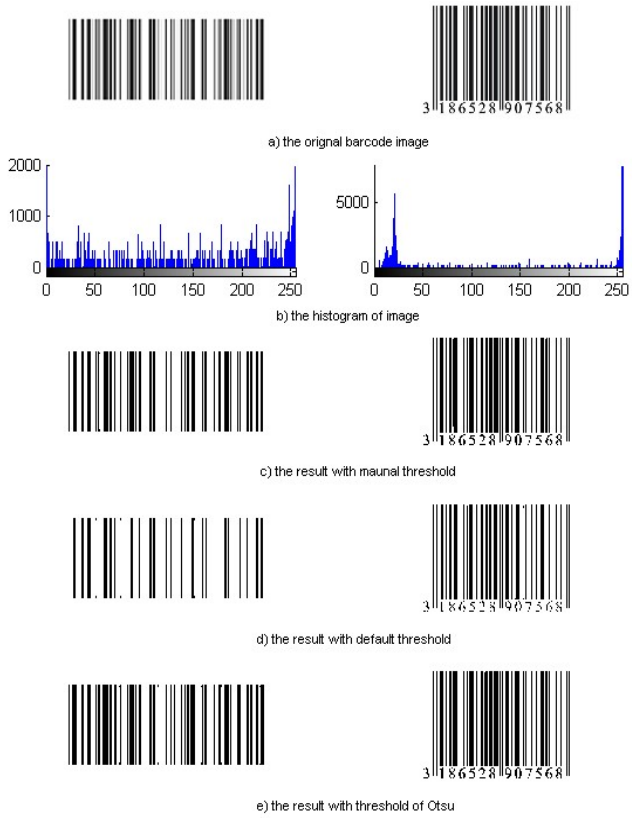

Fig. 3 Experimental comparison on barcode images

Table 1: Comparison segmentation processes

Image	Manual threshold	Default threshold	Otsu
Image1	159	123	155
Image2	146	215	140

Therefore, the barcode image that binarization processed with the dynamic threshold method has satisfactory performance. However, the optimal threshold may be available after several attempts if without Otsu method.

Because of the relatively low measurement accuracy, laser scanning usually cannot satisfy the requirements for the measurement of the barcode positioning system. Through analysis in principle and lots of experiments, a BP neural network model can be established to realize soft-ware compensation for the measurement error [13].

5. Conclusions

Regard the real-time of barcode positioning system and the characteristic of laser scanned barcode image as the starting point, the simulation experiments are realized with barcode image binarization base on Otsu method. Besides, we give the calculation of histogram and derive a formula of Otsu method. The method selects the optimal threshold according to its own information of barcode image. After binarization processing, the edge of barcode image is clear and the background noise is little, so that it provides a favorable foundation for the barcode positioning system.

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References

[1] G. Hueber, T. Ostermannn, T. Bauernfeind, R. Raschhofer, R Hanelauer, "New Approach of Ultrasonic Distance Measurement Technique in Robot Applications ", 5th International Conference on Signal Processing Proceedings, 2000, pp. 2066-2069.
[2] L. Jiang, “The Barcode Location and Recognition Base on Run-length Coding”, Electronics World, Vol. 3, 2012, pp. 16-19.
[3] Otsu N, “A Threshold Selection Method From Gray-level Histograms”, IEEE Transaction on Systems, Man and Cybernetics, Vol. 9, No. 1, 1979, pp. 62-66.
[4] J. P. Wu, Z. X. Yang, D. Han and Z. F. Bai, “2D Barcode Image Binarization Based on Wavelet and Otsu Method”, Computer Engineer, Vol. 36, No. 10, 2010, pp. 190-192.
[5] L. L. Li, S. X. Deng and X. H. Ding, “Binarization Algorithm Based on Image Partition Derive From Da-Jing Method”, Control & Automation, Vol. 21, No. 8, 2005, pp. 76-77.
[6] X. Y. Xu, E.M. Song and L. H. Jin, “Characteristic Analysis of Threshold Based on Otsu Criterion”, Acta Electronica Sinica, Vol. 12, 2005, pp. 2716-2719.
[7] Y. S. Wu, J. Deng, “Barcode Location by Extracting Edge Lines”, Journal of Computer Applications, Vol. 30, No. 5, 2010, pp. 1246-1250.
[8] Q. Du, J. Y. Xiang and S. C. Yuang, “An Improved Method of Maximum Classes Square Error”, Infrared Technology, Vol. 25, No. 5, 2003, pp. 33-36.
[9] C. H. Hu, Z. F. Nie and Z. J. Zhou, “Maximum Classes Square Error Bi-histogram Algorithm”, System Simulation Technology, Vol. 6, No. 4, 2010, pp. 259-262.
[10] X. F. Chen and D. G. Chen, “Study of Barcode Positioning Technology Based on Interested Region Detection”, Packaging Engineering, Vol. 30, No. 12, 2009, pp. 27-29.
[11] X. J. Hu and D. Xu. MATLAB Application of Image Processing, Place: Xi'an Electronic Science &Technology University Press, 2011.
[12] X. L. Ping, Y. L. Gong, W. J. Wang and B. Z. Zhou, “Error Analysis and Compensation for Laser Scanning Base on BP Algorithm”, Mechanical Science and Technology for Aerospace Engineer, Vol. 27, No. 10, 2008, pp. 1127-113129.
[13] X. Y. Yang, J. G. Yang and H. Zhou, “Error Compensation for Positioning System Based on BP Neural Networks”, Microcomputer Information, Vol. 26, No. 11, 2010, pp. 247-248.

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