第45卷第4期 中国科学技术大学学报 Vol. 45, No. 4
2015年4月 JOURNAL OF UNIVERSITY OF SCIENCE AND TECHNOLOGY OF CHINA Apr. 2015

文章编号:0253-2778(2015)04-0321-08

Recognition of ancient Chinese characters based on hybrid kernel WLS-SVR

HU Gensheng[1], SUN Yingying[1], XU Lingying[2], LIANG Dong[1], SUN Xiaoqi[1]

(1. *School of Electronics and Information Engineering, Anhui University, Hefei* 230601, *China*;
2. *Editorial Department of Anhui University, Hefei* 230039, *China*)

Abstract: The shapes of ancient Chinese characters are often uncertain, which reduces the accuracy of recognition by many classifiers. To solve this problem, a new recognition algorithm combining adaptive weighted least squares support vector regression (WLS-SVR) with hybrid kernel function was proposed to recognize ancient Chinese characters. The weight coefficients of WLS-SVR decayed at a rate of the exponential function of prediction errors. The hybrid kernel was constructed using the wavelet kernel function with local properties and RBF kernel function with global properties. For feature extraction, global point density and component structure are fused with local features of pseudo 2D elastic mesh and local point density. Experiment results show the good robustness and high recognition accuracy of the proposed method.

Key words: ancient Chinese characters recognition; WLS-SVR; hybrid kernel; feature fusion

CLC number: TP18 **Document code**: A doi: 10.3969/j.issn.0253-2778.2015.04.010

Citation: HU Gensheng, SUN Yingying, XU Lingying, et al. Recognition of ancient Chinese characters based on hybrid kernel WLS-SVR[J]. Journal of University of Science and Technology of China, 2015, 45(4): 321-328.
胡根生,孙莹莹,徐玲英,等. 基于混合核 WLS-SVR 的古汉字识别[J]. 中国科学技术大学学报,2015,45(4):321-328.

基于混合核 WLS-SVR 的古汉字识别

胡根生[1],孙莹莹[1],徐玲英[2],梁 栋[1],孙小棋[1]

(1. 安徽大学电子信息工程学院,安徽合肥 230601;2. 安徽大学学报编辑部,安徽合肥 230039)

摘要:针对现有多种分类器对具有不确定字形的古汉字识别精度不高的问题,提出了一种基于混合核加权最小二乘支持向量回归(WLS-SVR)的古汉字识别算法. WLS-SVR 的权重系数采用预测误差的指数衰减函数,混合核是由具有良好局域特性的小波核函数与具有良好全局特性的 RBF 核函数构成. 在特征提取阶段,由于全局点密度与部件结构具有全局特征,而伪二维弹性网格与局部点密度具有局部特征,因此融合了古汉字的全局和局部特征. 仿真实验表明,该算法具有较高的准确率与良好的鲁棒性.

关键词:古汉字识别;WLS-SVR;混合核;特征融合

Received: 2014-06-10; **Revised**: 2014-12-29

Foundation item: Supported by the National Natural Science Foundation of China (61172127), Natural Science Foundation of Anhui Province (1408085MF121).

Biography: Hu Gensheng (corresponding author), male, born in 1971. PhD/ associate professor. Research field: Machine learning, remote sensing image processing and intelligent algorithm. E-mail: hugs2906@sina.com

0 Introduction

Ancient Chinese characters recorded a large amount of political, economic and historical data and so on, and thus have a very high historical value. Ancient Chinese characters are always appeared in the forms of inscription and handwriting, these characters' strokes are very different from the current printed characters. Furthermore, many existing ancient Chinese characters are deformed or incomplete, making them hard to read or recognize. Therefore it is of great significance to recognize ancient Chinese characters and realize the digital management of classical Chinese literature by using modern recognition technology [1].

Lv et al. [2] proposed the Fourier descriptor-FDCH based on curvature histogram to classify inscriptions on bones. Since the inscriptions on bones are pictographic, the curvature based method proved to be practical. However, the algorithm includes the search for a character's center of gravity. The recognition rate is high for single structure characters, but for the left-right or up-down structure characters, the recognition rate is low.

Chen et al. [3] proposed a method to extract features of inscriptions on bones based on the cross points of strokes and the relative positions of characters. However, it is difficult to recognize characters with a particularly large number of strokes using such features.

Many characteristics of ancient Chinese characters, such as irregular strokes, variant forms, deformity or incompleteness, indicate that the optical OCR system for the recognition of modern Chinese characters isn't suitable for recognizing ancient Chinese characters[4], which is a difficult problem in the field of pattern recognition.

Support vector machine (SVM), proposed by Vapnik et al. [5], has good generalization ability and learning performance. It has been widely used in fields of classification, function estimation, density estimation and so on. SVM needs to solve a model of quadratic programming. Suykens et al. proposed least squares support vector machine (LS-SVM) by using square loss function instead of ε insensitive loss function [6-8]. LS-SVM reduces the computational complexity by solving a model of linear programming. Although LS-SVM has solved the computational complexity of SVM, it loses the sparsity and robustness of SVM [9-12]. This paper proposes a classification algorithm that combines adaptive weighted least squares support vector regression with hybrid kernel function for ancient Chinese character recognition. The proposed algorithm has the advantages of high robustness and low computational complexity, thus improving the accuracy of recognition.

1 Hybrid-kernel WLS-SVR

LS-SVR can be expressed as the following optimization problem:

$$\min J(\boldsymbol{\omega},\boldsymbol{e}) = \frac{1}{2}\boldsymbol{\omega}^{\mathrm{T}}\boldsymbol{\omega} + \frac{1}{2}\gamma\sum_{i=1}^{N} e_i^2$$
$$\text{s.t.}\quad y_i = \boldsymbol{\omega}^{\mathrm{T}}\boldsymbol{\varphi}(x_i) + \boldsymbol{b} + e_i,\ i = 1,\cdots,N \tag{1}$$

where $\boldsymbol{\omega}$ is the weighted vector, γ is the balance constant, $\boldsymbol{\varphi}$ is a map function and $e_i (i = 1,\cdots,N)$ is the estimation error for the ith sample. Eq. (1) can be converted into the following form by Lagrange multiplier and matrix transformation method:

$$\begin{bmatrix} 0 & 1_v^{\mathrm{T}} \\ 1_v & \boldsymbol{\Omega} + \frac{1}{\gamma}\boldsymbol{I} \end{bmatrix} \begin{bmatrix} \boldsymbol{b} \\ \boldsymbol{\alpha} \end{bmatrix} = \begin{bmatrix} 0 \\ \boldsymbol{y} \end{bmatrix} \tag{2}$$

where $\boldsymbol{y} = [y_1,\cdots,y_N]^{\mathrm{T}}$ is sample output vector, $1_v = [1,\cdots,1]^{\mathrm{T}}$, $\boldsymbol{I} = \mathrm{diag}\{1,\cdots,1\}$, $\boldsymbol{\alpha} = [a_1,\cdots,a_N]^{\mathrm{T}}$ is Lagrange multiplier, and $\boldsymbol{\Omega}$ is kernel matrix, $\boldsymbol{\Omega}_{ij} = \boldsymbol{\varphi}(x_i)^{\mathrm{T}}\boldsymbol{\varphi}(x_j) = \boldsymbol{K}(x_i,x_j)$ for $i,j = 1,\cdots,N$. By solving Eq. (2), the prediction function can be obtained and has the following form:

$$\boldsymbol{y}(x) = \sum_{i=1}^{N} a_i \boldsymbol{K}(x,x_i) + \boldsymbol{b} \tag{3}$$

The basic idea of WLS-SVM [13] is that a weighted factor ω_i will be given to the corresponding error variable e_i of each sample x_i. The optimization problem changes to

$$\left.\begin{aligned} &\min J^*(\boldsymbol{\omega}^*, \boldsymbol{e}^*) = \frac{1}{2}\|\boldsymbol{\omega}^*\|^2 + \frac{1}{2}\boldsymbol{C}\sum_{i=1}^{N}\boldsymbol{\omega}_i\boldsymbol{e}_i^{*2} \\ &\text{s. t. } y_i = \boldsymbol{\omega}^{*\mathrm{T}}\boldsymbol{\varphi}(x_i) + \boldsymbol{b}^* + \boldsymbol{e}_i^*, i = 1, \cdots, N \end{aligned}\right\} \tag{4}$$

Using the Lagrange multiplier method and according to the KKT conditions, the dual problem of Eq. (4) can be expressed as:

$$\begin{bmatrix} 0 & 1_v^{\mathrm{T}} \\ 1_v & \boldsymbol{\Omega} + \boldsymbol{V}_r \end{bmatrix}\begin{bmatrix} \boldsymbol{b} \\ \boldsymbol{\alpha} \end{bmatrix} = \begin{bmatrix} 0 \\ \boldsymbol{y} \end{bmatrix} \tag{5}$$

where the matrix $\boldsymbol{V}_r = \operatorname{diag}\left\{\frac{1}{C\omega_1}, \cdots, \frac{1}{C\omega_N}\right\}$. In this paper, the weighted factor ω_i is constructed as:

$$\boldsymbol{\omega}_i = e^{-\left|\frac{e_i}{s}\right|} \tag{6}$$

where $s = \frac{\mathrm{IQR}}{2 \times 0.6745}$. IQR is the quartile of sample error. The proposed weighted factor decays with the exponential function of prediction errors. We can see from Fig. 1 that larger error corresponds to smaller weight. Thus the effect of the error and noise to the model can be reduced.

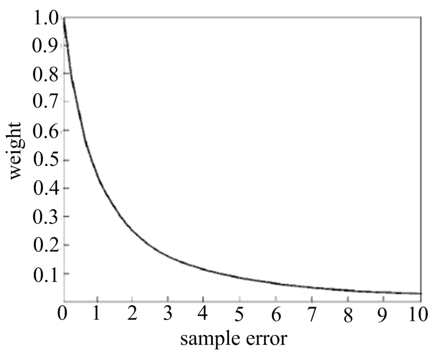

Fig. 1 Schematic diagram of the relationship between weighted factors and prediction errors

The performance of WLS-SVM is greatly influenced by the selection of kernel function. RBF kernel function is defined as follows:

$$K_{\mathrm{RBF}}(x_i, x) = \exp\left(-\frac{\|x - x_i\|^2}{2\sigma^2}\right) \tag{7}$$

RBF kernel function has good global properties, so it has a strong learning ability for adjacent samples. Wavelet kernel function is defined as follows:

$$K_{\mathrm{wav}}(x, x') = \prod_{i=1}^{N} h\left(\frac{x_i - x_i'}{\alpha}\right) = \prod_{i=1}^{N}\left(1 - \frac{(x_i - x_i')^2}{a_i^2}\right)\exp\left(-\frac{\|x_i - x_i'\|^2}{2a_i^2}\right) \tag{8}$$

which has good local properties. Wavelet kernel function is sensitive to local singularities.

A single kernel function is restricted in aspects of prediction accuracy and generalization. This paper constructs a hybrid kernel [14] by combining wavelet kernel function with RBF kernel function as follows:

$$K(x_i, x) = \beta K_{\mathrm{wav}}(x_i, x) + (1 - \beta)K_{\mathrm{RBF}}(x_i, x) \tag{9}$$

where β is a weighted factor.

2 Feature extraction

Due to the randomness and irregularity of ancient Chinese characters, recognition based on a single feature leads to a high rate of misclassifications. Multi-feature fusion can optimize feature vectors and improve recognition rates [15].

Global features are not sensitive to image noise, handwriting deformation and scale variation. Local features can distinguish ancient Chinese characters with similar structures. Therefore, the combination of global features with local features can guarantee the robustness and accuracy of recognition of ancient Chinese characters.

Structure feature is one of the global features. Stroke structure as a structure feature has been widely used in modern Chinese character recognition. Strokes of ancient Chinese characters are mainly curved, and the curvatures are different even for the strokes of the same character. The directional features such as horizontal line, top-down vertical line, left-downward slope line and short pausing stroke are not suitable for recognition of ancient Chinese characters. This paper extracts four kinds of component structures, namely left-right, up-down, in-out and independence as structure features. Component structures of ancient Chinese characters are not sensitive to noise and scale variation. Besides, the global point density feature has a strong anti-noise capability and can adapt to handwriting deformation. So, two global features, component structure feature and global point density feature, are selected to realize a rough classification of ancient Chinese characters. In order to realize accurate recognition of ancient Chinese characters, global features are combined with local features. The local point density of each pixel within the elastic mesh can well adapt to the local deformation and distinguish ancient Chinese characters with similar structures. So four kinds of features have been extracted for recognition of ancient Chinese characters: component structure feature, global point density feature, pseudo 2D elastic mesh feature and local point density feature.

The schematic diagram of component structure feature extraction is shown in Fig. 2.

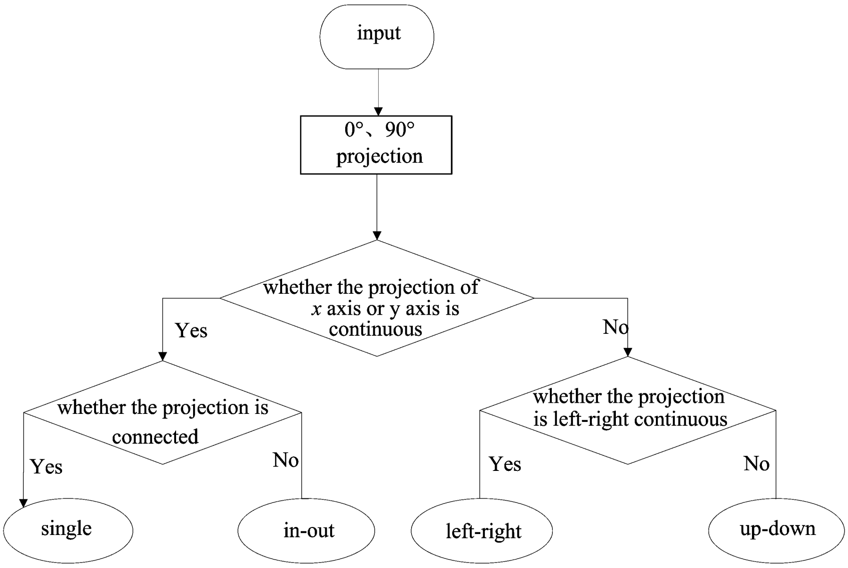

Fig. 2 Schematic diagram of component structure feature extraction

The global point density of the character image after binarization is defined as follows[16]:

$$\alpha=\frac{\sum_{i=1}^{n}\sum_{j=1}^{n}f(i,j)}{n^2},\ 1\leqslant n\leqslant 128 \tag{10}$$

where $f(i,j)$ represents the pixel value at position (i,j), n represents the image size and α is the global point density.

Pseudo 2D elastic mesh is suitable for a large number of variants caused by different writers, which uses local fuzzy linear density function instead of global density projection function to obtain a good absorption capacity for local deformation of ancient Chinese characters[17]. Local fuzzy linear density functions are defined as follows:

$$\left.\begin{aligned}\rho(u,v_0)&=\sum_{v=1}^{V}d_u(u,v)\frac{1}{\sqrt{2\pi}\sigma}\mathrm{e}^{-(v-v_0)^2/(2\sigma^2)}\\ \rho(u_0,v)&=\sum_{u=1}^{U}d_v(u,v)\frac{1}{\sqrt{2\pi}\sigma}\mathrm{e}^{-(u-u_0)^2/(2\sigma^2)}\end{aligned}\right\}\tag{11}$$

where σ^2 is the variance of Gaussian fuzzy function, u,v represents the row or column of the pixel, u_0, v_0 is a particular row or column, $d_u(u,v)$ or $d_v(u,v)$ is the interval density function of strokes. Accumulating local fuzzy linear density functions by rows or columns, we have

$$\left.\begin{aligned}H(x,v_0)&=\sum_{u=0}^{x}\rho_x(u,v_0),\ x=1,2,\cdots,U\\ S(u_0,y)&=\sum_{v=0}^{y}\rho_y(u_0,v),\ y=1,2,\cdots,V\end{aligned}\right\}\tag{12}$$

The generation functions of the pseudo 2D elastic mesh are defined as follows:

$$\left.\begin{aligned}f_h(m/M,v_0)&=\{x\mid H(x,v_0)=(m/M)H(U,v_0)\}\\ f_s(u_0,n/N)&=\{y\mid S(u_0,y)=(n/N)S(u_0,V)\}\end{aligned}\right\}\tag{13}$$

where U,V represents the width and height of an image of a ancient Chinese character, M and N

represent the number of rows and columns of the pseudo 2D elastic mesh, respectively.

The local linear density function at each row or column is different. The mesh line is curved rather than straight which can′t be described by linear equation. Here, the expression of mesh(m,n) can be converted to the point coordinate set of mesh lines:

$$\left.\begin{aligned} x_1(m) &= \{(f_h((m-1)/M),v_0),v_0) \mid v_0 = 1,2,\cdots,V\} \\ x_2(m) &= \{(f_h(\frac{m}{M},v_0),v_0) \mid v_0 = 1,2,\cdots,V\} \\ y_1(n) &= \{f_s(u_0,\frac{n-1}{N}),u_0) \mid u_0 = 1,2,\cdots,U\} \\ y_2(n) &= \{f_s(u_0,\frac{n}{N}),u_0) \mid u_0 = 1,2,\cdots,U\} \end{aligned}\right\} \tag{14}$$

The pseudo 2D elastic mesh can be obtained by connecting point coordinates of each mesh line.

Local point density of each pixel within the elastic mesh is defined as follows:

$$\boldsymbol{B} = \frac{\sum_{u=x}^{x+1}\sum_{v=y}^{y+1} f(u,v)}{(u_{x+1}-u_x)(v_{y+1}-v_y)} \tag{15}$$

where $x \in f_h(0,M)$, $y \in f_s(0,N)$, $\boldsymbol{B}$ represents the local point density matrix.

This paper firstly fuses local point density feature and the pseudo 2D elastic mesh feature. The fusion expression is as follows:

$$\boldsymbol{P} = \lambda_1 \boldsymbol{B} \cdot \boldsymbol{I}_0 + \lambda_2 \boldsymbol{B} \cdot \boldsymbol{I}_{90} + \lambda_3 \boldsymbol{B} \cdot \boldsymbol{I}_{45} + \lambda_4 \boldsymbol{B} \cdot \boldsymbol{I}_{135} \tag{16}$$

where $\boldsymbol{I}_0$ represents the left-right direction, $\boldsymbol{I}_{90}$ represents the up-down direction, $\boldsymbol{I}_{45}$ represents the lower-left direction and $\boldsymbol{I}_{135}$ represents the upper-right direction, $\lambda_i (i = 1,\cdots,4)$ represents weight coefficient, namely the ratio of strokes of each direction to ancient Chinese characters.

Then the fused feature is combined with component structure feature and global point density feature to obtain the feature vector for recognizing ancient Chinese characters.

3 Steps of recognition

Step 1 Input image. Papery images should be converted into electronic ones by a camera.

Step 2 Preprocessing. Since the input image is a whole page of ancient Chinese characters, character segmentation must be carried out. Then, in order to remove noise and facilitate the feature extraction in later stage, we need to conduct binarization, normalization and denoising operations to characters.

Step 3 Feature extraction. Since it is difficult for the single feature to fully reflect the information of ancient Chinese characters, global features are fused with local features. Multi-feature fusion can reflect ancient Chinese characters from all sides.

Step 4 Classification. The training sample features are used to train the WLS-SVM classifier model firstly. Then the test sample features are input to decide the parameters of a classifier. Finally ancient Chinese characters are recognized as shown in Fig. 3.

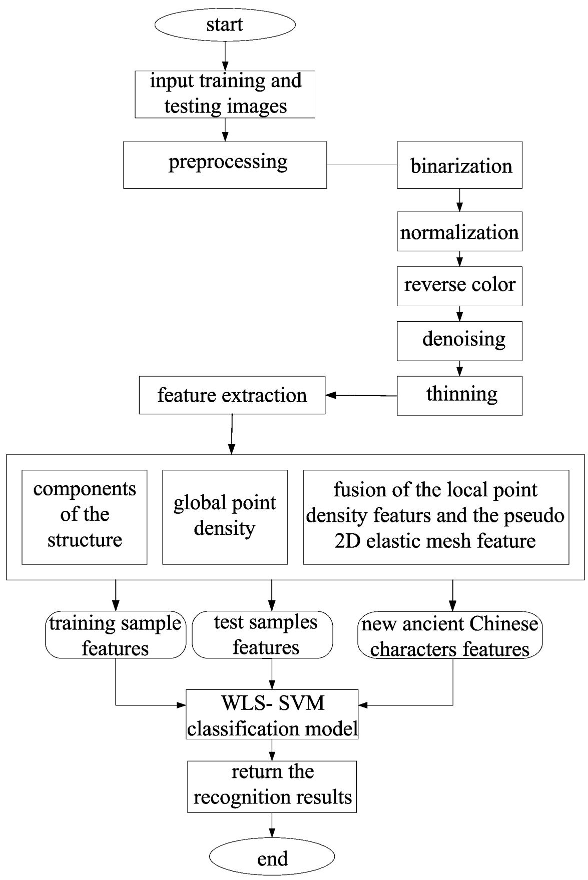

Fig. 3 Recognition process of ancient character

4 Experiments and results analysis

Pictures were taken and a character library was built from "Ancient Lao Tze Words". The selected ancient Chinese characters include four component structure features, namely left-right, up-down, in-out and independence. Characters chosen for the experiments are 國，及，久，仁，什，守，吾，也，大，各，多，a total of eleven character sets, each set including several variant subsets. If each variant subset is regarded as a separate class, there are a total of thirty-eight classes. Four samples of each class in the thirty-eight classes are selected for training, two for testing and the rest for recognition. Fig. 4 shows three variants of "及" after operations of binarization, denoising and corrosion expansion.

Fig. 4 Three variants of "及"

After operations of normalization, reverse color and thinning, images of "及" are shown in Fig. 5.

Fig. 5 Images of "及" after operations of normalization, reverse color and thinning

The four component structure features that can be recognized are left-right, up-down, in-out and single. In order to describe the component structure more clearly, the four structure features are defined in Tab. 1.

Tab. 1 The feature values corresponding to the four component structure features

feature value			
up-down	left-right	single	in-out
10	20	30	40

Due to the limited number of samples, the sample set of each component structure is divided into three categories, namely easy, medium and complex according to the global point density feature. The division parameters are shown in Tab. 2, where a_i $(i=1,2)$ represents classification coefficient that is a simple division of difficulty degree; Δ_i $(i=1,2)$ is the adjustment factor that is set to avoid misclassification and leakage.

Tab. 2 Thresholds of division parameters of global point density

structure feature	threshold			
	a_1	Δ_1	a_2	Δ_2
up-down	0.019	0.003	0.028	0.006
left-right	0.015	0.005	0.032	0.004
in-out	0.018	0.004	0.028	0.008
single	0.017	0.004	0.031	0.004

After obtaining the component structure feature and the global point density feature, we extract the ancient Chinese character image from the pseudo 2D elastic mesh features. The size of each mesh is 8×8, a total of 64 grids. The density of each grid is calculated for the local point density feature. Meanwhile, the image is scanned at 0° at left-right direction, 90° at up-down direction, 45° at lower-left direction and 135° at upper-right direction, respectively. The left-right, up-down, lower-left, upper-right directions have 7 scan lines respectively. By calculating pixel values of each scan line, we can get the feature matrix $\boldsymbol{I}_0$, $\boldsymbol{I}_{90}$, $\boldsymbol{I}_{45}$, $\boldsymbol{I}_{135}$. By fusing the local point density matrix with the feature matrix obtained before, we can get the column vector.

For example, the second variant of "及" can be fused according to expression Eq. (16). Since the value of $\lambda_i (i = 1, \cdots, 4)$ in Eq. (16) generated small impact on the experiment for the limited samples, so it takes the same value. The local point density matrix is shown as follows:

$$\boldsymbol{B} = \begin{bmatrix} 0.0587 & 0.1207 & 0.1655 & 0.1655 & 0.1878 & 0.2018 & 0.0291 \\ 0.1281 & 0.2500 & 0.2667 & 0.2889 & 0.2600 & 0.2000 & 0.1234 \\ 0.2500 & 0.2738 & 0.2381 & 0.2381 & 0.3857 & 0.3175 & 0.2036 \\ 0.1927 & 0.2917 & 0.4074 & 0.2593 & 0.4333 & 0.3889 & 0.1986 \\ 0.1696 & 0.2143 & 0.2381 & 0.3333 & 0.3000 & 0.2381 & 0.1641 \\ 0.1281 & 0.1750 & 0.2667 & 0.2889 & 0.2800 & 0.2889 & 0.1213 \\ 0.0521 & 0.1068 & 0.1140 & 0.1111 & 0.1872 & 0.1111 & 0.0169 \end{bmatrix} \tag{17}$$

Grid scanning method is used to get column vectors corresponding to different directions. The final fusion matrix $\boldsymbol{P}$ is shown as follows:

$$\boldsymbol{I}_0 = \begin{bmatrix} 1 \\ 4 \\ 18 \\ 3 \\ 10 \\ 4 \\ 1 \end{bmatrix}, \boldsymbol{I}_{45} = \begin{bmatrix} 0 \\ 1 \\ 3 \\ 7 \\ 3 \\ 2 \\ 1 \end{bmatrix}, \boldsymbol{I}_{90} = \begin{bmatrix} 2 \\ 3 \\ 5 \\ 29 \\ 7 \\ 2 \\ 2 \end{bmatrix}, \boldsymbol{I}_{135} = \begin{bmatrix} 1 \\ 0 \\ 2 \\ 9 \\ 5 \\ 1 \\ 0 \end{bmatrix}, \boldsymbol{P} = \begin{bmatrix} 2.7170 \\ 3.8306 \\ 4.0748 \\ 6.3722 \\ 5.5052 \\ 4.9104 \\ 2.5404 \end{bmatrix} \tag{18}$$

In order to verify the validity of the proposed algorithm, this paper compares it with two traditional methods, LIB-SVM and LS-SVM, which have been widely used in recognition. The experiment is conducted using the same sample data sets containing 266 samples of 38 classes. The optimal parameters and the indexes of quantitative comparison are shown in Tab. 3.

Tab. 3 The quantitative comparison of three recognition algorithms

algorithm	parameters	training time(s)	training accuracy(%)	recognition time(s)	recognition accuracy (%)
LIB-SVM	$\gamma=128, \sigma^2=0.0078$	0.0390	92.82	0.0041	75
LS-SVM	$\gamma=2, \sigma^2=2$	0.0837	94.40	0.0645	78
WLS-SVR	$\gamma=0.8, \sigma^2=8$	0.4639	97.46	0.2125	82

From Tab. 3, we can see that the effect of WLS-SVR based algorithm works best, with the LS-SVM and LIB-SVM occupying the second and third places. The algorithm proposed in this paper has a high accuracy. Although it takes the longest time for training and recognition because of its complexity, it is still within the acceptable range. Overall, the method in the paper is effective.

5 Conclusion

Because of the high uncertainty in the shapes of ancient Chinese characters, the recognition accuracy of existing classifiers is low. Support vector regression has advantages of good generalization ability and learning performance. This paper proposed a recognition algorithm that combines a hybrid-kernel function with adaptive weighted least squares support vector regression for ancient Chinese character recognition. The wavelet kernel function with local properties and RBF kernel function with good global properties are combined to construct the hybrid-kernel. The weight coefficients decay at a rate of the exponential function of prediction errors. Experiment results show that the proposed method has good robustness and high recognition accuracy. future research is to find a faster solution for the WLS-SVR algorithm to reduce recognition time.

References

[1] Zhang P. Research of digital construction of Paper files and relics [J]. Cultural Relics of Central Plains, 2009 (5):104-107.

[2] Lv X Q, Li M N et al. An oracle classification method based on figure recognition [J]. Journal of Beijing University of Information Science and Technology, 2010(25):92-96.

[3] Chen D, Li N, Li L. Online handwriting recognition research of ancient character[J]. Journal of Beijing Institute of Mechanical Industry, 2008(4):32-37.

[4] Zang G Q. Experiment and Improvement of accuracy of OCR for text-digital image [J]. Intelligence, Information and Sharing, 2010(3):62-67.

[5] Vapnik V. The Nature of Statistical Learning Theory [M]. New York: Springer-Verlag, 1995.

[6] Suykens J A K, Vandewalle J. Least Squares Support Vector Machine Classifiers [J]. Neural Process Letters, 1999 (3):293-300.

[7] Miranian A, Abdollahzade M. Developing a Local Least-Squares Support Vector Machines-Based Neuro-Fuzzy Model for Nonlinear and Chaotic Time Series Prediction[J]. IEEE Transactions on Neural Networks and Learning Systems, 2013, 24(2): 207-218.

[8] Wang L G , Liu D F , Wang Q M et al. Spectral Unmixing Model Based on Least Squares Support Vector Machine With Unmixing Residue Constraints [J]. IEEE Geoscience and Remote Sensing Letters, 2013, 10(6): 1592-1596.

[9] Liu B Y, YangR G. A novel method based on PCA and LS-SVM for power load forecasting [C]. International Conference on Electric Utility Deregulation and Restructuring and Power Technologies, NanJing, 2008: 759-763.

[10] Zhang H R, Wang X D, Zhang C J et al. Soft sensor technique using LS-SVM and standard SVM[J]. IEEE International Conference on Information Acquisition, Hong Kong and Macau, 2005: 124-127.

[11] Xie J H. Printed character recognition using Kernel CCA with LS-SVM method [C]. Computer and Automation Engineering, 2010: 284-287.

[12] Yin D Y, Wu Y Q. Detection of Small Target in Infrared Image Based on KFCM and LS-SVM[C]. International Conference on Intelligent Human-Machine Systems and Cybernetics, 2010: 309-312.

[13] Suykens J A K, de Brabanter J, Lukas L, Vandeewalle J. Weighted Least squares support vector machines: robustness and sparse approximation [J]. Neurocomputing, 2002(48):85-105.

[14] Smits G F, Jordaan E M. Improved SVM regression using mixtures of kernels [C]. textitin Neural Networks, International Joint Conference on, 2002, 3: 2785-2790.

[15] 温昌兵. 基于特征融合的脱机手写体汉字识别[D]. 北京,北京科技大学,2005.

[16] Zhang X B, Huang H, Zhang S J. A FCM clustering algorithm based on Semi-supervised and Point Density Weighted[C]. Intelligent Computing and Intelligent Systems, 2010: 710-713.

[17] Tu Y K, Chen Q H, Huang L. Handwritten Chinese character recognition based on pseudo two-dimensional elastic mesh [J]. Journal of Huazhong University of Science and Technology, 2010(38):38-40.