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PREDICTION OF PASSENGER FLOW ON THE HIGHWAY BASED ON THE LEAST SQUARE SUPPORT VECTOR MACHINE

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Abstract. A support vector machine is a machine learning method based on the statistical learning theory and structural risk minimization. The support vector machine is a much better method than ever, because it may solve some actual problems in small samples, high dimension, nonlinear and local minima etc. The article utilizes the theory and method of support vector machine (SVM) regression and establishes the regressive model based on the least square support vector machine (LS-SVM). Through predicting passenger flow on Hangzhou highway in 2000–2008, the paper shows that the regressive model of LS-SVM has much higher accuracy and reliability of prediction, and therefore may effectively predict passenger flow on the highway.

Keywords: support vector machine, statistical learning theory, least square support vector machine, regressive model, passenger flow, prediction.

1. Introduction

The prediction of passenger flow on the highway is very important dynamic analysis. It plays a key role in the rational allocation of resources and manages the investment structure of a corporation. However, the factors having an influence on passenger flow are rather complex. Traditional prediction methods have straight-line extrapolation, exponential smoothing, regression analysis and moving average (Chatfield 2003). However, these models have some limitations on solving highly nonlinear problems, so these models cannot meet objective requirements. In recent years, some prediction methods such as the grey system (Lin, Liu 2005; Zhang, Shi 2005), neural network (Vlahogianni *et al.* 2005; Junevičius, Bogdevičius 2009; Cigizoglu 2005; Ma *et al.* 2004), etc. have been introduced. These methods are some good solutions to solve nonlinear problems; nevertheless, they have some shortcomings. Although artificial neural networks have nonlinear mapping ability and generalizing capacity, the speed of algorithm training is very slow, and the errors of learning processes are converged easily to local minimum. Therefore, artificial neural networks are inefficient to ensure the accuracy of learning processes. In addition, the artificial neural network can guarantee empirical risk minimization under conditions of limited samples. In case of a number of samples, artificial neural networks can easily get into dimension disasters; they hardly generalize and explain the obtained results due to overfitting (Peng *et al.* 2007). The essence of grey prediction is exponential growth prediction (Xie, Liu 2005). Grey prediction requires that original time series should be non-negative monotonic functions and can accord with exponential laws. Then, the condition of grey prediction may fail to be satisfied. For these reasons, it is necessary to seek for new ways to accurately predict passenger flow on the highway.

The Support Vector Machine (SVM) based on the statistical learning theory was originally proposed by Vapnik (1998) and is a new type of classification and regression tools. As the best small-sample learning theory, SVM applications have been successfully developed in some areas such as pattern recognition, function approximation and financial time series (Kim, Sohn 2009; Vapnik 1998). Compared with the neural network, SVM could well solve some problems of small sample size, high dimensionality, nonlinear and local minima (Suykens, Vandewalle 1999). However, when dealing with serious sample problems, SVM also faces some problems. Taking quadratic programming (QP) as an example, QP should undertake the matrix operations of the kernel function in each of the iterations, but the matrix memory of the kernel function was squared up with the number of samples. Owing to the accumulation of iteration error, the accuracy of algorithms would not be accepted. The least squares support vector machine (LS-SVM) is the extension of SVM. Compared with standard SVM, LS-SVM substitutes equality constraints for inequality constraints on the SVM algorithm; solutions to QP problems are directly transformed into the solution to linear equations.

The article is divided into five sections. Section 2 contains the basic principle of SVM and LS-SVM. Section 3 constructs the prediction model of passenger flow on the highway according to characteristics of highway passenger transport. Section 4 introduces passenger flow on Hangzhou highway, makes a prediction and presents experiment results. Finally, Section 5 summarizes the paper.

2. Introduction to SVM and LS-SVM

SVM (Cao, Tay 2003) is based on the statistical learning theory and is a new machine learning method. The basic idea showing that SVM (Vapnik 1999) solves the problems of regression is to map input space into higher feature dimensional space by non-linear mapping. In higher dimensional space, SVM utilizes the principle of structural risk minimization to construct a linear decision function and do linear regression in new feature space.

2.1. SVM

Given a sample dataset:

$$D=\{(x_1,y_1),...,(x_i,y_i),...,(x_l.y_l)\}\in(x,y)^l, \tag{1}$$

where: input feature vectors – $x_i \in R^n$; target values – $y_i \in R$ and – $i = 1, 2,\dots, l$.

Our goal is to construct a regression function that represents the dependence of sample output y on inputs x. Let's define the form of this function as:

$$f(x)=\omega\cdot x+b, \tag{2}$$

where: ω is weigh vector; b is deviation.

In order to measure deviations between the estimate and target value, we first define ε-insensitive loss functions in the following form:

$$R(y,x)=\left|y_i-(\omega\cdot x_i+b)\right|_{\varepsilon}. \tag{3}$$

Then, we find optimal ω and b to approximate the minimum of empirical risk function R_{emp} or the minimum of the loss function as:

$$R_{emp}=\min\frac{1}{l}\sum_{i=1}^{l}\left|y_i-(\omega\cdot x_i+b)\right|_{\varepsilon}. \tag{4}$$

Supposed that all training data could be fitted inerrably by the linear function within the scope of ε according to Eq. (2), the regression problem is converted into the minimizing decision function expressed by Eq. (5):

$$L(\omega,\xi,\xi^*)=\frac{1}{2}\|\omega\|^2+c\sum_{i=1}^{l}(\xi_i+\xi_i^*);$$

$$\text{Subject to }\begin{Bmatrix}\omega\cdot x_i+b-y_i\le\varepsilon\\ y_i-\omega\cdot x_i-b\le\varepsilon\end{Bmatrix},\ i=1,2,\dots,l, \tag{5}$$

where: $c > 0$; $\omega=(\omega_1,\omega_2,...,\omega_l)^T$; ξ_i and ξ_i^* are an upper and a lower limit of a slack variable, the first term of Eq. (5) is responsible for finding a smooth solution while the second one minimizes training errors (c is the trade-off parameter between the terms).

Consequently, Lagrange can be formed as:

$$L(\omega,B,\xi,\xi^*,\alpha,\alpha^*,\gamma,\gamma^*)=\frac{1}{2}\|\omega\|^2+c\sum_{i=1}^{l}(\xi_i+\xi_i^*)-$$
$$\sum_{i=1}^{l}\alpha_i[\xi_i+\varepsilon-y_i+f(x_i)]-\sum_{i=1}^{l}\alpha_i^*[\xi_i^*+\varepsilon-y_i+$$
$$f(x_i)]-\sum_{i=1}^{l}(\xi_i\gamma_i-\xi_i^*\gamma_i^*), \tag{6}$$

where: α_i, $\alpha_i^*\ge 0$; γ_i, $\gamma_i^*\ge 0$; $i = 1, 2,\dots, l$.

According to the coincidence theorem, the above Eq. (6) can be converted into the following dual problem with an objective function and constrains:

$$W(\alpha,\alpha^*)=\frac{1}{2}\sum_{i,j=1}^{l}(\alpha_i-\alpha_i^*)(\alpha_j-\alpha_j^*)(x_i\cdot x_j)+$$
$$\sum_{i,j=1}^{l}(\alpha_i-\alpha_i^*)y_i-\sum_{i,j=1}^{l}(\alpha_i+\alpha_i^*)\varepsilon;$$
$$\text{Subject to }\sum_{i=1}^{l}\alpha_i-\alpha_i^*=0;\ 0\le\alpha_i;$$
$$\alpha_i^*\le C;\ i=1,2,\dots,l, \tag{7}$$

where: the parameters of α_i and α_i^* are Lagrange multipliers.

After calculating Eq. (7), the coefficient of the regression equation in Eq. (2) is as follows:

$$\omega=\sum_{i=1}^{l}(\alpha_i-\alpha_i^*)x_i. \tag{8}$$

2.2. LS-SVM Regression

LS-SVM (Burges 1998) is a variant of SVM proposed by Suykens. The standard SVM regression by Vapnik is modified to transform the QP problem into a linear problem (Suykens, Vandewalle 1999, 2000). These modifications are formulated in the definition of LS-SVM as follows:

$$\min_{\omega,\xi}\frac{1}{2}\|\omega\|^2+\frac{1}{2}\gamma\sum_{i=1}^{l}\xi_i^2. \tag{9}$$

Subject to $y_i=\omega^T\varphi(x_i)+b+\xi_i$, $i = 1, 2,\dots, l$,

where: ω is a full vector; ξ_i is error variable; b is deviation and γ is an adjustable constant.

From Eq. (9), the following Lagrange function can be formed:

$$L(\omega,b,\xi,\alpha)=\frac{1}{2}\|\omega\|^2+\frac{1}{2}\gamma\sum_{i=1}^{i}\xi_i^2-$$
$$\sum_{i=1}^{i}\alpha_i[\omega^T\varphi(x_i)+b+\xi_i-y_i], \tag{10}$$

where: the parameters of α_i are Lagrange multipliers.

Conditions for optimality are the following:

$$\begin{cases} \dfrac{\partial L}{\partial \omega} = 0 \rightarrow \omega = \sum_{i=1}^{l} \alpha_i \varphi(x_i); \\ \dfrac{\partial L}{\partial b} = 0 \rightarrow \sum_{i=1}^{l} \alpha_i = 0; \\ \dfrac{\partial L}{\partial \xi_i} = 0 \rightarrow \alpha_i = \gamma \xi_i, i = 1,2,...,l; \\ \dfrac{\partial L}{\partial \alpha_i} = 0 \rightarrow \omega^T \varphi(x_i) + b - y_i + \xi_i = 0, \end{cases} \quad (11)$$

where: $i = 1, 2, \ldots, l$.

The corresponding linear equation set (a Karush-Kuhn-Tucker system, see Suykens *et al.* 2002) is:

$$\begin{bmatrix} 0 & l_v^T \\ l_v & \Omega + \frac{1}{\gamma} I \end{bmatrix} \begin{bmatrix} b \\ \alpha \end{bmatrix} = \begin{bmatrix} 0 \\ y \end{bmatrix}, \quad (12)$$

where: $y = (y_1, \ldots, y_l)$; $l_v = [1, 1 \ldots 1]$; $\alpha = (\alpha_1, \ldots, \alpha_l)$; $\Omega = k(x_i, x_j) = [\varphi(x_i) \bullet \varphi(x_j)]$ is the kernel function.

Finally, the regression model for LS-SVM can be obtained in the form of:

$$y(x) = \sum_{i=1}^{l} \alpha_i k(x_i, x) + b. \quad (13)$$

3. Construction of the Regression Model Based on LS-SVM

According to the basic principle of the LS-SVM regression problem, the regression process of SVM is shown in Fig.1. The actual steps are as follows:

Step 1: The determination of influencing factors and data samples. Based on the goals of prediction, we determine the factors that influence prediction goals and form training and testing datasets.

Step 2: Scaling data. In order to increase computing speed and prediction accuracy and avoid too high or low characteristic value, we need to scale the sample dataset. The transformation equation is shown as follows:

$$x'_{ij} = \frac{x_{ij} - x_{i\min}}{x_{i\max} - x_{i\min}}, \quad (14)$$

where: x'_{ij} is scale values and passenger flow; $x_{i\min}$ and $x_{i\max}$ are the minimum and maximum of scale values and passenger flow respectively.

Step 3: Determine the input vectors of LS-SVM and establish mapping from input vector $x_n = [x_{n-1}, x_{n-2}, ..., x_{n-m}]$ to output vector $y_n = [x_n]$, $R^m \rightarrow R$, m is embedding dimension. The function is expressed as:

$$x = \begin{bmatrix} x_1 & x_2 & \ldots & x_m \\ x_2 & x_3 & \ldots & x_{m+1} \\ \ldots & \ldots & \ldots & \ldots \\ x_{n-m} & x_{n-m+1} & \ldots & x_{n-1} \end{bmatrix}; \; y = \begin{bmatrix} x_{m+1} \\ x_{m+2} \\ \ldots \\ x_n \end{bmatrix}. \quad (15)$$

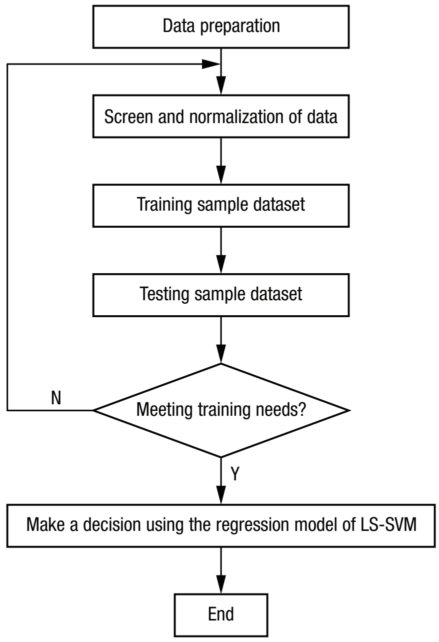

Fig. 1. Regression flow chart of LS-SVM

Step 4: Selecting the kernel function. A selection of the kernel function and parameters both directly influence generalization capacity of LS-SVM. In LS-SVM model, the commonly used Kernel function includes the following:

- Linear:

$$K(x, y) = xy; \quad (16)$$

- Polynomial:

$$K(x, x_i) = [(x, x_i) + 1]^q; \quad (17)$$

- Radial basis function (RBF):

$$K(x, x_i) = \exp\left\{ -\frac{|x - x_i|^2}{\sigma^2} \right\}; \quad (18)$$

- Sigmoid:

$$K(x, x_i) = \tanh[v(x, x_i) + \alpha]. \quad (19)$$

Step 5: Parameter optimization and model application. We train the sample dataset by utilizing LS-SVM model. Through cross validation, we find the best training parameters of LS-SVM, including penalty coefficient(C), kernel function parameter (σ), etc. and input the testing dataset to predict passenger flow by using Eq. (13).

Step 6: Performance evaluation. The accuracy evaluation of the model is as follows:

- Prediction error:

$$E_{MA} = \left| \frac{y_i - y_i^*}{y_i} \right|; \quad (20)$$

- Root mean square error:

$$E_{MSE} = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (y_i - y_i^*)^2}; \quad (21)$$

- Prediction accuracy:

$$A = 1 - E_{MSE} = 1 - \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - y_i^*)^2}\ , \qquad (22)$$

where: y_i is the actual value of the sample; y_i^* is the estimated value according to LS-SVM model; n is the number of the prediction value.

4. Empirical Case Studies

4.1. Architecture of the Index System

The prediction of passenger flow on the highway is based on historical data and influencing factors, and therefore, must accord with the characteristics and development trend towards passenger flow on the highway (Junevičius, Bogdevičius 2009).

In general, a highway traffic system is a complex one (Junevičius, Bogdevičius 2007). There are many influencing factors (Fig. 2) in predicting passenger flow on the highway, including economic (for example, urban economic development level) and non-economic factors (urban scale and urban population):

1. ***Urban economic development level.*** Demand for highway passengers mainly comes from two different fields: production and consumption. Economic development not only increases the activities of production, but also stimulates travels of consumers and drives a stable increase in travelling passengers along with economical development.
2. ***Urban scale and urban population.*** The quantity and structural changes of urban population will cause changes in traffic demand. Normally, when the frequency of travelling remains unchanged, population increase will cause a rise in highway passenger flow. In addition, with an increase in non-agricultural population, rural surplus labour will transfer to the town and result in an increase in passenger flow on the highway.

4.2. Data Preparation

The data presented in the article come from passenger flow on the highway, registered in Hangzhou Statistical Yearbook (1998–2008) and is provided by Hangzhou Bureau (*http://www.hzstats.gov.cn*). We have selected eight prediction indexes that greatly influence passenger flow: population (agricultural population, non-agricultural population), gross domestic product (primary industry, secondary industry and tertiary industry), per capita disposable income, the total retail sales of social consumer goods, civilian vehicle ownership. Specific descriptions of prediction indexes are shown in Table 1 and those of the sample data in Fig. 3.

4.3. Data Preprocessing

First, we construct a training dataset of eight inputs and one output referring to the data obtained within the period 2000–2005. Then, we make the corresponding testing sample set using data collected for the period 2006–2008 and apply the LS-SVM model for training and testing.

Second, we scale data on training and testing datasets for passenger flow on Hangzhou highway because scaling can avoid attributes in great numeric ranges and numerical difficulties during calculation. The data displayed in the article are scaled to (0, 1). The normalized results are shown in Table 2.

4.4. Regression Prediction of LS-SVM

One of the most important factors in building the prediction regression model using LS-SVM is the selection of the kernel function. In general, there are four main types of kernel: linear, polynomial, radial basis function (RBF) and sigmoid. In this article, the RBF kernel function is used as the default kernel, because RBF has better advantage than the other kernel function under a lack of prior knowledge. First, the RBF kernel can map nonlinear samples into higher dimensional feature space and deal with samples when relation between regression data and an attribute is nonlinear (Suykens *et al.* 2002).

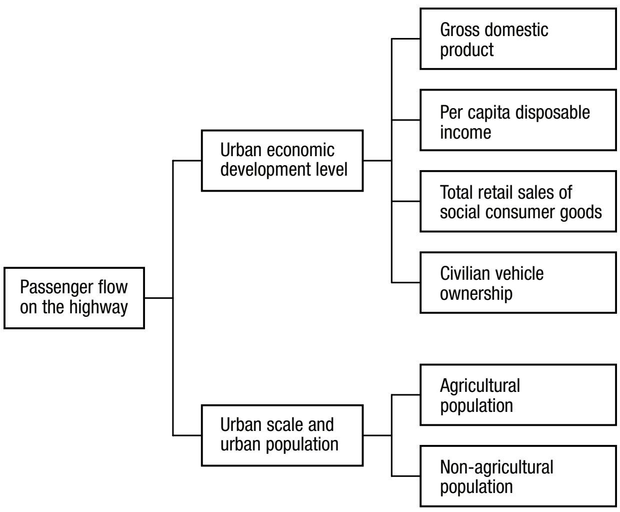

Fig. 2. Influencing factors of passenger flow on the highway

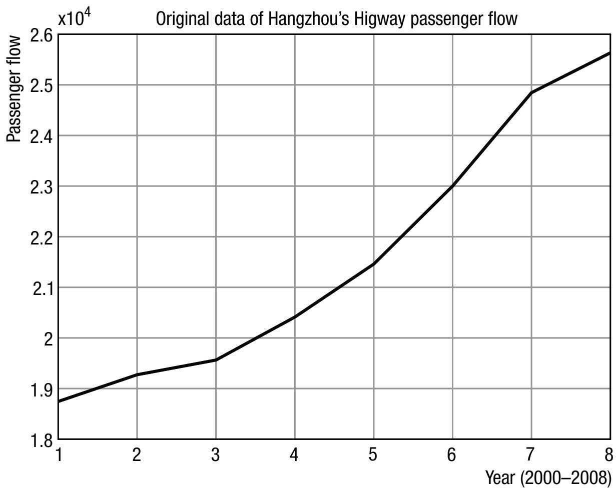

Fig. 3. Original data on passenger flow on Hangzhou highway

Table 1. Original data and influencing factors regarding passenger flow on Hangzhou Highway

Year	Population (10000 persons)		Gross domestic product (billion Yuan)			Per capita disposable income (Yuan)	Total retail sales of social consumer goods (billion Yuan)	Civilian vehicle ownership (10000 persons)	Highway's passenger flow (10000 persons)
	agricultural population	non-agricultural population	primary industry	secondary industry	tertiary industry				
2000	394.59	226.99	103.96	709.32	569.28	9668	514.68	172343	17102
2001	391.37	237.77	111.46	793.58	662.98	10896	579.01	204223	18707
2002	384.79	252.02	114.64	901.82	765.37	11778	660.65	250018	19213
2003	379.11	263.67	126.59	1075.78	897.4	12898	742.58	329436	19510
2004	369.1	282.58	132.23	1318.23	1092.72	14565	855.45	414355	20372
2005	362.91	297.54	148.21	1496.94	1297.5	16601	975.43	495876	21431
2006	356.53	309.78	154.86	1734.58	1552.07	19027	1112.37	596385	22961
2007	348.6	323.75	163.47	2056.93	1879.77	21689	1296.31	712398	24836
2008	336.88	340.76	178.64	2389.38	2213.14	24104	1558.38	822677	25630

Source: Hangzhou Statistical Yearbook (1998–2008) – *http://www.hzstats.gov.cn*

Table 2. Normalized data and influencing factors regarding passenger flow on Hangzhou Highway

Year	Population (10000 persons)		Gross domestic product (billion Yuan)			Per capita disposable income (Yuan)	Total retail sales of social consumer goods (billion Yuan)	Civilian vehicle ownership (10000 persons)	Highway's passenger flow (10000 persons)
	agricultural population	non-agricultural population	primary industry	secondary industry	tertiary industry				
2000	1	0	0	0	0	0	0	0	17102
2001	0.944204	0.094753	0.100428	0.050153	0.057	0.085065	0.061636	0.049021	18707
2002	0.830185	0.220005	0.14301	0.114579	0.119286	0.146162	0.139858	0.119439	19213
2003	0.731762	0.322405	0.303026	0.218123	0.199603	0.223746	0.218358	0.241557	19510
2004	0.558309	0.488617	0.378548	0.362433	0.318421	0.339221	0.326502	0.372135	20372
2005	0.451048	0.620111	0.592528	0.468805	0.442994	0.480258	0.441458	0.497487	21431
2006	0.340496	0.727696	0.681575	0.610252	0.597855	0.64831	0.572665	0.652037	22961
2007	0.203084	0.850488	0.796867	0.80212	0.797203	0.83271	0.748903	0.830427	24836
2008	0	1	1	1	1	1	1	1	25630

Second, in terms of performance, the linear kernel is a special case of RBF (Keerthi, Lin 2003). The linear kernel having parameter C performs similarly to the RBF kernel having parameters (C, γ). Third, the number of hyperparameters influences the complexity of the regression model, and therefore the polynomial kernel has more hyperparameters than the RBF kernel (Kim *et al.* 1999). Finally, the RBF kernel has few numerical difficulties because the kernel value lies between zero and one. On the contrary, the polynomial kernel value may go to infinity or zero when the degree is high. Then, the RBF kernel is used for building the default prediction regression model for passenger flow on the highway.

When the RBF kernel is selected as a default function, two parameters(C, γ) associated with the RBF kernel also need to be decided. Upper bound C and kernel parameter γ play important role in the performance. Keerthi and Lin (2003) suggested a practical guideline for SVM using grid-search and cross validation the reason for which is that the latter function can prevent from the overfitting problem; grid-search can avoid searching for an exhaustive parameter and may find good parameters for computational time. In addition, each parameter (C, γ) is independent, and thus grid-search can be easily parallelized.

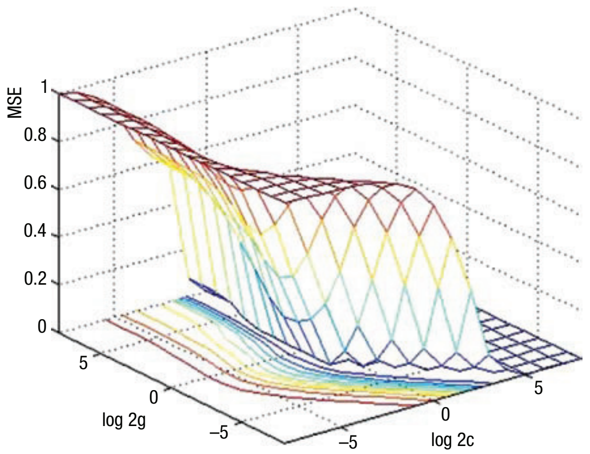

Fig. 4. A parameter map of the kernel function in coarse grid

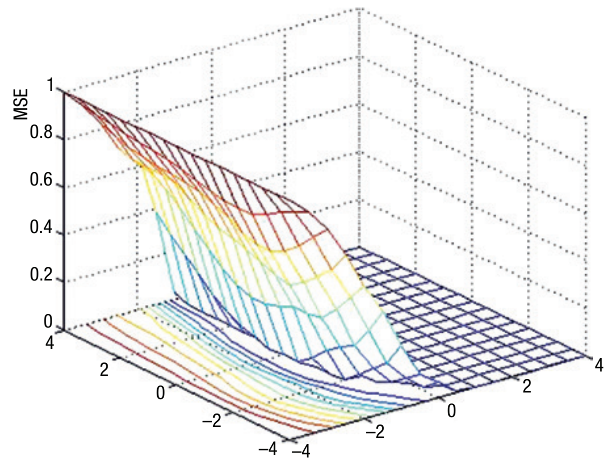

Fig. 5. A parameter map of the kernel function in a finer grid

The article uses the methods of RBF, cross validation and grid-search to determine the optimal parameters of LS-SVM in accordance with the procedures of mesh generation and gradual refinement. First, we use a coarse grid (Fig. 4) and find out that the best (C, γ) is (32, 0.0039) with the cross validation rate of 98.56%. Next, we use finer grid search (Fig. 5) and establish that the best (C, γ) is (1, 0.125) with the cross validation rate of 0.995971%. After the best (C, γ) is found, the whole training dataset is retrained to generate the final regression result of passenger flow on the highway for the period 2006–2008 (Table 3).

4.5. Results

This article uses the regression method of LS-SVM to predict passenger flow on the highway for the period 2006–2008 and measures the results of predictions applying four performance indexes (Table 4). The obtained data show that LS-SVM model has higher predicting accuracy and fitting degree (Fig. 6). In addition, through adjusting constants for LS-SVM model (Table 5), the article reduces error and strengthens the smooth degree of the regression function as soon as possible. Therefore, we suppose it is feasible and effective to predict passenger flow on the highway using the regression method of LS-SVM.

Table 3. Prediction results and error of passenger flow on the Hangzhou highway

Time	2006	2007	2008
Actual value	22961	24836	25630
Prediction value	22955	24321	25559
Prediction error	0.00026	0.02073	0.0028

Table 4. The performance index of prediction model

Maximum difference	515	E_{MA}	0.00793
E_{MSE}	0.0008	Prediction accuracy	99.5971%

Table 5. Model parameters and optimized contrast of LS-SVM

	MSE	C	γ	Squared correlation coefficient
Initialize results	0.0076	32	0.0039	0.98555
Optimize results	0.0082	1	0.1250	0.995971

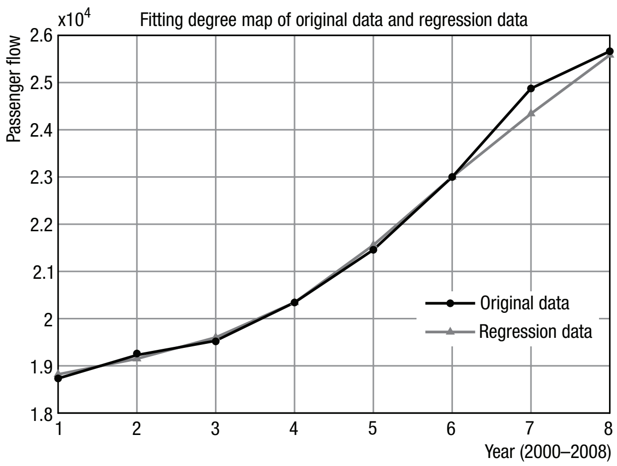

Fig. 6. A corresponding degree between original data and regression data

5. Conclusions

1. LS-SVM based on the statistical learning theory is a machine learning method having a strict theoretical basis and able to solve some problems of small sample size, high dimensionality, nonlinear and local minima. Due to its excellent merit, the article constructs the nonlinear regression model based on LS-SVM, and uses the example of nine samples to make a prediction. The obtained result shows that the prediction method based on LS-SVM is feasible and accurate and can provide a new method for passenger flow on the highway.

2. Passenger flow on the highway is an important index that reflects passenger capacity on the highway and has a very important meaning of grasping development trend, characteristics and rules for passenger flow on the highway. However, the prediction methods of passenger flow on the highway have still been based on the total amount by now. In fact, the prediction of the total passenger flow is only an aspect of prediction. In fact, the prediction of the total passenger flow is only an aspect of prediction. While discussing passenger flow, we should also consider space position and passenger distribution because these are important factors in formulating development plan for the highway and arranging stations.
3. A traffic system on the highway is a complex one. There are many influencing factors in predicting passenger flow on the highway, including economic, non-economic, quantitative and qualitative factors. To some extent, the method discussed in the article is mainly based on data, thus some limitations can be observed. In case some qualitative analyses should be added, it could compensate for a shortage of quantitative methods.

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