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RESEARCH PAPER

Urban Road Traffic Condition Pattern Recognition Based on Support Vector Machine

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Abstract: As an important part of the modern intelligent transportation system, urban transport condition recognition is the base of intelligent control, guidance and synergy system. This paper establishes a three-dimensional space with traffic volume, average speed and occupation ratio. It then classifies transportation condition patterns in terms of blocking flow, crowded flow, steady flow and unhindered flow based on wide literature review. Furthermore, this paper presents the algorithm with the MATALB LiBSVM toolbox. To process the data, this paper compares the classification result of different SVM kernel functions and thus realizes the transport condition pattern recognition via the support vector machine (SVM). The results reveal that the selected indexes effectively reflect the characteristics of the traffic conditions. The SVM kernel function can separate different patterns from traffic flows with high classification accuracy, and the data normalization has a significant influence on the result of classification.

Key Words: urban road traffic; traffic state; pattern recognition; support vector machine (SVM); LiBSVM

1 Introduction

Urban road traffic condition recognition is an important part of modern intelligent transportation systems (ITS). It is common to analyze traffic data through various discrimination algorithms based on real-time road traffic data acquisition. Compared with the prior traffic condition standard, we can see what current traffic system conditions are and thus realize intelligent control, management, and induction of the transport systems according to the results[1]. It is important to guarantee fast and effective traffic condition recognition for real-time intelligent and effective urban traffic controls. The present study on urban road traffic condition classification recognition mainly focuses on two aspects: one is road traffic condition classification which emphasizes traffic real-time data classification; the other is traffic condition recognition based on prior classification, which lays stress on the method of traffic condition recognition.

Sadek *et al.*[2] summarized 25 different cases from different typical traffic network conditions that include 25 modes. Palmieri *et al.*[3] proposed a non-linear, cycle-based traffic classification method which is steady regardless of the dynamic traffic port considering traffic network conditions. Lozano *et al.*[4] proposed a recognition algorithm for road congestion levels by analyzing real-time traffic flow data based on the K-means clustering analysis algorithm. Montazeri-Gh *et al.*[5] proposed a mathematical method for traffic condition recognition based on the K-means clustering analysis orienting to driving the environment condition recognition problem. Abdel-Aty *et al.*[6] analyzed the relationship between real-time traffic flow parameters and traffic accidents and designed a BAYES classifier based on a neural network for recognition of accident speed and non-accident speed. Ruta *et al.*[7] identified and analyzed traffic conditions considering the problem of real-time traffic signal recognition by specifically analyzing video image recognition indicators. The U.S. Highway Capacity Manual[8] includes levels of service to describe the operating conditions among vehicles and subjective feelings of drivers and passengers, which is divided into grades A to F. Levels of service A to C represent smooth traffic flow, while E and F represent congested conditions.

A research conducted in the ITS Research Center at Tongji University used the cluster analysis method to analyze the raw

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traffic data collected by traffic detectors. They chose traffic flow, average speed, and share ratio as the classification characteristics. Road conditions were divided into four categories: blocked flow, congested flow, steady flow, and smooth flow. Additionally, the diagram for the flow-density relationship was presented. Li *et al.*[9] studied urban traffic conditions by the fuzzy support vector machine; however, only vehicle speed was chosen as the characteristic parameter. Most scholars[10,11] obtained reliable results about traffic flow classification in studying traffic condition classification recognition. The methods of case-based reasoning and cluster analysis provide different grades for traffic conditions, which establish a good research base and theoretical foundation. However, most of the index systems selected about traffic condition identification and simulation were single which could not reflect the actual situation. Therefore, there is still a wide range of exploration in this subject.

In modern intelligent transportation systems, various discrimination algorithms are often used for real-time traffic condition judgment. The detection classification algorithms mainly fall into four categories: direct comparison, space-time prediction, pattern recognition, and artificial intelligence. Built upon previous studies, this research focuses on urban road traffic condition recognition using the SVM pattern recognition algorithm by considering traffic multidimensional characteristics. Data experiments were completed under the MATLAB platform.

2 Theories and methods of urban road traffic condition classification based on SVM

2.1 Parameter extraction from road traffic condition

In traffic engineering, average speed, occupancy, and average flow are important parameters to reflect traffic flow characteristics. These parameters reflect different regions, sections, junctions, and specific periods of traffic flow[12]. We investigate three characteristic parameters[13] including traffic flow, average speed, and occupancy, which provide appropriate amendments to the corresponding formula to meet simulation system parameter settings. According to the study, a three-dimensional sample space is constructed. The related indicators are defined as follows:

(1) Traffic flow f: sum of the number of vehicles of various types for a single lane within 2 min multiplied by the corresponding proportion.

$$f = \frac{\sum_{i=1}^{k} \omega_i \times n_i}{t} \tag{1}$$

where n_i is the number of vehicles within period t of type i, ω_i is the conversion coefficient for such vehicle type in a time period of 2 min. For further analysis and consistency with previous studies, the unit is converted to pcu/h.

(2) Average speed V: average speed of all vehicles on a single lane within 2 min which is calculated by:

$$V = \frac{v_1 f_1 + v_2 f_2}{f_1 + f_2} \tag{2}$$

where v_1: average speed within the first minute, mile/h; v_2: average speed within the second minute, mile/h; f_1: flow within the first minute; f_2: flow within the second minute.

(3) Share ratio O: a time proportion of vehicles on a point detector on a single lane within 2 min, the unit is percentage.

$$O = \frac{f_t \times l_t}{t \times v_t} \times 100\% \tag{3}$$

where f_t: flow within time period t ;l_t: vertical length within time period t; v_t: average speed within time period t; t: time interval, equal to 2 min.

2.2 Definition of urban road traffic conditions

According to the indicators, urban road traffic conditions are studied by cluster analysis combined with existing theoretical research. The relevant cluster center is shown in the following matrix:

$$V = \begin{vmatrix} v_1 & v_2 & v_3 & v_4 \\ 1260 & 2100 & 1260 & 360 \\ 16 & 25 & 55 & 70 \\ 60 & 36 & 11 & 3 \end{vmatrix}$$

The first row of the matrix represents flow, the second row represents speed, and the third row represents the share ratio. v_1, v_2, v_3, v_4 represent block flow, congested flow, steady flow, and smooth flow cluster centers respectively.

3 SVM multi classification model

A new generic learning method was proposed by Vapnik *et al*. based on statistical theory and the support vector machine, which was on the basis of statistical theory of the VC dimension and structural risk minimization principle. The method seeks the best compromise between the complexity of the model and the learning ability according to limited sample information to obtain the best generalization ability. SVM can solve practical problems such as small sample, nonlinearity, high dimension, and local minima points[14]. In recent years SVM has made a breakthrough in theoretical research and algorithm realization, which was successfully applied to aspects of classification, function approximation, time series predictions, and so on[15].

In the process of urban traffic condition recognition, the definition of the observation matrix is [flow, speed, occupancy] combined with the actual conditions. The appropriate kernel function is selected and the observation matrix is put into the SVM discriminant function to achieve a condition classification.

SVM is proposed from an optimal classification under the linearly separable condition whose solving classifier is as:

$$f(\mathbf{x}) = \mathrm{sgn}(\mathbf{w} \cdot \mathbf{x} + b) = \mathrm{sgn}(\sum_{i=1}^{n} a_i y_i (\mathbf{x_i} \cdot \mathbf{x}) + b) \tag{4}$$

where a_i is the solution of the quadratic optimization problem,

$$\max_{\alpha} Q(\boldsymbol{\alpha}) = \sum_{i=1}^{n} a_i - \frac{1}{2}\sum_{i,j=1}^{n} a_i a_j y_i y_j (\mathbf{x_i} \cdot \mathbf{x_j}) \tag{5}$$

Subjected to $\sum_{i=1}^{n} y_i \alpha_i = 0 \quad 0 \le \alpha_i \le C \quad i = 1, 2, \cdots, n$ (6)

In Eq. (4), b can be obtained from the samples which can establish the following equation (support vector),

$$y_i (\sum_{i=1}^{n} \alpha_i (\mathbf{x_i} \cdot \mathbf{x}) + b) - 1 = 0 \tag{7}$$

For conditions of linear inseparability, SVM achieves a non-linear transformation by meeting the Mercer conditions of nuclear functions instead of vector product operations of the original pattern space, rather than explicitly using the specific forms of non-linear transformations. The essence is that it transforms the original pattern space into a high-dimensional or even infinite dimensional Hilbert space[16,17]. If we perform a non-linear transformation for $\boldsymbol{x}$, the new feature can be expressed as $z=\varphi(\boldsymbol{x})$. It can be proven that regardless of the specific transformation forms, the effect of the transformation to SVM is that it turns the inner products $(\boldsymbol{x_i} \cdot \boldsymbol{x_j})$ of the meta-feature space into a new space[18].

The kernel function is denoted as $K(\boldsymbol{x_i}, \boldsymbol{x_j})=(\varphi(\boldsymbol{x_i}) \cdot \varphi(\boldsymbol{x_j}))$. Thus the SVM of the transformation space is as follows:

$$f(\mathbf{x}) = \operatorname{sgn} \sum_{i=1}^{n} a_i y_i K(\mathbf{x_i}, \mathbf{x}) + b \tag{8}$$

Coefficient α is the solution of the following optimization problem:

$$\max_{\alpha} Q(\boldsymbol{\alpha}) = \sum_{i=1}^{n} a_i - \frac{1}{2}\sum_{i,j=1}^{n} a_i a_j y_i y_j K(\mathbf{x_i}, \mathbf{x_j}) \tag{9}$$

Subjected to $\sum_{i=1}^{n} y_i \alpha_i = 0 \quad 0 \le \alpha_i \le C \quad i=1,\ 2,\cdots,n$ (10)

where b can be obtained by solving the following equation (i.e., support vector);

$$y_i (\sum_{i=1}^{n} \alpha_i K(\mathbf{x_i}, \mathbf{x}) + b) - 1 = 0 \tag{11}$$

The kernel function can be generally divided into three classes as follows:

(1) Polynomial kernel function

$$K(\mathbf{x}, \mathbf{x'}) = (\gamma(\mathbf{x} \cdot \mathbf{x'}) + 1)^q \tag{12}$$

(2) Radial Basis Function (RBF) kernel function

$$K(\mathbf{x}, \mathbf{x'}) = \exp(-\gamma \frac{\|\mathbf{x} - \mathbf{x'}\|^2}{\sigma^2} \tag{13}$$

(3) Sigmoid kernel function

$$K(\mathbf{x}, \mathbf{x'}) = \tanh(v(\mathbf{x} \cdot \mathbf{x'}) + c) \tag{14}$$

The road traffic condition recognition system described in this paper is a multi classification problem. The traditional SVM method only considers a binary classification problem, so it is necessary to extend the SVM model to establish multiple SVM classifiers. Presently, two methods are used to construct SVM multi classifiers: one is a direct method which modifies the objective function. Parameters solving for multiple classification surfaces are merged into an optimization problem. It is done once to achieve multi classification by solving the optimization problem. This method involves a relatively high computational complexity, is difficult to achieve and is only suitable for small problems. The other one is an indirect method, mainly achieving multi classifiers through the combination of binary classifiers. In this paper, we use the LIBSVM toolbox a one-on-one method to build multi classifiers.

4 Experimental analyses with Matlab platform

Under setted block flow, congested flow, steady flow, smooth flow, average speed, and share ratio are obtained by using a simulation. We generated 50 samples per traffic condition, totalling 200 sets of observational data, among which 40 samples were training data, and 10 sets were detection data. Data pre-processing was completed using the LIBSVM toolbox and mapminmax function of MATLAB[14,19] to normalize data to a range of [0, 1]. Different kernel functions were chosen for training and classification, and the specific results are as Fig. 1.

Sample distributions of each dimension are shown in Fig. 1, there is no abnormality point in the box diagram.

Sample distributions in the featured space are shown in Fig. 2. As seen in the feature space, the sample distributions present a good clustering effect, which reveal that the feature space has some positive effect on distinguishing the category of the sample data.

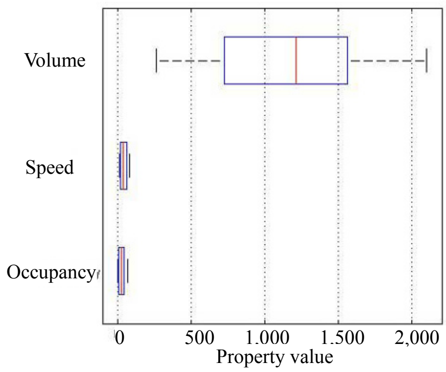

Fig. 1 Visualization box diagram of sample data

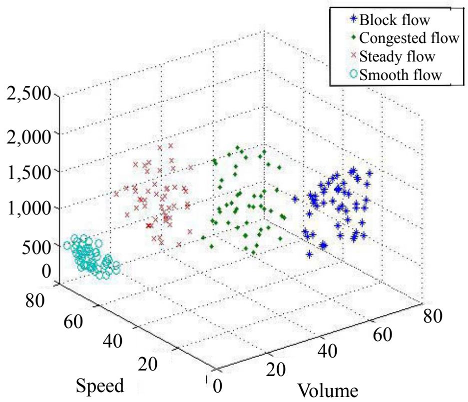

Fig. 2 Sample distribution in the featured space

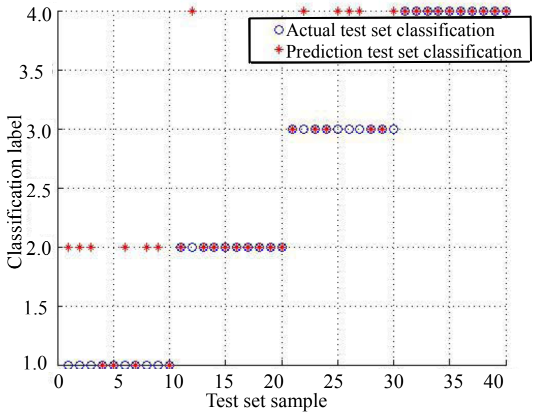

Fig. 3 Normalized data classification results under the polynomial kernel function

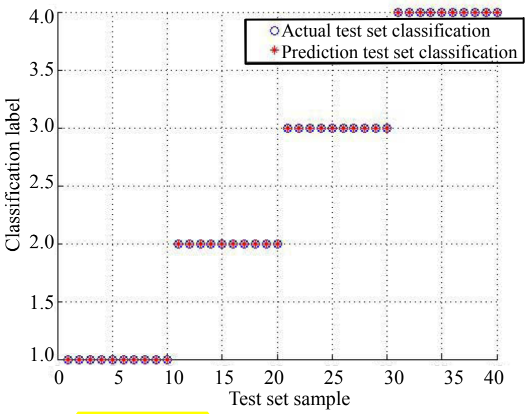

Fig. 4 Unnormalized data classification results under the polynomial kernel function

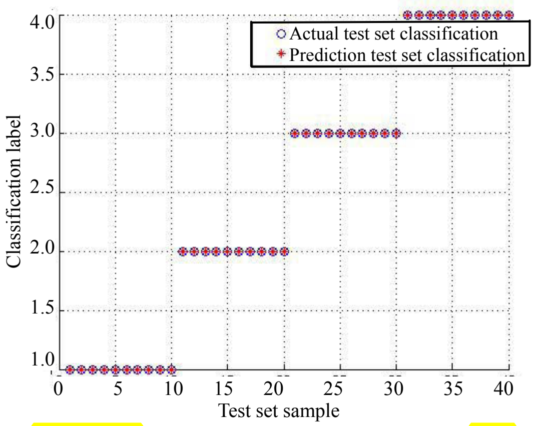

Fig. 5 Normalized data classification results under the RBF kernel function

Normalized classification results using the polynomial kernel function are shown in Fig. 3. As seen in Fig. 3, the effects of the test set classification results are less than ideal. Among 40 test samples 12 samples are misclassified with a 70% correction rate.

Unnormalized classification results using the polynomial kernel function are shown in Fig. 4. As seen in Fig. 4, the effects of the test set classification results are ideal. The correction rate is 100%.

We can see that it is useless to improve the classification effect of the polynomial kernel function by normalizing data after comparing the results of normalized and unnormalized process. In contrast the effects of the unnormalized data classification are better.

Normalized classification results using the RBF kernel function are shown in Fig. 5 on condition that c=2 and g=1. As seen in Fig. 5, effects of the test set classification results are ideal. All samples can be classified correctly with a correction rate of 100%.

Unnormalized classification results using the RBF kernel function are shown in Fig. 6 on condition that c=2 and g=1. As seen in Fig. 6, the effects of the test set classification results are not so good. Only 10 of the samples are classified correctly with a correction rate of 25%.

Normalized classification results using the sigmoid kernel function are shown in Fig. 7. As seen in Fig. 7, effects of the test set classification results are ideal with a correction rate of 100%.

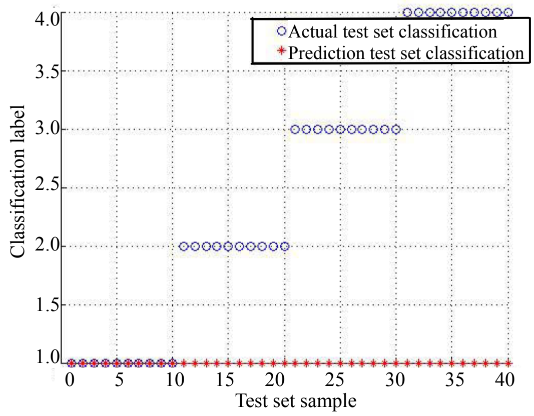

Fig. 6 Unnormalized data classification results under the RBF kernel function

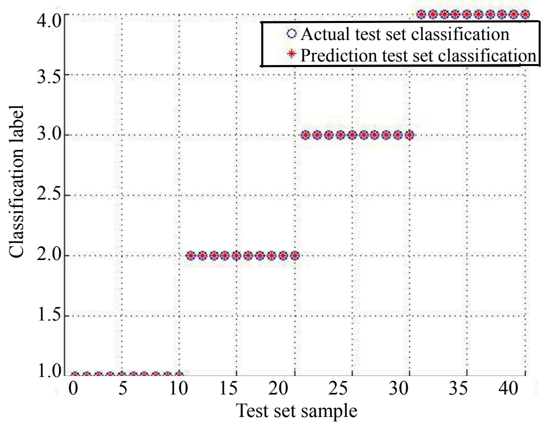

Fig. 7 Normalized data classification results under the sigmoid kernel function

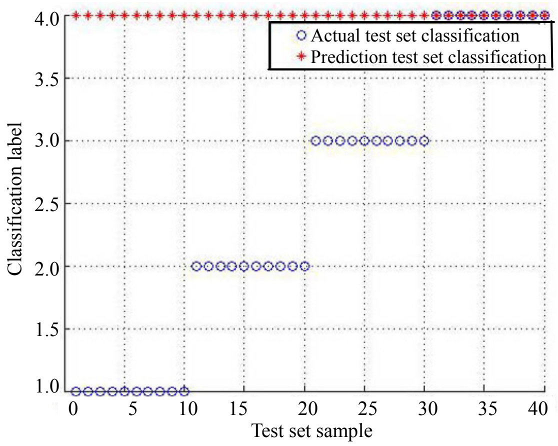

Fig. 8 Unnormalized data classification results under sigmoid kernel function

Table Parameter setting and classification results comparison among different SVM kernel functions

Function name	Polynomial		Radial basis function		Sigmoid	
Parameter settings	γ=1, q=3		c=2, g=1		v=1, c=0	
Normalization	Yes	No	Yes	No	Yes	No
Classification correction ratio	70%	100%	100%	25%	100%	25%

Unnormalized classification results using the sigmoid kernel function are shown in Fig. 8. As seen in Fig. 8, the effects of test set classification results are not so good. Only 10 of the samples are classified correctly giving a correction rate of 25%.

In comparing the above results, we can see the RBF and sigmoid functions help the data normalized classification while the unnormalized data classification effect is not so satisfactory. Parameter settings and different classification results are different under distinct SVM kernel function, which are shown in Table.

5 Conclusions

A three-dimensional parametric system including urban road traffic single-lane flow, average speed, and share ratio was studied based on literature and a simulation experiment. According to the indices mentioned above, road traffic flow includes block flow, congested flow, steady flow, and smooth flow. SVM algorithm experimental analyses were achieved under the MATLAB platform for the purpose of traffic condition classification and recognition. The study reached the following major conclusions:

(1) The indices of urban road traffic single-lane flow, average speed, and share ratio are chosen to reflect traffic conditions. Four kinds of traffic flows reflect important traffic parameters. At the same time they can be used as characteristic parameters of effective traffic condition recognition.

(2) By comparing various types of SVM kernel functions, we see that every kernel function can produce a highly accurate classification, which indicates good application effects.

(3) Whether data is normalized or not has an important impact on the SVM classification. By comparing normalized and unnormalized data classification results under different kernel functions, the effect of the RBF kernel function and sigmoid kernel function proves to be excellent for normalized data under the condition of the same parameters, while the polynomial kernel function is good for unnormalized data.

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References

[1] Pi X L, Yang X G, Sun Y. Application research of traffic state classification method based on collected Information from Loop Detector. East China Highway, 2006, 1: 33–38.

[2] Sadek A W, Demetsky M J, Smith B L. Case-based reasoning for real time traffic flow management. Computer-Aided Civil and Infrastructure Engineering, 1999, 14: 347–356.

[3] Palmieri F, Fiore U. A nonlinear recurrence-based approach to traffic classification. Computer Networks, 2009, 53(6): 761–773.

[4] Lozano A, Manfredi G, Nieddu L. An algorithm for the recognition of levels of congestion in road traffic problems. Mathematics and Computers in Simulation, 2009, 79(6): 1926–1934.

[5] Montazeri-Gh M, Fotouhi A. Traffic condition recognition using the k-means clustering method. Transportation Research Part B, 2011, 18(4): 930–937.

[6] Abdel-Aty M, Pande A. Identifying crash propensity using specific traffic speed conditions. Journal of Safety Research, 2005, 36(1): 97–108.

[7] Ruta A, Li Y M, Liu X H. Real-time traffic sign recognition from video by class-specific discriminative features. Pattern Recognition, 2010, 43(1): 416–430.

[8] U.S. Transportation Research Board . Highway capacity manual, Beijing: China Communications Press, 2007.

[9] Li Q Q, Gao D Q, Yang B S. Urban road traffic status classification based on fuzzy support vector machines. Journal of Jilin University (Engineering and Technology Edition), 2009, 39: 131–134.

[10] Li Z H, Sun D, Jin X X, *et al.* Pattern—based study on urban transportation system states and properties with fuzzy reasoning methods. Journal of Transportation Systems Engineering and Information Technology, 2008, 8(5): 83-87.

[11] Ren J T, Ou X L, Zhang Y, *et al.* Pattern recognition of traffic States. Journal of Highway and Transportation Research and

Development, 2003, 20(2): 63–67.

[12] Kannal L. Patterns in pattern recognition. IEEE Trans. on Information Theory, 1974, 20(6): 1968–1974.

[13] Li Z M. Traffic Engineering, Beijing: China Communications Press, 2000.

[14] Yang S Y. Pattern recognition and intelligent computing——MATLAB technology realization, Publishing House of Electronics Industry, 2011.

[15] Marques de Sá J P, Wu Y F. Pattern recognition——Principle, Method and Application, Beijing: Tsinghua University Press, 2002.

[16] Sun J X. Modern Pattern Recognition, Beijing, China: Higher Education Press, 2008.

[17 Duda R O, Hart P E, Stork D G, *et al*. Pattern classification, Publishing House of Electronics Industry, China CITIC Press, 2010.

[18] Zhang X G. Pattern Recognition (3rd edition), Tsinghua University Press, 2010.

[19] Hsu C W, Chang C C, Lin C J. A Practical Guide to Support Vector Classification, http://www.csie.ntu.edu.tw/~cjlin.