

# Handwritten Character Recognition Based on Weighted Integral Image and Probability Model

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**Abstract.** A system of the off-line handwritten character recognition based on weighted integral image and probability model is built in this paper, which is divided into image preprocessing and character recognition. The objects of recognition are digitals and letters. In the image preprocessing section, an adaptive binarization method based on weighted integral image is proposed, which overcomes the drawbacks in the classic binarization algorithms: noise sensitivity, edge coarseness, artifacts etc.; In the character recognition section, combined with statistical features and structural features, a probability model based on the Bayes classifier and the principle of similar shapes is developed. This method achieves a high recognition rate with rapid processing, strong anti-interference ability and fault tolerance.

**Keywords:** Character recognition · Weighted integral image · Probability model · Statistical features · Structural features

## 1 Introduction

In 1929, Tausheck first filed a patent for the optical character recognition and pulled open the prelude of the character recognition. After decades of development, the character recognition technology has achieved rapid development and progressing. Among them, the recognition of the off-line handwritten characters are applied widely, but as a result of varieties of types and huge number of characters, as well as different writing styles, the recognition rate and speed need to be improved.

The off-line handwritten character recognition must conduct a series of image preprocessing operations, including binarization, de-noising, character segmentation, etc. Among them, the image binarization directly affects the efficiency and accuracy of the character recognition. Generally, in view of the selection methods of threshold for image pixels, the binarization methods can be categorized into two types: the global binarization and the adaptive binarization.

The global binarization methods attempt to define a single threshold for all pixels, the commonly-used global binarization methods are Otsu's method [1, 2], the iterative

method, etc. The adaptive binarization methods are combined the pixel values of the investigated point and its neighborhood points to determine the pixel value of the investigated point. Bernsen's method and Sauvola's method [1] are the representative algorithms.

Farrahi and Cheriet [2] propose AdOstu algorithm by combining the grid-based modeling and the estimated background map, the algorithm is applied to uneven illumination conditions. Bradley and Roth [3] put forward a technique for real-time adaptive binarization using the integral image, their method is robust to illumination changes in the images, but after binarization, sometimes, there exists some noises at the edge of the images, even appears artifacts (unexpected strokes obtained by the noises in the background). For this point, an adaptive binarization algorithm is presented by Nicolaou et al. [4] based on the local binary pattern, which gives different weights to the points around the investigated point and solves the phenomenon of artifacts effectively.

After image preprocessing, feature extraction and classifier are applied for character recognition. Feature extraction methods have been based mainly on two types of features: statistical derived from statistical distribution of points and structural. Methods based on statistical features, such as template matching, zoning method [5] etc., have a low complexity and the advantage of simple training, but their abilities to resist deformation are poor as well as inconformity for similar characters. Methods based on structure features, such as skeleton, outline, shape features, etc., are robust to deformation, but the complexity of algorithms are high.

Classification methods based on artificial neural network (ANN) [6], hidden markov model (HMM) [6], Bayesian network [7] or other technologies have been applied to the character recognition. Due to plenty of characters and the multiplicity of writing styles, using only a single feature extraction method has been unable to satisfy the demand of the character recognition. Therefore, zoning method based on Voronoi diagrams is used by Impedovo et al. [8], and the geometric features such as concave-convex features of the characters are made full use.

Giri and Bashir [9] suggest that combining statistical and structure features, building the characteristic matrix of the characters and using the decision tree classifier are favorable to the character recognition. Meanwhile, it is shown that approaches which employ a hierarchical recognition model combining multiple classifiers have considerable advantages compared to approaches with a single classifier, which can not only improve the recognition accuracy but also reduce the computational cost as well [10]. HMM and ANN are tight hang together by Espana-Boquera et al. [6], which achieves a high recognition rate. Pan et al. [11] combines statistic features and structure features, the preliminary classification is realized through designing four simple classifiers based on statistical features, and then the decision tree classifier based on structure features is applied to decide the final recognition result. The above studies show that different methods of feature extraction methods and classifiers are interactive designed for building the character recognition model, which can be helpful to improve the recognition accuracy and speed.

In our work, on the basis of Bradley's algorithm [3], combined with the grid-based model [2] and the weight-based model [4], the adaptive binarization method based on weighted integral image is presented in this paper, which overcomes the shortcomings

of Bradley’s algorithm. In the character recognition stage, the advantages of the statistic features and structure features [10] are integrated, the Bayes classifier based on zoning [5] is used to select range of characters first, and then, the probability model based on shape features [8, 9] is utilized to determine the final recognition result. The experimental results show that the character recognition system not only ensures the recognition efficiency but also improves the accuracy of the character recognition.

## 2 The Adaptive Binarization Algorithm

### 2.1 Bradley’s Algorithm

In this section, a form of the adaptive binarization algorithms called Bradley’s algorithm [3] is presented. The main idea in Bradley’s algorithm is that the pixel value of each point is determined by the average pixel value of the surrounding points. An integral image (also known as a summed-area table) is applied in Bradley’s algorithm, the value of the arbitrary point in the integral image refers to the sum of a rectangle region in the original image. The procedure of achieving an integrate image takes as follows: in the original image, we set the upper-left corner as the origin of coordinate and set the pixel value of the point  $d_{(x,y)}$  as  $P_{(x,y)}$ .  $S_{(x,y)}$  is the value in the integrate image and can calculate by the following formula:

$$S_{(x,y)} = \sum_{i=1}^x \sum_{j=1}^y P_{(i,j)} \tag{1}$$

As shown in Fig. 1, the value of each rectangle in the left image represents the pixel value of each point in the original image, and the right image is its corresponding integral image.

After achieving the integral image, the pixel value of each point in the original image after binarization is determined by the integral image. The binarization rendering is shown in Fig. 2. The area of the shaded part is  $w \times w$  ( $w$  is an eighth of the width of the original image).  $S_{(a,b)}$ ,  $S_{(c,d)}$ ,  $S_{(c,b)}$  and  $S_{(a,d)}$  in the integral image represent the corresponding value of the lower-right point  $d_{(a,b)}$ , the upper-left point  $d_{(c,d)}$ , the lower-left point  $d_{(c,b)}$  and the upper-right point  $d_{(a,d)}$  in the origin image. The procedure is as follows:

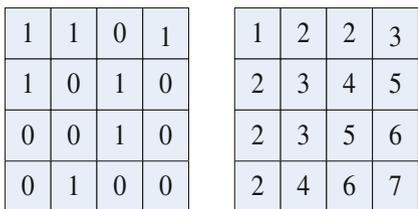


Fig. 1. Original image and integral image

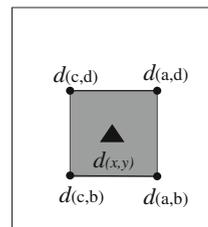


Fig. 2. Binarization rendering

(1) The sum pixel of points in the shaded area:

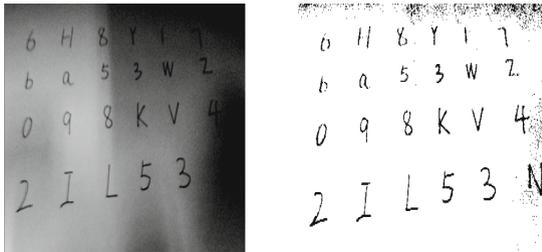
$$\text{sum} = S_{(a,b)} - S_{(c-1,b)} - S_{(a,d-1)} + S_{(c-1,d-1)} \tag{2}$$

(2) The pixel value of the center point  $d_{(x,y)}$  in the shaded area after binarization:

$$E_{(x,y)} = \begin{cases} 0 & P_{(x,y)} \times w^2 < \text{sum} \times 0.85 \\ 255 & \text{others} \end{cases} \tag{3}$$

### 2.2 The Adaptive Binarization Algorithm Based on the Weighted Integral Image

Bradley’s algorithm is simple, efficient and especially suitable for images under the uneven illumination conditions, but the processed image is not perfect. As shown in Fig. 3, the left image is a gray image contained handwritten characters and the right image is the image binarized by Bradley’s algorithm. Through observing the images, the upper edge of the right image exist a lot of noises and artifacts appear nearby the character of N, and same low-gray target points are lost (such as 6 and b in the upper-left corner).



(a) Grayscale (b) Binarization rendering

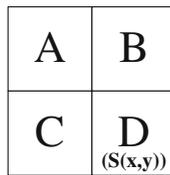
**Fig. 3.** Binarization renderings by Bradley’s algorithm

Analyzing Bradley’s algorithm can be found that, the pixel value of the investigated point after binarization is determined by the average pixel value of the surrounding points in the  $w \times w$  region. That is to say, the impact of the surrounding points on the investigated point is the same, but in fact, taking into account the illumination and other environmental factors, the closer the point is to the investigated point, the greater impact of this point on the investigated point. Therefore, simply using the average pixel value of the surrounding points as the basis of binarization, due to uneven illumination etc., will inevitably lead that some low-gray target points which are similar to the surrounding points are misclassified as the background points, thus those target points

are lost, and some high-gray background points which are similar to the target points are misclassified as the target points, thus appeared artifacts and noises. A more reasonable method should be chosen to achieve the pixel values of points after binarization. In addition, if the size of the original image is large, the value of the lower-right part in the integral image obtained by Bradley’s algorithm may be too large to consume a great vast of computer memory space.

Combined with the weight-based model [4], a weighted integral image is proposed. As shown in Fig. 4, there are four points A, B, C and D in the origin image. The pixel value of each point is in order of A0, B0, C0 and D0. According to Bradley’s algorithm, the corresponding value  $S_{(x,y)}$  of point D in the integral image can be calculated as:

$$S_{(x,y)} = A0 + B0 + C0 + D0 \tag{4}$$



**Fig. 4.** Weighted integral image

In order to reflect the distances between the point D and other points which can influence the binarization results, we set the distances between points A, B, C to point D as m, n, k (here, points A, B, C and D adjoin each other, therefore, m = n = k = 1). The parameter t is the weighted value reflecting the distances between the points, t = 6 [4]. The corresponding value  $S_{(x,y)}$  of point D in the weighted integral image can be given as:

$$S_{(x,y)} = \frac{\left( A0\left(1 - \frac{1}{t}\right)^m + B0\left(1 - \frac{1}{t}\right)^n + C0\left(1 - \frac{1}{t}\right)^k + D0 \right)}{\left(1 - \frac{1}{t}\right)^m + \left(1 - \frac{1}{t}\right)^n + \left(1 - \frac{1}{t}\right)^k + \left(1 - \frac{1}{t}\right)^0} \tag{5}$$

The general formula of the Eq. (5) is:

$$S_{(x,y)} = \frac{\sum_{i=0}^N P_i \times \left(1 - \frac{1}{t}\right)^{A_i}}{\sum_{i=0}^N \left(1 - \frac{1}{t}\right)^{A_i}} \tag{6}$$

where N is the number of points which are at the upper-left of point  $d_{(x,y)}$  (including point  $d_{(x,y)}$ ),  $A_i$  is the distance between each point to point  $d_{(x,y)}$  and  $P_i$  is the pixel value of each point.

Apparently, according to the formula 6, the influence of different distances on the investigated point can be fully reflected by  $S_{(x,y)}$ .

In addition, for the sake of improving the efficiency of the algorithm and simplifying the algorithm implementation, the corresponding value  $S_{(x,y)}$  of point  $d_{(x,y)}$  in the weighted integral image can be simply achieved by the corresponding value  $S_{(x-1,y)}$  of point  $d_{(x-1,y)}$ . The amount of recalculation is reduced by applying this iterative principle, namely:

$$S_{(x,y)} = \frac{\left( S_{(x-1,y)} \left( 1 - \frac{1}{t} \right) + \sum_{i=0}^y \left( P_{(x,i)} \times \left( 1 - \frac{1}{t} \right)^{(y-i)} \right) \right)}{\sum_{i=0}^y \left( 1 - \frac{1}{t} \right)^{(y-i)} + 1} \tag{7}$$

After obtaining the weighted integral image, the pixel values of points after binarization can be determined. Because the values in the weighted integral image are weighted mean rather than sum, this algorithm is no longer like Bradley’s algorithm to acquire the average value of points in a region. This algorithm seeks to the average value  $T_{(x,y)}$  of nine points surrounding the investigated point (including the investigated point) in the weighted integral:

$$T_{(x,y)} = \left( \begin{array}{c} S_{(x,y)} + S_{(x-1,y-1)} + \\ S_{(x-1,y)} + S_{(x,y-1)} + \\ S_{(x+1,y+1)} + S_{(x+1,y)} + \\ S_{(x+1,y-1)} + S_{(x,y+1)} + \\ S_{(x-1,y+1)} \end{array} \right) / 9 \tag{8}$$

The pixel value  $E_{(x,y)}$  of the investigated point after binarization can be acquired by the weighted average value  $T_{(x,y)}$ :

$$E_{(x,y)} = \begin{cases} 0 & P_{(x,y)} < T_{(x,y)} \times 0.85 \\ 255 & \text{others} \end{cases} \tag{9}$$

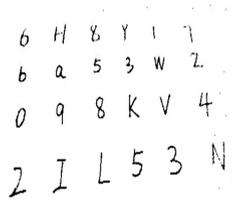
where 0.85 is reference to Bradley’s algorithm.

Figure 5 is the processed image by our algorithm, artifacts nearby the character N disappear, the number of noises in the image is also less than the number of noises in the Fig. 3.

### 3 The Probability Model

#### 3.1 The Training Phase

The system adopts the Bayes classifier, so the character training is necessary before recognition. The training process is the feature extraction and the procedure of saving the extracted eigenvalue to the training document. At first, the static zoning method [5] is applied. The sample images which contain a single character are divided into the



**Fig. 5.** Binarization rendering by our algorithm

regular grids  $2 \times 4$ . Namely, the sample images are divided into eight equal parts, and then the thirteen-dimensional feature extraction method [12] is applied to extract the statistical features of the characters, which can achieve thirteen eigenvalues of the characters. The concrete steps as follows: statistical of the percentage of the black points in the eight equal parts as eight eigenvalues; statistical of the number of black points in 1/3 and 2/3 horizontal direction of the image and divided by the height as two eigenvalues; statistical of the number of black points in 1/3 and 2/3 vertical direction of the image and divided by the height as two eigenvalues; statistical of the percentage of the black points in the whole image as the thirteenth eigenvalue.

The training samples of the system are from the special database 19 [13] by the United States National Institute of Standards and Technology (NIST). 6000 training images are chosen. In order to reduce the size of the training document and shorten the time of reading and processing training document, thirteen eigenvalues obtained by the thirteen-dimensional feature extraction method are made comparison with a selected decimal. This paper selects the decimal as 0.1. If the eigenvalue is bigger than 0.1, 1 is assigned to the eigenvalue, otherwise, 0 is assigned to the eigenvalue. Thirteen eigenvalues are converted to the binary code of 0 or 1.

## 3.2 Recognition Phase

The objects of character recognition are letters and digits which is a total of 62 characters. Combining with the statistic features and the structure features of characters, the Bayes classifier based on zoning is applied to the recognition firstly, and the Bayes classifier returns five similar characters, and then, the probability model based on shape features is applied to determine the final result.

### 3.2.1 The Bayes Classifier Based on Zoning

According to the principle of the Bayes [7], the Bayes classifier based on zoning is designed and steps of algorithm are as follows:

- (1) Calculating the prior probability of each character, which is the number of each character divided by the total number of characters;
- (2) Calculating the class conditional probability of each character, which is the probability density of the characters in the feature space of the known categories;
- (3) The Bayes formula is applied to calculate the posteriori probability;

- (4) Selecting five characters of which the posteriori probability are larger than others' and their corresponding posterior probability as the returned value.

### 3.2.2 Probability Model Based on Shape Features

Shape features of characters [8, 9] refer to the concave-convex characteristic, the number of the inner rings and the number of endpoints etc. Six characteristics are used in this paper, as shown in Fig. 6, which are the number of concaves, the right number of concaves, the number of grooves, the left number of concaves, the number of inner rings, the number of endpoints. The background-assignment method [14] is applied to detect the number of the concave-convex characteristic and the inner rings, the value of each characteristic is obtained by detecting the number of the corresponding interconnected domain. If there is only one adjacent black point of the black investigated point in the image, the black investigated point is an endpoint. The system has been established the value table of shape features of 62 characters, as shown in Table 1, due to limited space, only part of the characters listed in Table 1. The remaining characters are similar.

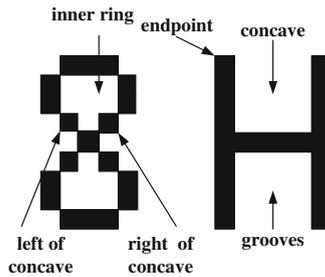


Fig. 6. Shape features of characters

Table 1. The value table of shape features of part of the characters

Characters	Concaves	Right of concaves	Grooves	Left of concaves	Inner rings	Endpoints
3	0	1	0	2	0	3
6	0	1	0	0	1	1
b	0	0	0	0	1	1
h	0	0	1	0	0	3
H	1	0	1	0	0	4
Z	0	1	0	1	0	2

The shape features of the handwritten characters are easily affected by the writers' writing styles. The shape features of the same characters writing by different people are not always exactly the same features. Therefore, the probability model based on shape features is applied to the character recognition.

The concrete implementation process is: first of all, six shape features of the character are extracted, and then, the six eigenvalues are respectively made comparison with the eigenvalues of the five characters selected by the Bayes classifier (set as 'a', 'b', 'c', 'd' and 'e'). For example, the six eigenvalues of 'a' are compared with the six eigenvalues of the character one by one. If the two eigenvalues are exactly the same, the value of probability is 100 %. If the difference value of the two eigenvalues is 1, the value of probability is 50 %. If the difference value of the two eigenvalues is 2, the value of probability is 25 %. Otherwise, the value of probability is 0. The values of 6 probability are added, and then, the sum is multiplied by the posteriori probability of 'a'. The product of the similar-probability of 'a', 'b', 'c', 'd' and 'e' are similar. Finally, the maximum is selected by comparing with the five similar-probabilities, and its corresponding character is the final recognition result.

## 4 Evaluation and Experimental Results

Experiment of this paper is based on VS2010 and OpenCV 2.31 (computer vision library) [15]. Respectively, the adaptive binarization method based on weighted integral image and the probability model based on the Bayes classifier and the principle of similar shapes have been analyzed in this section.

### 4.1 The Experiment of the Adaptive Binarization Method

A grayscale of uneven illumination is selected for this experiment, the experimental results are shown in Fig. 7. Figure 7(b) is the binary image using Otsu's method. Otsu's method belongs to the global binarization method. It is an inevitable problem that the binarization rendering is uncomplete when using the global binarization method. Figure 7(c) is the binary image using the CvAdaptiveThreshold function of OpenCV [15]. Gaussian smoothing is applied to the investigated point and its neighborhood points, and then the threshold is obtained by calculating the mean of those points. Figure 7(d) is the binary image using Bradley's algorithm [3]. Both cvAdaptiveThreshold function and Bradley's algorithm belong to the adaptive binarization algorithms. Contrasting images show that, when using cvAdaptiveThreshold function, some low-gray target points in the rendering are lost, and when using Bradley's algorithm, there are a lot of noises at the edge of the rendering and even exist artifacts nearby the character 'd', which affect the character recognition. Figure 7(e) is the binary image using the adaptive binarization method based on weighted integral image. The algorithm improves the quality of the image, removes the artifacts, largely reduces the number of noises and saves the complete character information.

A grayscale of even illumination is selected to illustrate the versatility of the algorithm, the results as shown in Fig. 8, it is not hard to see, this algorithm is less affected by the illumination conditions.

In order to reflect the influence of the algorithm on the recognition results, on the basis of the Fig. 7(d) and (e), after the processing of the de-noising and the character segmentation, the Fig. 9(a) and (b) are obtained respectively. It can be seen that,

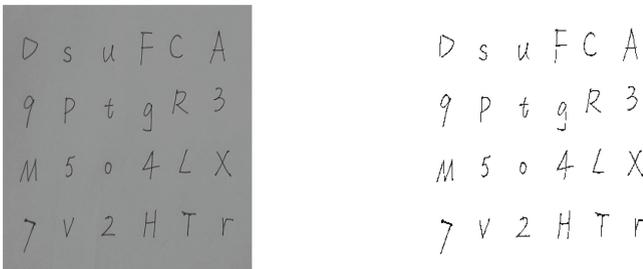


(a) Grayscale (b) Binarization rendering by Otsu (c) Binarization rendering by cvAdaptiveThreshold



(d) Binarization rendering by Bradley's algorithm (e) Binarization rendering by our algorithm

**Fig. 7.** Binarization renderings under the uneven illumination conditions by each algorithm

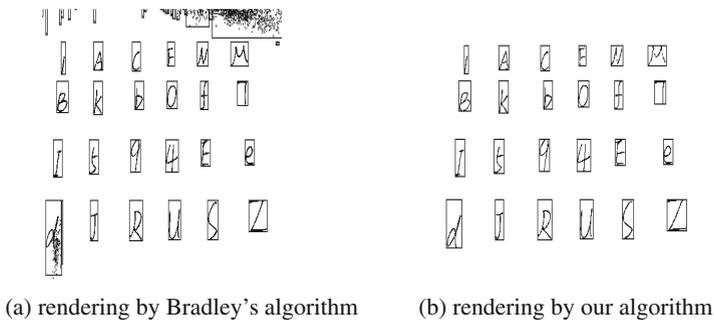


(a) Grayscale (b) Binarization rendering by our algorithm

**Fig. 8.** Binarization renderings under the even illumination conditions by our algorithm

because of the existence of plenty of noises and artifacts in the Fig. 9(a), the characters cannot properly be divided (such as the character 'd') and the non-character informations are erroneous segmented at the upper edge. In the guarantee of the integrity of the character informations, the simple de-noising algorithm cannot achieve great results. In order to obtain favorable character recognition results, a complex de-noising algorithm must be designed, which cannot offer a perfect guaranteed result. It is

difficult to eliminate the artifacts nearby the character 'd'. On the other hand, it will undoubtedly increase the difficulty of designing the character recognition system and the recognition time as well as reduce the accuracy of the character recognition. The binary images which are obtained by our algorithm is shown in Fig. 9(b), and the excellent segmentation effect can be obtained by removing few of the isolated noises. Therefore, our algorithm can improve the accuracy of the character recognition and the recognition efficiency in a certain extent.



**Fig. 9.** Character segmentation renderings

## 4.2 The Experiment of the Probability Model

Under the premise that the characters have been trained, after a series of image pre-processing operations including image-graying, binarization, de-noising, smoothing, thinning, single-character segmentation, normalization etc., the character recognition can be carried out.

The test samples of this paper are 10000 test images selected from the NIST special database 19 and 100 handwritten character images collected from 100 people. The Table 2 is obtained by statistical analyzing the five most similar characters which are achieved by the Bayes classifier. The Table 2 shows us that the confusing lowercase and uppercase letters, such as C and c, V and v, Z and z etc., can be distinguished by the Bayes classifier according to their size. Because the image is full filled by the uppercase letters, but there is a great blank area at the top of the images contained the lowercase characters. The Table 3 is obtained by statistical analyzing the easily confusing characters which are achieved by the probability principle based on the similar shapes. The Table 3 shows us that the characters which have the same shape features, such as C and c, K and k etc., may be unable to be identified properly. A comparison with Tables 2 and 3 is made, which shows that the confusing characters of the two methods are scarcely overlapped. Finally, combining with the two methods, the probability model based on Bayes classifier and the principle of similar shapes is tested and analyzed by the confusing characters (each pair of the confusing characters have 100 samples). The results are shown in Table 4, it can be seen that this method has a superior recognition rate for the similar characters.

**Table 2.** Easily confused characters based on the Bayes classifier

1、l、J、I、i、j、7、T、f	2、3
5、S、8	6、b、h、G、k (lowercase letter)、E
A、8、B、6、9、R	a and e、2 and Z
0 (digital)、O (uppercase letter)、U、D、Q	V and U、V and X
r and t、7 and T	P and F、4 and A

**Table 3.** Easily confused characters based on the principle of similar shapes

C and c, K and k, L and l, M and m, N and n, O and o, P and p, S and s, U and u, V and v, W and w, X and x, Y and y, Z and z	
2、Z、z、S、s	b、0(digital)、o、O (uppercase letter)、Q、p
4、b、d、p、P、D、a	9、g、q、a
A and R、C and G、h and n	r、x、X、u、U
V、v、y、Y、J、l (lowercase letter)	S、s、Z、z; f、t、F

**Table 4.** Test results of easily confused characters

Confused character	Recognition rate/%	Confused character	Recognition rate/%	Confused character	Recognition rate/%
1 and l	93	S and 8	100	r and t	96
J and I	95	2 and Z	86	P and F	99
I and T	96	0 and O	85	V and U	96
5 and S	93	O and D	90	O and Q	98
8 and B	96	4 and A	99	i and j	97
C and G	98	9 and g	91	7 and T	93

The simulation is under an Intel Core2 E6550 (2.13 GHz), 4 GB DDR3, a GT 7300 graphics card and a 32-bit Windows 7 operating system. The Table 5 is obtained by testing 10000 images of NIST (among them, Ciresan et al. [16] realize the character recognition based on convolutional neural network(CNNs); Pawar et al. [17] present the extended fuzzy hyperline segment neural network algorithm (EFHLSNN. They all adopt the NIST database. The identify data come from the original experimental section). The Table 6 is obtained by testing 100 handwritten character images. It can be seen that after narrowing the scope of the recognition by the Bayes classifier, the characters are recognized by the principle of similar shapes finally. Our method, compared with the single method, can improve the recognition accuracy of the handwritten characters in the condition of guaranteeing the recognition efficiency. At the same time, this algorithm gains a higher accuracy of character recognition than the CNNs and EFHLSNN algorithms. Due to up to 196 features which extracted in the EFHLSNN algorithm, while there are 19 features in our algorithm, its recognition time is much longer than our algorithm's. Experimental results show that the probability model based on Bayes classifier and the principle of similar shapes, which realizes the

**Table 5.** Recognition accuracy by each algorithm (NIST)

Recognition methods	Recognition rate/%	The average time of single character recognition/ms
Bayes classifier	69.2	142
The principle of similar shapes	58.3	131
CNNs [16]	88.12	NULL
EFHLSNN [17]	76.6	1777
Our algorithm	90.3	155

**Table 6.** Recognition accuracy by each algorithm (actual images)

Recognition methods	Recognition rate/%	The average time of single character recognition/ms
Bayes classifier	63.6	159
The principle of similar shapes	56.7	162
CNNs [16]	83.6	140
EFHLSNN [17]	73.5	1962
Our algorithm	88.3	170

interactive design of different feature extraction methods (statistic features and structure features) and classifiers (the Bayes classifier and the probability method classifier), indeed improve the accuracy of character recognition in the premise of guaranteeing the efficiency.

## 5 Conclusion

In allusion to the two major difficulties in the process of the off-line handwritten character recognition: the binarization processing and the character recognition, this paper proposes the adaptive binarization algorithm based on weighted integral image and the probability model based on Bayes classifier and the principle of similar shapes. A practical system is developed by compiling the source codes, and plenty of images (10000 standard images and 100 actual images) are used in the experiment which can verify the correctness and operability of the theoretical model. The experimental results show that the recognition time is short (single character 155 ms (NIST), 170 ms (the actual images)) and the recognition rate is high (90.3 % (NIST), 88.3 % (the actual images)).

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