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Maize Disease Recognition via Fuzzy Least Square Support Vector Machine

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Abstract. In this paper, we propose a new approach to recognize the maize disease, which is based on fuzzy least square vector machine (FLSVM) algorithm. According to the texture characteristics of Maize diseases, it uses YCbCr color space technology to segment disease spot, and uses the co-occurrence matrix spatial gray level layer to extract disease spot texture feature, and uses FLSVM to class the maize disease. In this method, the sample mean is calculated, and the center of each class is got; then the distance between the sample and the center is calculated, according to the distance sample's initial membership is got; by finding K neighbors for each sample point, the sample membership degree is calculated according to the fuzzy K nearest neighbor method. Extensive experiments on public datasets show that the algorithm can effectively identify the disease image, the accuracy was as high as 98% or more.

Keywords: Maize disease; Support vector machine; Image processing; traffic sign

1. Introduction

China is the largest rice-producing country in the world, and food production is a major issue which has great impact on people's livelihood. Com is the most important food crop in China, and it plays a decisive role in food production. However, in recent years, the com diseases have had a trend to aggravate year by year, and the yield and quality of com have badly affected by diseases. Therefore, dealing with the com diseases is an important and urgent task. Accurate type of information of diseases can provide scientific basis for integrated control of plant diseases. Throughout the disease control system, disease classification and recognition technology play a crucial role. Nevertheless, the traditional method of disease identification has a slow speed, a high cost and a poor real-time [1]. With the development of science and technology, machine vision, digital image processing and pattern recognition techniques have been greatly developed and applied, and it has also made fruitful application in agriculture.

Maize disease pathogens lead to different types of leaf spots of different textures because of its different pathogenic properties. They can be based on computer image processing technology to extract the com lesion characteristics. This Article is based on YCbCr [2] color space segmentation lesion images, using the space gray matrix to extract three kinds of texture features which have the greatest effect on classification, combining with fuzzy least square vector machine (FLSVM) to accurately identify and classify the com disease.

A least square SVM (LSSVM) approach [3] is very popular. Relative to Vapnik's SVM, the LSSVM can transform a quadratic programming problem into a linear programming problem thus reducing the computational complexity. The main motivation of this study is to use a relatively new machine learning method to the field of credit risk evaluation and compare its performance with some typical credit risk evaluation techniques.

In many practical applications，some elements of training set are often not clear，there are even some noise，these training points on the surface to determine the classification does not make sense，So if we want to reduce the impact of these points ,we need to calculate the degree of membership of the class point，this will be extended to support vector machine theory with Fuzzy Information Support Vector Machine[4].

2. THE PREPROCESSING STEPS

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2.1. IMAGE SEGMENTATION

YCbCr color system is a common color system,which is applied by the most widely used JPEG image.YCbCr uses Y, Cb and Cr, which respectively indicates a luminance component and two color component signals. Different from other color models, YCbCr color model is orthogonal, which fully takes important factors of composition of RGB from other colors into account. YCbCr color space model is Ofien used in image compression. Application of YCbCr color model of color information encoded signals from at least redundant information.

$$\begin{aligned} Y &= 0.299*R+0.587*G+0.114*B \\ Cr &= (R-Y)*0.713+128 \\ Cb &= (B-Y)*0.564+128 \end{aligned} \qquad (1)$$

(a) original image (b) the segmented result

Figure 1. The image segmentation

3. THE PROPOSED TRAFFIC SIGNS DETECTION METHOD

Visual saliency often appears in all kinds of visual scales, different regions also have different visual attention. In order to comprehensively consider locality and integrity for the image saliency region, in this paper, we present an improved algorithm (MPCA) on the basis of Duan's model to compute traffic sign saliency map. And then we extract traffic sign part from original image using automatic segmentation method obtained by loading auto-generated strokes.

3.1. Least Square support vector machine algorithm

LSSVM models are an alternate formulation of SVM regression [5] proposed by [6]. Let the patterns to be classified be denoted by a set of *m* row vectors $A_i\,(i=1,2...m)$ in the *n*-dimensional real space R_n, where $A_i=(A_{i1},A_{i2},...A_{in})^T$ .Also, let $y_i \in \{-1,1\}$ denote the class to which the *i*th pattern belongs. We first consider the case when the patterns belonging to the two classes are strictly linearly separable. Then, the plane described by

$$w^T \cdot x + b = 0 \qquad (2)$$

Distance of closest point on hyperplane to origin can be found by maximizing the *x* as *x* is on the hyper plane. Similarly for the other side points we have a similar scenario. Thus solving and subtracting the two distances we get the summed distance from the separating hyperplane to nearest points. Maximum Margin = M = 2 / ||w||.

Now maximizing the margin is same as minimum. Now we have a quadratic optimization problem and we need to solve for w and b. To solve this we need to optimize the quadratic function with linear constraints. The solution involves constructing a dual problem and where a Langlier's multiplier α_i is associated. We need to find *w* and *b* such that Φ (w) =½ $|w'||w|+ \gamma\frac{1}{2}\sum_{k=1}^{N} e_k^2$ is minimized, for all $\{(x_i, y_i)\}$: $y_i\,(w * x_i + b) \geq 1$.

Now the classifying function will have the following form:

$$f(x) = \Sigma\alpha_i\, y_i\, x_i * x + b \qquad (3)$$

The hyper-plane can be obtained by minimizing $\frac{1}{2}\|w\|^2 + C\sum_{i=1}^{l}\xi_i$, where ξ_i is a slack variable to allow the boundary singular *C*, also called punishment parameter, is a parameter comprised between wide boundary and small boundary singular, and the constraint is:

$$y_i f(\mathbf{x}_i) \geq 1 - \xi_i,\ \xi_i \geq 0 \text{ for all } i=1,2...N \qquad (4)$$

Applying Lagrange optimization methods and statistical theory converts the solution problem into:

$$W(a)=\sum_{i=1}^{n}\alpha_i-\frac{1}{2}\sum_{i,j}^{n}a_ia_jy_iy_j(x_i.x_j) \tag{5}$$

Simultaneously the optimal solutions must meet KKT requirement:

$$\alpha_i\{y_i(w^Tx+b)\}=0 \tag{6}$$

where α_i is selected at random and not equal to 0, and b can be solved depending on the above equation. Thus the classification hyper-plane equation is:

$$f(x)=\operatorname{sgn}\{\sum_{i=1}^{n}\alpha_i y_i(x_i\cdot x)+b\} \tag{7}$$

3.2. Fuzzy Least Square support vector machine algorithm

The proposed fuzzy support vector machine support vector classification method can solve the problem with fuzzy information. For conventional support vector machines，each training points for each class can equally affect the determination of the optimal classification surface, but the importance is not considered. That is to say, support vector machines are more suitable for ordinary set. The design of membership function is the key to fuzzy algorithm，this requires membership function to be objectively and accurately reflected the distribution characteristics of the samples.

In order to combine the distance of sample and the center and the relationship of samples，firstly, according to the distance between sample and sample class center to calculate the initial membership；Then use the fuzzy K-nearest neighbor algorithm once for each sample and then seek membership，such it will take the relationship between the sample into the calculation of the degree of membership [7]，specific steps are as follows：

Let the sample mean xc for the class center，define the radius $R=\max\|x_i-x_c\|$，the initial membership is defined as：

$$\mu_0(x_i)=1-\|x_i-x_c\|/(R+\delta) \tag{8}$$

If only according to the K-nearest neighbor based on the sample to calculate the degree of membership of the sample，sample x_1 can be set as the K-nearest neighbors x_2，…，x_k. The degree of membership of the sample：

$$\mu(x_i)=\sum_{j=1}^{k}\mu_0(x_j)(1/\|x_i-x_j\|^b)\Big/\sum_{j=1}^{k}(1/\|x_i-x_j\|^b) \tag{9}$$

Equation 9 shows that，in the course of the second sample solution its role is largely weakened, if the sample set is compact，deviation of the sample is not too large membership, and it can reduce the noise. When faced with the sparse sample set, although the samples have been taken into account from the difference，the degree of membership of the sample is almost the K nearest neighbor samples from these decision. The sample itself has a membership degree of information loss, membership sample bias may be therefore unduly corrected. Especially when there is noise, the noise point of sample points with a normal sample of the K-nearest neighbors, then equation 8 is amended, this point may be normal noise samples with similar membership.

To further validate the sample in a two-dimensional feature sets，taking the random 10 and 50 samples，according to Equation 8 and Equation 9, the obtained memberships are showed in Figures 1 and 2.

In the figure, X and y coordinates respectively represent the two eigenvalues of the samples, the obtained big points correspond to the membership degree, its top (or bottom) of the small dot is determined according to the equation 2 the value of the membership degree, visible sparse set of edges of the sample values of the two membership compact set bigger than the difference, when using the formula 2, sparse set sample membership was greatly improved. While this effectively increases the sample time of the classification effect relationship, but inevitably will be a corresponding increase noise。

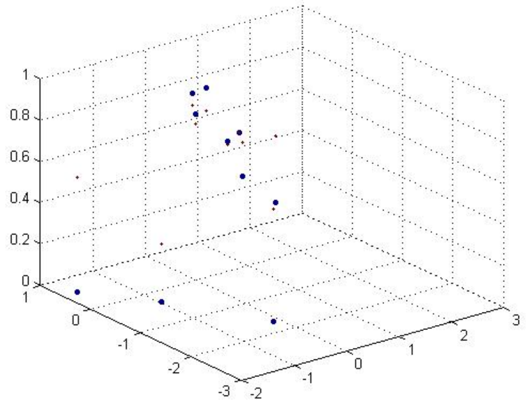

Figure 1 membership degree distribution of 10 samples

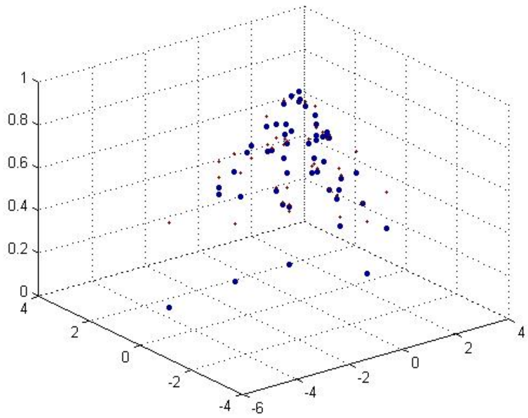

Figure 2 membership degree distribution of 50 samples

In order to avoid the excessive impact of relationship between the samples on membership, this method is the initial sample to a certain percentage of membership into the second calculation, this allows the relationship of sample and the sample-to-center distance to combine, the final sample is designed to membership：

$$\mu(x_i)=(1-\alpha)\mu_0(x_i)+\alpha\sum_{j=1}^{k}\mu_0(x_j)(1/\|x_i-x_j\|^b)\Big/\sum_{j=1}^{k}(1/\|x_i-x_j\|^b) \quad (10)$$

The fuzzy membership degree based on K-nearest neighbor defined by Equation 10, under certain circumstances， sample the greater distance to the sample collection center, the sample belongs to the membership of the sample set smaller; Sample to the sample collection center in certain circumstances, sample set is more close， the adjust membership of sample is smaller. Conversely the larger sample membership adjustment, the greater the degree of membership, so the membership values using equation 9 can be used in support vector machines.

4. Experimental results

Our algorithm is implemented in VC++ 7.0 on a 2.8-GHz Intel Pentium IV PC. Extensive experiments are performed to validate the proposed method. In the experiments, we set the kernel Gaussian function $K(x,x_i)=\exp(-|x-x_i|^2/(2\sigma^2))$, $\sigma=300$, C=1000. Respectively, we take 12 pictures of corn leaf blight, sheath blight, southern leaf blight, and calculate 0 degrees, 45 degrees, 90 degrees, 135 degrees of the matrix to each of them. Put five texture features which extract as the input, and take hidden layer obtained with 10 nodes, starting Fuzzy Least Square support vector machine training. We take the 30 samples to test judge samples whether the correct classification. Giving the Samples the number in turn, round leaf spot value is 1, sheath blight value is 2, small leaf spot value is 3. Part of the test results as the following table.

Table 1 Sample mean and Fuzzy Least Square support vector machine output table

Number	Expectations	support vector machine output
1	1	1.006764
2	1	1.007925
3	2	2.005486
4	1	0.998581
5	3	2.999682
6	3	3.020844
7	2	2.016879
8	2	2.014533
9	1	1.010135
10	3	2.982335
11	2	2.012987
12	3	3.013776

Table 2 Maize disease detection error results of different classification methods

	10	10	10
NN	7%	6%	6%
SVM	4%	5%	6%
FSVM	3%	5%	4%
FLSVM	2%	1%	2%

From table 2， we can see that firstly normal function fitting maize gray histogram can be identified on the disease; secondly, FLSVM shows smaller errors in the identification process and when the samples number is too small, the training sample selection under the condition of unbalanced can achieve better results.

5. Conclusions

This study has described FLSVM model for prediction of Maize disease. The performance of FLSVM model is encouraging. User can use the developed equation for prediction of Maize disease. The developed FLSVM also gives prediction uncertainty. This article shows that the developed FLSVM is a robust model for prediction of Maize disease.

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