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A study on offline handwritten Chinese character recognition based on chaotic iteration

W. B. Yu [1] , T. T. Ma [2,]*

[1,2]Department of Computer Science, Dalian University, University of Technology, China[2,*] yu_wb@126.com[1],17863275955@163.com

A B S T R A C T

Offline handwritten Chinese character recognition technology has important practical value in the field of automatic machine entryomit, and is one of the research hotspots of intelligent technology. In this paper, a handwritten Chinese character feature extraction method based on dynamic system iteration is constructed by using chaos theory. Firstly, from the perspective of system iteration, the Chinese character image is preprocessed to optimize the image information. Secondly, the iterative matrix constructed by the auxiliary function is combined with the handwritten Chinese character image dot matrix to avoid repetiton the discrete dynamic system, and the approximate chaotic attractor is iteratively generated as the image feature. Then, the similarity of the image is determined according to the size of the Pearson correlation coefficient. Finally, multiple auxiliary functions with large differences are selected to generate multiple discrete chaotic dynamic systems. The above operations are repeated, and the unrecognized image set is used as the next data set to be identified. The experimental results show that the recognition algorithm has achieved good recognition results on the HCL2000 Chinese character database.

Keywords: *chaotic attractor;offline handwritten Chinese character recognition; dynamical system; iteration;feature extraction.*

1. Introduction

So far, offline handwritten Chinese character recognition research has important theoretical significance and practical value in many fields,such as finance, government, healthcare and education, such as office automation, test paper correction, signature scanning recognition, insurance and card identification. Although some progress has been made by deep learning and other methods[1-6], it is valuable to conduct further study on handwritten Chinese characters because they characterized by a large number of classifications, many stylistic differences, and many morphological similarities, which makes handwritten Chinese character recognition extremely difficult. Currently, handwritten Chinese character recognition can be divided into offline and online handwritten Chinese character recognition[7]. As shown in Figure 1.

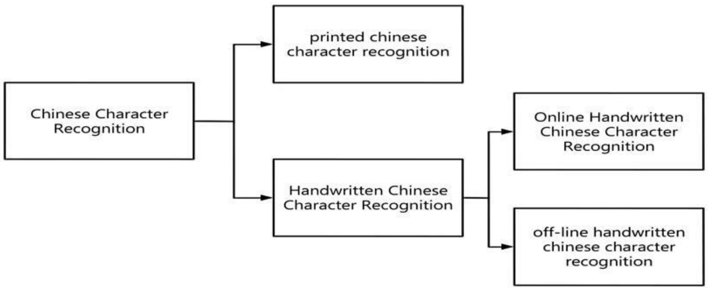

Figure 1 Classification of Chinese Character Recognition

The Chinese character recognition method mainly extracts the structural features or statistical features of the image to represent the image information. The structural features include the analysis and extraction of the feature points, isolated points, strokes and whether there are closed strokes[8]. The statistical features include Gabor [9], gradient [10] and directional features. These two methods have their own advantages and disadvantages, but the practicality is still lacking. In order to improve the shortcomings of traditional methods, classifier models and artificial neural networks have also been proposed, such as improved quadratic discriminant function[11] (MQDF), support vector machine[12] (SVM), and so on.

With the solution of the over-fitting problem of neural network training and the high theoretical exploration value of deep learning in many fields, it has received extensive attention. At present, deep learning models can achieve significantly better than traditional methods in the field of handwritten Chinese character recognition are mainly based on Convolutional Neural Network (CNN) and its various improved methods[13]. It is worth noting that some methods now combine attention mechanisms with deep neural networks[14-15].

Although the research of deep learning in the field of Chinese character recognition has obtained recognition rates far exceeding those of traditional methods, demonstrating the great potential of deep learning[16], many existing methods still have problems such as numerous parameters, large arithmetic volume, large and relatively complex model architecture, large required storage capacity, long training time, and high environmental requirements for experiments[17].

It is noteworthy that some scholars have recently investigated the use of approximate chaotic attractors of images as image features for image recognition. For example, literature[18] based on the existing methods, used Euler's method to iterate and employed the obtained approximate attractors as image feature dots, and the recognition accuracy was 70.91% in Yalefaces face database. Then by changing to spline interpolation to get the attractor data as well as taking the mean value and grayscale automatic adjustment after obtaining the Radon data of the same group of images, the original method image is too smooth and the sequence is caught in the cycle point while other problems are improved, and the recognition accuracy reaches 87.33%. Literature[19] uses the discrete cosine transform basis function matrix as an auxiliary function to construct a dynamical system with video images and found that the approximate attractor obtained can be used as a basis for video image segmentation. It was also found that the original image can be reconstructed by using multiple DCT basis function matrices to construct the dynamical system with the same image separately to generate multiple approximate attractors. Literature[20] proposes a chaos-based local descriptor for texture recognition technique, which applies chaotic mapping to the three-dimensional representation of an image, remaps the mapping results after each iteration into the image space, and calculates the distribution of local descriptors to compose representative feature vectors, and the results obtained confirm that chaos theory can be used for image recognition. Literature[21] studies and analyzes the diversity and oscillatory properties of the DCT basis function matrix, and then constructed a dynamical system using multiple auxiliary functions with chunked face images, which were synthesized together after obtaining multiple attractors through an iterative algorithm for face image recognition. The method can be close to 100% recognition rate for multiple generalized image libraries with each image participating in the training, and the algorithm is simple and the time used for training and recognition is short. Yu et al., the authors of the literature[18,19,21], applied the iteration-based face recognition method to handwritten Chinese character recognition, for example, in the literature[22], a linear combination of cosine function is used as an auxiliary function to construct a discrete dynamical system with the image, and the iterative trajectory of the image is extracted as the feature matrix of the image to carry out the research related to the recognition of Chinese characters. In view of the fact that there are many differences between handwritten Chinese character images and face images, it is proposed to solve the convergence problem of the system by adding beveled surfaces, shifting superposition, and constructing font surfaces, among others.

Although the applications based on chaos theory are become more and more widespread[23-25], there are relatively few explorations of the idea of pattern recognition[26-27], so there is still a lot of research space of the complete combination of iterative chaotic attractor characterization of image features and image recognition[28]. We propose on the basis of existing algorithms:

In an iterative manner, the matrix constructed by some new auxiliary functions is used to construct a discrete dynamical system with the handwritten Chinese character image dot matrix, and then the approximate attractor is obtained and used as the handwritten Chinese character image feature matrix. Specifically:

(1) Improve the problem of system convergence due to the large flat area of the image by cropping the edges, adjusting the gradient of the font pixel values, and other operations, and increasing the number of iterations so that its feature matrix can describe the image information more comprehensively.

(2) Select a number of auxiliary functions with strong differences used with the Chinese character images for constructing the power system respectively, and use the image set that is not recognized successfully each time for the next recognition of the to-be-operated dataset, and recycle the recognition many times.

2. Iterative dynamical system construction and analysis

In addition to symbolic functions, many other complex functions such as exponential, trigonometric and hyperbolic functions can be used to construct chaotic systems[29]. Construct the dynamical system shown in equation (1):

$$\begin{cases} Z_1 = f(u,v) \\ Z_2 = g(u,v) \end{cases} \tag{1}$$

Where, $f(u,v)$is the auxiliary function, $g(u,v)$is the grayscale image; $Z_2$is the pixel point value (grayscale value) of the image at point (u,v).

In this paper, we will use an iterative approach, that is, given the initial value of u, v, bring it into the (1) equation for iteration, to get the iterative trajectory (Z_1, Z_2), record the point and use $Z_1$and Z_2as the new values of u, v, respectively, and then substitute into the (1) equation, you can get a new (Z_1,Z_2), and so on to repeat the above operation.

2.1 Selection of auxiliary functions

In order to obtain the image feature information as comprehensively as possible, a total of five recognitions are carried out in this study, and the two-dimensional auxiliary functions with large differences are chosen for each of the five times. As shown in equation (2).

$$\begin{cases} Z_1 = 0.1x + 0.9y \\ Z_2 = 0.4x + 0.6y \\ Z_3 = 0.9x + 0.1y \\ Z_4 = xy \\ Z_5 = 0.5(x^2 + y^2) \end{cases} \tag{2}$$

where $1 \le x, y \le 64$. The three-dimensional images of the five functions in the range of their defining domains are shown in Figure 2. The images of the functions projected on the X and Y coordinate axes are shown in Figure 3.

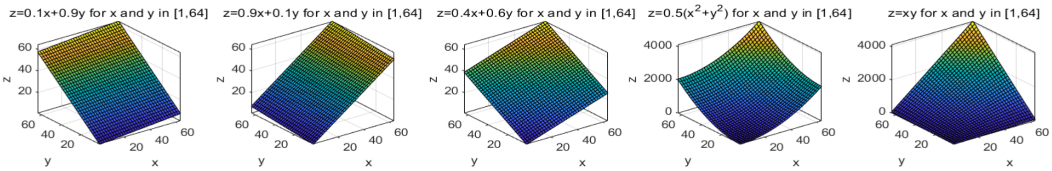

Figure 2 3D images of auxiliary functions

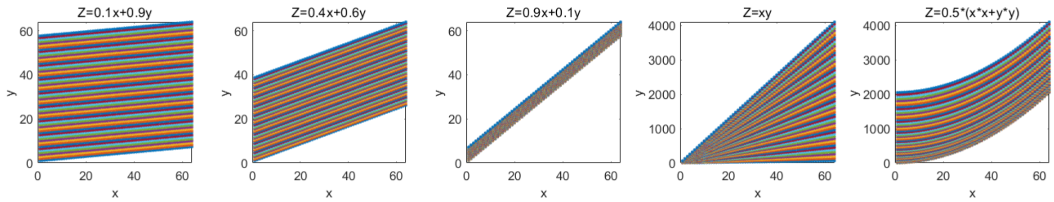

Figure 3 Plot of plane projection of auxiliary function

The five functions in the formula (2) are used to construct the dynamic system with the handwritten Chinese character image, and the features are extracted iteratively. These five functions have their own characteristics, and are all planes passing through the origin of the coordinates, but the slopes (partial derivatives) are different, so when iterating, different features of the image can be extracted ; they are all surfaces, the former is hyperboloid, and the latter is spherical. When iterating, the feature points obtained are different. There are 5 auxiliary functions, and the feature point sets obtained are different, which is exactly what is needed for recognition.

2.2 Image Preprocessing

In the experimental process, it is found that: due to the handwritten Chinese character image exists a large flat area as well as the pixel value is too concentrated and other problems, which leads to the poor chaotic characteristics of the dynamical system, the system is easy to converge, so when the initial value (u, v) is relatively small and the number of iterations is high,when the sequence points obtained are less, and can not get a better sequence of iterative trajectories. In order to avoid the system converging too quickly to the point that the number of approximate attractor points is too small, some relevant processing is performed on the image of Chinese characters to maximize the use of various image information, so that the feature matrix (attractor) can more avoid repetition characterize the image, and also to facilitate the subsequent operations on the image. The main steps include:

1. Crop the image

Through the loop, the white edges around the original image are partially intercepted, and after cropping, the image is expanded to its original size (e.g., 64×64) and normalized with the help of bilinear interpolation.

2. Black and white area gradient adjustment

Each image is traversed by rows and the black and white regions of the target image are adjusted separately to adjust the continuous blank blocks as well as the pixel values of the black portion to resemble a hill-like shape to improve the problem of overly flat pixel values of the image. Firstly, the position information of the start point of the black part and the terminal of the black part is recorded, and secondly, the pixel value of the white area is adjusted first, and then the gradient value of the black part is adjusted.

(1) White part

Due to the singularity of the gray value of the blank area, the blank area with more than three consecutive points is adjusted, i.e., the value of this part of the pixel point is uniformly adjusted as a smooth rise from 0 to the middle, and then smoothly lowered to 0.

(2) Black part

On the basis of the processing of the white part, the value of the pixel point of the black part is substituted into the sine trigonometric function, and the value obtained is used as the new pixel value of the point.

Taking the first image of Figure 4 as an example, the pixel plane distribution map obtained after the above operation is shown in Figure 4, and the pixel three-dimensional distribution map is shown in Figure 5.

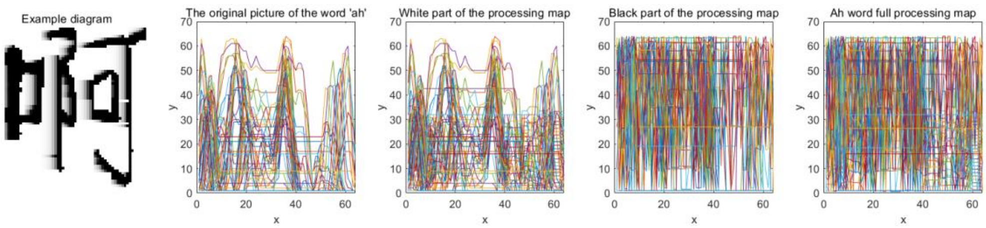

Figure 4 Plan view of Chinese character pixel distribution

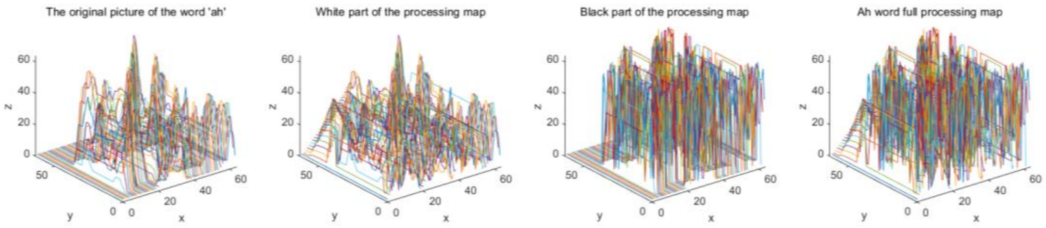

Figure 5 Three-dimensional map of the distribution of Chinese character pixels

Among them, the first image in Figure 4 is the cropped image, the second image is the original pixel distribution map of the cropped image, the third image is the distribution map obtained after processing the white part of the first image, the fourth image is the distribution map after processing the black part of the first image, and the fifth image is the pixel distribution map obtained after processing the whole (black + white) of the first image. Figure 5 is the three-dimensional distribution maps of the pixels corresponding to the second to the fifth images in Figure 4.

The experimental results show that through the above operation, the number of iterations and the number of iterative trajectory points are significantly increased, which effectively improves the problem of fast convergence of the system iteration caused by the large area flatness of the image, and then improves the efficiency of offline handwritten Chinese character recognition.

2.3 Image feature point set extraction

Algorithm 1. Extract image feature point set
Input: matrix of offline handwritten Chinese character images
Output: Matrix of positional information for the start and end points of the black section

```
1.  for x=0:63
          for y=0:63
              A1(x+1,y+1)=f(x, y);        %f(x, y)is an auxiliary function
          end
    end
   Maximum-minimum normalization of the A1 matrix yields the A2 matrix2;
2.  yii=zeros(c1,64,64);
    for jj=1:c1
      for ii=1:c2
          Read the handwritten Chinese character image;
            Crop the edges and curvature adjustment to get the matrix H;
              yi=zeros(c1,64,64);
              for uj=1:2:64
                for vj=1:2:64
                  u=uj;v=vj;
                  if u>0 && u<=64
                    if v>0 && v<=64
                      for i=1:2
```

```
                z1=A2(u,v);
                z2=H(u,v);
                u=z1;v=z2;
                yi(jj,u,v)=1;
              end
            end
          end
        end
      end
      yii(jj,:,:)=yii(jj,:,:)+yi(jj,:,:);
    end
end
```

3. Keep the points for which yii iterates more than K times and set their point value to 1 and the rest to 0;

Three Chinese characters are randomly selected in the HCL2000 data set as an example, and they are iterated using these five auxiliary functions to generate a comprehensive feature point distribution map, as shown in Figure 6.

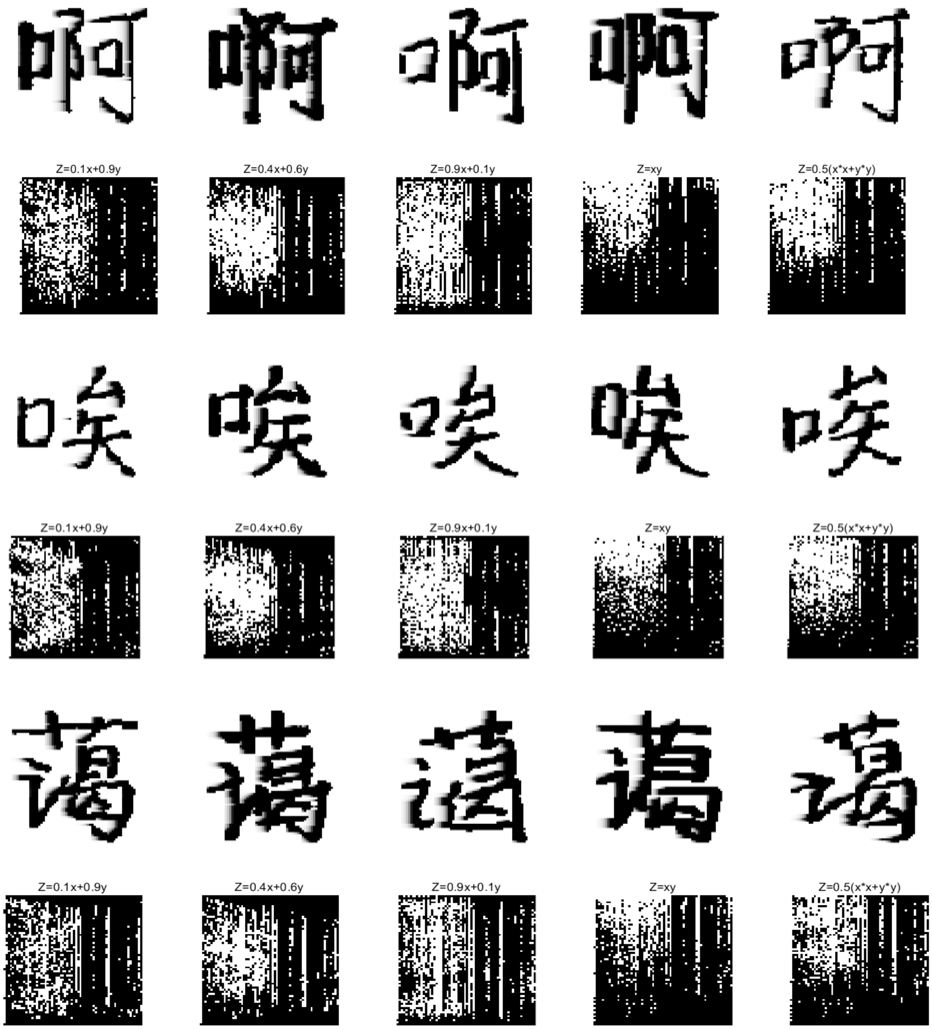

Figure 6 Distribution of feature points generated by the original handwritten Chinese characters and different auxiliary functions

The nature of the auxiliary function affects the motion trajectory of the iteration of the dynamical system and determines the final result of the chaotic dynamical system.

By observing the above images, we can easily see that for the same Chinese character, there are obvious differences in the chaotic attractors generated by iterating different linear functions as auxiliary functions. Because the gray values of the handwritten Chinese character images are used as the column coordinates of the feature points (matrix) during the iteration, and because their gray values are more when they are small, the white points of the feature point matrix are mostly concentrated on the left side. Therefore, this method can be used to characterize handwritten Chinese character image features and is suitable for offline handwritten Chinese character recognition research.

3. algorithm design

Proven by experiments, it is proved through experiments that it is not very effective to experiment directly by constructing the dynamical system with the function expression and image function, but the effect will be improved a lot by using the iterative assignment of the function expression and the iterative matrix obtained with the image to construct the dynamical system. This method is used to construct the dynamical system. The specific algorithm is shown below.

Algorithm 2. Handwritten Chinese Character Recognition Algorithm with a Single Auxiliary Function

```
1.   for x=0:63
         for y=0:63
             A1(x+1,y+1)=f(x, y);          %f(x, y)is an auxiliary function
         end
     end
       The A1 matrix is normalized to produce the A2 matrix;
       yii=zeros(c1,64,64);
2.  %The training process
       for jj=1:5        %number of written characters
           for ii=1:10     %number of people
                 Read the handwritten Chinese character image;
                 Crop the edges and curvature adjustment to get the matrix H;
                %Iterative generation of chaotic attractors
                 yi=zeros(c1,64,64);
                 for uj=1:2:64
```

```
                    for vj=1:2:64
                       u=uj;v=vj;
                       if u>0 && u<=64
                          if v>0 && v<=64
                             for i=1:2
                                z1=A2(u,v);
                                z2=H(u,v);
                                u=z1;v=z2;
                                yi(jj,u,v)=1;
                             end
                          end
                        end
                    end
                 end
                 yii(jj,:,:)=yii(jj,:,:)+yi(jj,:,:);
              end
   end
```

Filtering feature points in yii that match the condition (yii > k);

3. %The identification process

```
   RaN=zeros(N1,N2,64,64);
   for jjN=1:5                 %number of written characters
      for iiN=10:20            %number of people
         Read the handwritten Chinese character image;
         crop the edges and curvature adjustment to get the matrix HN;
         %Iterative generation of chaotic attractors
               for ui=1:2:64
                  for vi=1:2:64
                     uN=ui;vN=vi;
                     if uN>0 && uN<=64
                        if vN>0 && vN<=64
                           for iN=1:2
                              z1N=A2(uN,vN);
                              z2N=HN(uN,vN);
```

```
                    uN=z1N;vN=z2N;
                    RaN(jjN,iiN,uN,vN)=1;
                  end
                end
              end
            end
          end
        end
      end
```

The identification is accomplished by calculating the correlation coefficients of the H and HN matrices;

Algorithm 3. Comprehensive Recognition Algorithm with Multiple Auxiliary Functions

1. for x=0:63

    for y=0:63

      A11(x+1,y+1)=f(x, y);   %f(x, y)is an auxiliary function

    end

  end

  Training feature point set;

  Extract the feature point set of the image to be recognized;

  Calculate the correlation coefficient and store the number of the successfully recognized image in the M1 matrix;

2. for x=0:63

    for y=0:63

      A11(x+1,y+1)=f(x, y);   %f(x, y)is an auxiliary function

    end

  end

  Training feature point set;

  Extract the feature point set of the remaining images to be recognized after excluding the images that have been recognized successfully;

  Calculate the correlation coefficient and store the number of successfully recognized images in the M2 matrix;

Repeat the above steps, For example: the first auxiliary function using $Z_1 = 0.1x + 0.9y$; the second auxiliary function using $Z_2 = 0.4x + 0.6y$; the third auxiliary function using $Z_3 = 0.9x + 0.1y$; the fourth auxiliary function using $Z_4 = xy$;.The fifth auxiliary function using $Z_5 = 0.5(x^2 + y^2)$.Among them,$1 \leq x, y \leq 64$.

Among them, algorithm 3 is based on algorithm 2, by changing the feature point set with large difference generated by the iteration of the auxiliary function, and with the help of the difference complementarity between these lattices, the comprehensiveness of feature extraction of the target image is improved as much as possible.

Pearson's correlation coefficient is calculated by using corrected function in Matlab as a way to discriminate the similarity between images. The number of successfully recognized images is recorded and compared with the total number of samples to calculate the recognition rate.

4. Experimental results and analysis

4.1.Experimental data

The dataset used in this experiment is the HCL2000 Chinese character database. The image data of handwritten Chinese characters in this database are organized and stored in a writer-oriented manner. The sampled data are 3755 level 1 Chinese characters of GB2312-80. Each of them has a 512-byte file header to store the relevant information of the file. These digital images are standardized into 64×64-sized dot matrix, and the dots are stored by bit and compressed to 512 bytes during the storage process. The sample is shown in Figure 7 below.

Figure 7 Sample HCL2000 dataset

4.2. Experimental results

This experiment uses MATLAB to realize the experimental simulation. The training and to-be-recognized data parameters are changed several times to count the number of recognitions and calculate the recognition rate. The specific experimental results are shown in Table 1.

(1) Training: takes the first 20 Chinese characters written by the first N people for training, and get the comprehensive feature matrix

Recognition: modify the number of people to be recognized several times, and recognize the first 20 Chinese characters written by each person

(2) Training: takes the first N Chinese characters written by the first 10 people for training, and get the comprehensive feature matrix

Recognition: modify the number of characters to be recognized several times, and recognize the first N characters written by each person

(3) Training: take the first 20 Chinese characters written by the first N people for training, and get the comprehensive feature matrix

Recognition: modify the number of people to be recognized several times, and recognize the first 20 Chinese characters written by each person

(4) Training: take the first N Chinese characters written by the first 20 people for training, and get the comprehensive feature matrix

Recognition: modifies the number of people to be recognized several times, and recognize the first N characters written by each person.

Table 1 Experimental results

Sample data	**Sample statistics**	**recognize**	**Recognition rate**
1st-20th words for 11th-30th persons	400	353	88.25%
1st-20th words of 11th-50th persons	800	686	85.75%
1st-20th words of 11th-100th persons	1800	1516	84.22%

(1)

Sample data	**Sample statistics**	**recognize**	**Recognition rate**
1st-100th words for 11th-30th persons	2000	1253	62.65%
1st-150th words of 11th-30th persons	3000	1664	55.47%
1st-200th words of 11th-30th persons	4000	2072	51.80%

(2)

Sample data	**Sample statistics**	**recognize**	**Recognition rate**
1st-20th words for 21th-40th persons	400	355	88.75%
1st-20th words of 21th-60th persons	800	699	88.88%
1st-20th words of 21th-110th persons	1800	1588	88.22%

(3)

Sample data	**Sample statistics**	**recognize**	**Recognition rate**
1st-100th words for 21th-40th persons	2000	1442	72.10%
1st-150th words of 21th-40th persons	3000	1961	65.37%
1st-200th words of 21th-40th persons	4000	2409	60.23%

(4)

5. Conclusions and outlook

In this paper, different auxiliary functions are used several times with offline handwritten Chinese character images to construct a discrete dynamical system, and the chaotic attractors generated by iteration are used as image features in the field of offline handwritten Chinese character image recognition, which can minimize the time of training and its arithmetic volume, that leads final training to have better results The above analysis shows that the algorithm is suitable for image recognition problems that the system iteration converges too fast due to the excessive concentration of image pixel value distribution, such as black and white Chinese characters, black and white English, etc.This method is also an expansion of chaos theory for offline handwritten Chinese character recognition. However, since there is still room to improve the recognition rate of the algorithm, it is necessary to continue to improve the algorithm or expand the method to other research areas in the future.

References

[1] Li, Y., Yang, Q., Chen, Q., Hu, B., Wang, X., Ding, Y., & Ma, L. (2022). Fast and Robust Online Handwritten Chinese Character Recognition with Deep Spatial & Contextual Information Fusion Network. *IEEE Transactions on Multimedia*.

[2] Guo H, Liu Y, Zhao J, Song Y. Offline handwritten Tai Le character recognition using wavelet deep convolution features and ensemble deep variationally sparse Gaussian processes[J]. Soft Computing, 2023: 1-17.

[3] Dan, Y., & Li, Z. (2023). Particle Swarm Optimization-based Convolutional Neural Network for Handwritten Chinese Character Recognition. *Journal of Advanced Computational Intelligence and Intelligent Informatics*, *27*(2), 165-172.

[4] Wang, T. Q., Jiang, X., & Liu, C. L. (2022). Query pixel guided stroke extraction with model-based matching for offline handwritten Chinese characters. *Pattern Recognition*, *123*, 108416.

[5] Peng, D., Jin, L., Liu, Y., Luo, C., & Lai, S. (2022). Pagenet: Towards end-to-end weakly supervised page-level handwritten chinese text recognition. *International Journal of Computer Vision*, *130*(11), 2623-2645.

[6] Alnaasan, M., & Kim, S. (2023). Handwritten Multi-Scale Chinese Character Detector with Blended Region Attention Features and Light-Weighted Learning. *Sensors*, *23*(4), 2305.

[7] Li Yangjuan. Analysis of Research Progress in Chinese Character Recognition Technology [J] Technology and Industry, 2022, 22 (4): 180-187 DOI: 10.3969/j.issn.1671-1807.2022.04.029.

[8] Chang Qinghe, Wu Minhua, Luo Liming. Handwritten Chinese character skeleton extraction based on improved ZS refinement algorithm [J] Computer Applications and Software, 2020,37 (7): 107-113164 DOI: 10.3969/j.issn.1000-386x.2020.07.017.

[9] Alam, N. A., Ahsan, M., Based, M. A., & Haider, J. (2021). Intelligent system for vehicles number plate detection and recognition using convolutional neural networks. *Technologies*, *9*(1), 9.

[10] Xu, S., Liu, S., Wang, H., Chen, W., Zhang, F., & Xiao, Z. (2020). A hyperspectral image classification approach based on feature fusion and multi-layered gradient boosting decision trees. *Entropy*, *23*(1), 20.

[11] Wei, X., Lu, S., & Lu, Y. (2018). Compact MQDF classifiers using sparse coding for handwritten Chinese character recognition. *Pattern Recognition*, *76*, 679-690.

[12] Zhao Huan, Liu Xuhong, Li Ning . Research on Chinese Character Font Recognition Based on SVM [J] Journal of Beijing University of Information Technology (Natural Science Edition), 2017,32 (5): 62-66 DOI: 10.16508/j.cnki.11-5866/n.2017.05.012.

[13] Melnyk, P., You, Z., & Li, K. (2020). A high-performance CNN method for offline handwritten Chinese character recognition and visualization. *soft computing*, *24*(11), 7977-7987.

[14] Wang, Y., Yang, Y., Ding, W., & Li, S. (2021). A residual-attention offline handwritten Chinese text recognition based on fully convolutional neural networks. *IEEE Access*, *9*, 132301-132310.

[15] Yuan Jian, Zhang Haibo. A Chinese Entity Recognition Model Based on Multi granularity Fusion Embedding [J] Small Micro Computer Systems, 2022, 43 (4): 741-746,DOI: 10.20009/j.cnki.21-1106/TP.2020-0972.

[16] Cheng Ruoran, Zhou Haojun, Liu Lulu, He Yan. Improving Offline Handwritten Chinese Character Recognition on MobileNetV3 [J] Intelligent Computers and Applications, 2022, 12 (7): 160-164,DOI: 10.3969/j.issn.2095-2163.2022.07.029

[17] Geng Sumin, Zheng Kaidong. Chinese Character Recognition Based on Deep Learning [J] Information Technology and Informatization, 2022 (10): 208-211.DOI: 10.3969/j.issn.1672-9528.2022.10.050

[18] Yu Wanbo, Wang Daqing .The Chaotic Characteristics of Surface Iteration and Its Application in Face Recognition [J] Journal of Computer Aided Design and Graphics, 2015 (12): 2264-2271 DOI: 10.3969/j.issn.1003-9775.2015.12004.

[19] Yu Shuo, Li Sisi, Yu Wanbo. Extraction and Expression of Chaotic Patterns in Image Data [J] Microcomputers and Applications, 2016,35 (18): 39-41,44.DOI: 10.19358/j.issn.1674-7720.2016.18.11.

[20] Florindo, J. B. (2021). Reorganizing local image features with chaotic maps: an application to texture recognition. *Multimedia Tools and Applications*, *80*(19), 29177-29197.

[21] Yu Wanbo, Wang Xiangxiang, Wang Daqing. Facial image recognition based on discrete cosine transform basis function iteration [J] Journal of Graphics, 2020,41 (1): 88-92. DOI: 10.11996/JG.j.2095-302X.2020010088.

[22] Wan-bo, Y., Xiang-xiang, W. A. N. G., & Da-qing, W. A. N. G. (2020). Face image recognition based on basis function iteration of discrete cosine transform. *Journal of Graphics*, *41*(1), 88.

[23] Sun, L., Lin, H., Yu, W., & Zhang, Y. (2022). Application of feature extraction using nonlinear dynamic system in face recognition. *Evolving Systems*, 1-14.

[24] Bellmann, P., Thiam, P., Kestler, H. A., & Schwenker, F. (2022). Machine learning-based pain intensity estimation: Where pattern recognition meets chaos theory—an example based on the biovid heat pain database. *IEEE Access*, *10*, 102770-102777.

[25] Gao, S., Wu, R., Wang, X., Liu, J., Li, Q., & Tang, X. (2023). EFR-CSTP: Encryption for face recognition based on the chaos and semi-tensor product theory. *Information Sciences*, *621*, 766-781.

[26] Li, N., Wu, Z., Lin, X., Tang, X., Xia, G., & Deng, T. (2021). Bidirectional digital image secure transmission and recognition based on a long-distance chaos synchronization system with machine learning capability. *Nonlinear Dynamics*, *104*, 2745-2758.

[27] Wang Haoshi .Research on Chaotic Attractors of Images (D) Jilin University, 2015.

[28] Yu, W. B. (2017, December). Application of chaos in image processing and recognition. In *2017 International Conference on Computer Systems, Electronics and Control (ICCSEC)* (pp. 1108-1113). IEEE.

[29] Yu, W., Chen, X., & Li, X. (2023). An Image Recognition Method Based on Dynamic System Synchronization. *Recent Advances in Computer Science and Communications (Formerly: Recent Patents on Computer Science)*, *16*(6), 37-43.