2009 Second International Conference on Intelligent Networks and Intelligent Systems

Automation Recognition of Pavement Surface Distress Based on Support Vector Machine*

Nana Li, Xiangdan Hou, Xinyu Yang, Yongfeng Dong
School of Computer Science and Engineering, Hebei University of Technology
Tianjin, China
E-mail: hxdjoin@gmail.com

***Abstract*—In this paper, classification of pavement surface distress and the statistics of the distress data are discussed. In order to improve the accuracy and efficiency to identify the pavement surface distress by the image information, a new algorithm based on SVM is discussed. In this study, support vector classification (SVC), which is a novel and effective classification algorithm, is applied to crack images classification. In order to build an effective SVC classifier, parameters must be selected carefully. This study pioneered on using genetic algorithm to optimize the parameters of SVC. The performances of the SVC and the back-propagation neural network whose parameters are obtained by trial-and-error procedure have been compared with crack images data set. Experimental results demonstrate that SVC works better than the BPNN.**

Keywords-pavement surface distress; feature extraction; support vector machine; genetic algorithm

1. Introduction

With the rapid development of Chinese highway, the management work becomes also increasingly more important. In order to improve the level of determining pavement, there is an urgent need to improve the technology for pavement distress detection. The distress of pavement surface has several situations including cracks, loose and the other, but the crack is the most difficult detection of target. In recent years, neural network, in the classification problems of pavement distress, has been widely applied. Kaseko compared classification used neural networks and traditional methods and indicated that classification using neural network has much more advantages [1]. American scholar B.J.L and David Lee made a classification method for the types of road crack in the use of BP neural network in TRB2003 [2]. Wangxin Xiao proposed a new method used wavelet neural network to identify pavement distress image and has very well results [3]. Neural network has many advantages, but has some problems as well. The ability of generalization is not high and the convergence of speed is slow. Aiming at the case, we used the SVM method to solve the problems.

Our proposed scheme involves several steps as outlined below: Firstly, collect the crack data and extract the features of crack images. Secondly, generate the input/output training set. Here, the inputs are the set of features on crack images and the outputs are the class of crack images. Then, obtain SVM's parameters (C and σ) by the method named GA. At last, train the SVM and test the class for experimental data.

This paper is organized as follows. Firstly, we should introduce the method of extracting feature. Secondly, we should recall the SVM algorithm for typical nonlinear problems and introduce the method named GA. Finally, the experimental results show the validity of SVM scheme.

2. Feature Extraction

A typical classification method requires the definition of two main components: feature extraction and classifier strategy. In the following, we first introduce the feature extraction method, while in the next section we briefly describe the characteristics of the adopted classifier, namely the support vector machine (SVM) method. The feature extraction task is very important, because any successful classification scheme would depend on its ability to pick out relevant features.

Due to the rough surface and no uniform illumination, pavement images have a lot of noises. So now several researches are built based on sub-image. The processing steps are: Firstly, we obtain the binary image by image segmentation. Secondly, we divided the image into the sub-block image which the size is

* 413027 of Education Department of Hebei Province Plans

978-0-7695-3852-5/09 $26.00 © 2009 IEEE
DOI 10.1109/ICINIS.2009.95

40x40 pixels. At last, we calculate the percentages of distress pixels for the sub-block image. If the percentages of distress pixels are lower than 1%, the sub-block image is defined as value “0”, otherwise the sub-block image is defined as value “1”. The percentage value: 1% is obtained by painting and is the intersection of noise and distress pixels. At last, we obtain a 12x18 sub-block image that is similar to the binary image. Then, we extract the characteristics.

2.1 Density character

Density is the space extent for crack in the images. That is the numbers of statistical information through the crack in the vertical and horizontal directions. The calculation methods are as follow:

$$\partial_x = \sum_{i=1}^{h} x_i / h \qquad \partial = \sqrt{\partial_x^2 + \partial_y^2} \qquad \partial_y = \sum_{j=1}^{w} x_j / w \tag{1}$$

h is the height and w is the width of the image. X_i is the numbers of through crack for the ith horizontal scanning line. That is the numbers changed from 1 to 0. Y_j is the numbers of through crack for the jth vertical scanning line.

2.2 Proximity character

The second feature is extracted as follow [2]. We make vertical and horizontal direction of projections. Then, we can get: X(m)={X1,X2,…,Xm} and Y(n)={Y1,Y2,…,Yn}. At last，we calculate H and S.

$$S_y = \sum_{i=1}^{n} | y_{i+1} - y_i | \qquad S = \sum_{i=1}^{m} | y_i | \qquad S_x = \sum_{i=1}^{n} | x_{i+1} - x_i | \qquad H = \frac{S_y}{S_x} \tag{2}$$

2.3 Fractal dimension character

Crack is a random texture and we can calculate the fractal dimension to distinguish them. Here, we use a simple box counting method. We have the grid size value of ε covering the whole image, and we calculate the number of grid in which pixel value is 1. We continue to reduce the size of grid and count the grid number with pixel value of 1 until the minimum mesh size reaches pixel. Finally, we will map the data: $\mathrm{N}(\varepsilon)$ and ε into map: $\mathrm{In}(\mathrm{N}(\varepsilon)) \rightarrow \mathrm{In}(1/\varepsilon)$. If you can get a straight line, this illustrate that the data have the following relations: $\mathrm{N}(\varepsilon) \sim (1/\varepsilon)^D$. We have the data fitting and obtain the slope of a straight line and that is the fractal dimension D of images [4].

3. The Classification

At this point the features are submitted to the classification process. In the following we introduce the SVM classification and the method that selects the parameters with GA.

3.1 Support vector machine

Given training vectors $x_i \in R^d$, $i = 1,\cdots,l$ in two classes, and a vector $y \in R^l$ such that $y_i \in \{-1,1\}$, the SVM is used to solve the following primal problem:

$$\min_{w,b,\xi} \ \frac{1}{2} w^T w + C \sum_{\mathrm{i}=1}^{l} \xi_{\mathrm{i}} \tag{3}$$

Subject to: $y_i (w^T \phi(x_i) + b) \geq 1 - \xi_i, \xi_{\mathrm{i}} \geq 0$ (4)

Its dual is: $\min_{\alpha} \ \frac{1}{2} \alpha^T Q \alpha - e^T \alpha, 0 \leq \alpha_{\mathrm{i}} \leq C$ (5)

Subject to: $y^T \alpha = 0$. Where e is the vector with elements 1, C is a penalty parameter on the training error, Q is an l by l positive semi-definite matrix, $Q_{ij} = y_i y_j K(x_i, x_j)$, $K(x_i, x_j) = \phi(x_i)^T \phi(x_j)$ is the kernel function. Here training vectors x_i are mapped into a higher dimensional space by the function ϕ. We choose kernel functions are shown as follows. Radial basic function: $K\left(\boldsymbol{x}_i, \boldsymbol{x}_j\right) = \mathrm{e}^{-\frac{\|\boldsymbol{x}_i - \boldsymbol{x}_j\|^2}{\sigma^2}}$

Here, σ is the width of the RBF kernel. At last, the decision function is: $\mathrm{sgn}(\sum_{i=1}^{l} y_i \alpha_i K(x_i, x) + b)$

(6)

It can be seen that the above SVM is a two-class classification technique, which has to be modified to handle the multiclass tasks in classification of cracks. The common multiclass methods are the one against one (OAO) and one against all (OAA) techniques. In this paper, we use the OAO approach which involves constructing a machine for each pair of classes resulting in *N(N-1)/2* machines. When applied to a testing sample, each classification gives one vote to the winning class and the crack is labeled with the class having most votes [5].

3.2 The parameters of support vector machine

Our paper uses the method named genetic algorithm(GA) which optimizes SVM's parameters [6]. GA's details are described as follows: Firstly, when GA solves the problems, the real-valued parameters can be directly used to form the chromosome. The paper chooses same values about C and σ for each binary classifier in a multiclass decomposition. Secondly, the individuals' fitness considered the binary classifiers in the multiclass problem. The measure: $e(i) = val\_error$ is calculated for each i. The GA searches for solutions that minimize this measure, val_error refers to the error rate obtained by the classifier in a validation set. Then, a standard roulette wheel was employed in our model. At last, once a pair of chromosomes has been selected for crossover, one randomly selected position is assigned to the to-be-crossed chromosomes. The mutation operation follows the crossover operation and determines whether a chromosome should be mutated in the next generation.

4. Performance Evaluation

To study the performance of the proposed SVM classifier, we have used conventional BPNN classifier.

4.1 Sample description

As dealing with the pavement images difficultly, training datasets adopted computer generated images based on the real pavement images. The computer generated images imitated the method proposed by Wangxin Xiao in [3], included five classes: longitudinal cracks(90), transverse crack(90), block rack(90), no crack(90) and alligator crack(90). The real images were collected from the pavement in Hebei University of Technology near the southern and eastern yard. We obtained the real images that are divided into 5 categories: longitudinal crack(90), transverse crack (55), block rack(50), alligator crack(70) and no crack (40). The training numbers are 450 and the test numbers are 305 in total.

To obtain better estimates of the error rates of the classifiers generated in GA, all training datasets (450) were divided according to the 5-fold cross validation technique [7]. Accordingly, each dataset was divided into 5 subsets of approximately equal size (90). In every subset, alligator crack is defined as one class; the other is defined as another class.

4.2 Parameters of classifier

The GA method is applied for searching optimal parameters. The parameters are obtained when the fitness is minimum. Table 1 gives a GA's parameter settings that are recommended from Holland [8].

TABLE I. GA PARAMETER SETTINGS

Population size	50
Crossover probability	0.9
Mutation probability	0.2
Generations number	100

In the area of classification, the popular BPNN is introduced. The BPNN's parameters in our experiment were set as follows [3]. A standard three-layer network was used. The number of nodes for input layer was set to 4 represent crack features, 15 for hidden layer and 5 for output layer represent crack classes. The learning rate was set to 0.01. Considered the accuracy and time-consuming, the convergence criteria used for the training set was a maximum of 500 iterations.

4.3 Experimental results

Firstly, the results of parameters selection are shown. Fig.1 illustrates the correlation curves of GA method for the fitness versus the generation number. When the evolution reached generation 45, the fitness of five-fold cross validation converged, this indicated that the searching of the GA is excellent and efficiency. Within the overall searching process, the optimal fitness was obtained at Generation 45. At last, the parameters selection results of SVC are: σ is 0.246 and C is 4.269.

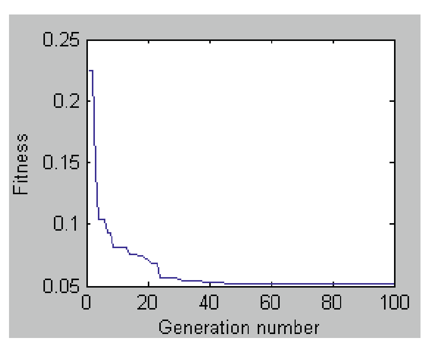

Figure 1. Fitness change during evolution

In order to test the SVM's performance for small samples, we select 100, 200, 300 and 450 samples respectively as training sample from training set and 305 samples as testing set. Table 2 compares BPNN with SVM on generalization ability by recognition rates of testing set. Shown from Table 2, in a small training sample of case, SVM's recognition rate is higher than BPNN and it has very good performance, this advantage is not comparable with other methods.

TABLE II. RECOGNITION RATES OF BPNN AND SVM

Training(Testing) sample	SVM	BPNN
100(305)	54.3%	45.4%
200(305)	60.5%	53.8%
300(305)	68.2%	57.3%
450(305)	78.4%	69.6%

Generalization ability is that the machine after studying makes a correct response to the test sample. The generalization ability of machine learning is the most important performance. There is no generalization ability means that machine learning is no significance. The following Fig.2 compares BPNN with SVM for generalization ability through practice. It shows the SVM and BPNN's recognition rate correctly at different training set for the testing set. The results show that the correct classification rate of SVM, in the different sample sets, were higher than BPNN. So SVM has more generalization ability than BPNN and is able to meet the requirements of practical applications.

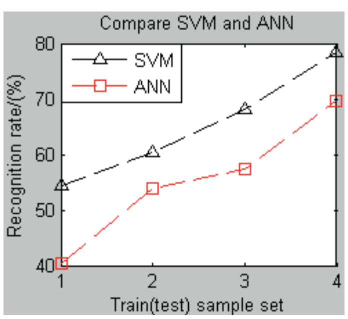

Figure 2. Comparison of BPNN and SVM

In order to obtain a more accurate training time, we turn off all other applications. Let the computer to run a separate MATLAB process. Choose the average time of 3 times training as their training time. Table 3 shows the results of SVM and BPNN's training time. The result indicates that the advantages of application of SVM is stronger than BPNN for the training time and has the good development of prospects.

TABLE III. COMPARE THE TIME OF BPNN AND SVM

Training sample	SVM(s)	BPNN(s)
100	3.594	6.562
200	6.125	8.750
300	9.922	19.312
450	16.766	37.406

5. Conclusions

SVM is a universal learning algorithm based on the small sample and has a strict theoretical foundation that can solve the problem of traditional assessment methods well that can not solve the actual problem about the nonlinear, high dimension and local minima. In this paper, by comparing the BP-NN and SVM, result shows SVM has much better classification results and generalization ability, at the same time, the training time of SVM also has an absolute advantage, so that it will have a very good application value and prospect for the automation recognition of pavement distress.

6. References

[1] Kasko M.S Ritchie, "Comparison of Traditional and Neural Classifiers for Pavement Crack Detection". ASCE ,1994, 120(4) :552～569.

[2] Bayoung Jik Lee, Hosin. David Lee, "A Robust Position Invariant Artificial Neural Network for Digital Pavement Crack Analysis". TRB 2003 Annual Meeting

[3] Wangxin Xiao, ZhangXue, "A New Method for Distress Automation Recognition of Pavement Surface Based on Density Factor and Image Processing". Journal of Transportation Engineering and Information, 2004 pp:82~89

[4] HanJie, "The Automatic Identification and Classification of Image-Based Road Surface Distress". Nanjing University of Science. 2007.06. pp:24~37

[5] Wang Xiang-ying, "Statistical learning theory and state of the art in SVM". The Second IEEE International Conference on Cognitive Informatics, 2003: 55~59.

[6] Kuan-Yu Chen, "Support vector regression with GA in forecasting tourism demand. Tourism Management", 2007 pp. 215~226.

[7] Duan, K., Keerthi, S, & Poo, A, "Evaluation of simple performance measures for tuning SVM hyper parameters" Technical report, Singapore, 2001.

[8] Holland, "Adaptation in natural and artificial systems", The University of Michigan Press, 1975