Vehicle Travel Time Predication based on Multiple Kernel Regression

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Abstract—With the rapid development of transportation and logistics economy, the vehicle travel time prediction and planning become an important topic in logistics. Travel time prediction, which is indispensable for traffic guidance, has become a key issue for researchers in this field. At present, the prediction of travel time is mainly short term prediction, and the prediction methods include artificial neural network, Kaman filter and support vector regression (SVR) method etc. However, these algorithms still have some shortcomings, such as high computation complexity, slow convergence rate etc. This paper exploits the learning ability of multiple kernel learning regression (MKLR) in nonlinear prediction processing characteristics, logistics planning based on MKLR for vehicle travel time prediction. The method for Vehicle travel time prediction includes the following steps: (1) preprocessing historical data; (2) selecting appropriate kernel function, training the historical data and performing analysis; (3) predicting the vehicle travel time based on the trained model. The experimental results show that, through the analysis of using different methods for prediction, the vehicle travel time prediction method proposed in this paper, archives higher accuracy than other methods. It also illustrates the feasibility and effectiveness of the proposed prediction method.

Index Terms—Logistics, Transportation, SVR

I. INTRODUCTION

With the rapid development of transportation and logistics economy, distribution bears the process of delivering goods and materials from the distribution center or warehouse to customers in the logistics operation. Logistics distribution is a core technique for logistics management activity, and it has very important economic and social significance [1]. The delay of the delivery will cause a loss to the relevant enterprises in the supply chain from the aspects of costs and service efficiency. So under the existing conditions, it should consider the distribution center that how to arrange the delivery time and make the distribution cost minimum. In other words, in the process of marching, travel time prediction is quiet important, and the accurate travel time prediction of the development of transportation and logistics distribution is important to research [2-4]. The exact prediction of vehicles travel time is the premise and foundation of carrying out logistics vehicle scheduling, providing basic data for the realization of logistics distribution and improving the logistics resources conversion rate.

Therefore, how to effectively predict logistics vehicle travel time and planning has become an issue that researchers are paying more and more concern to [2-4]. As one of the important indices reflecting traffic conditions and the essential content, the route travel time could support the traffic administrative department about the data on traffic management and control [5]. At the same time, it also provides some bases for travelers choosing a route or for adjusting traveling plan. Currently, there are lots of researches on travel time prediction methods [6]. Up to now, most of the research works are conducted for understanding the road traffic congestion conditions, and aims to get the short term prediction method of travel time by using the current traffic information of the small network and historical travel time data. In the process of prediction, the researchers use different kinds of tools. Some of them use loop testing data to identify automotive vehicle; some of them carry out the prediction based on the vehicle’s probe vehicle data and floating car data [7]. The common point of all current practices is the prediction that in a relatively narrow range lane and single road conditions, that is the single highway or a single urban and rural road [8]. They only consider the small scope and small networks of route limitation, using traffic data for short term traffic prediction.

In the traffic guidance system, travel time prediction as the main content of the research, in order to realize real time guidance of a vehicle, travel time prediction must have real time performance, reliability and higher precision. Travel time prediction model predicted travel time based on the analysis of the relationship between traffic parameters and traffic capacity, while it is not characterized with real time [9]. At present, there are lots of predictions about travel time, and they are all classified into two categories: One is aggregative model, it is of strong adaptability, but it also need more traffic parameters; one is time prediction model based on time of road section. It is of weak adaptability, but the model is simple and easy to calibrate. There are many travel time prediction model in China, but most are using simulation data, if used for practical prediction, there are a lot of factors to optimization and improvement.

Specifically, in the world, there are a lot of researches in the travel time prediction, especially on the historical travel time prediction [1, 3, 5], including neural network, mathematical statistics, linear regression and Kalman filter, the improved k-means clustering method, the
improved moving average method, Bayesian classifier and rule-based classifier to predict travel time. However, they all need a large amount of data sample size [10]. Neural network is a kind of data modeling method, it has the property of nonlinearity, adaptability and integration, and it can effectively implement real time prediction of traffic information, constitute a time-varying road impedance matrix, so this paper adopted the advantages of neural network method. Using Kalman filter to estimate traffic time has the characteristics of choosing predictive factor flexibly and high precision [11]. In order to apply the nonlinear character of short-time traffic flow changes, the prediction precision should remain in the ideal range as the prediction interval shorten. But using the method in non-peak period, the prediction precision is low.

Comparing the basic trend prediction model, we mainly use methods based on the mathematical statistics, the principle of this method is mainly need to assume the future predicted data and historical data having the same characteristics, then using historical data to predict traffic flow, traffic data and travel time, etc [12-13]. The main model used by this method is the historical average model. It has been widely used in the beginning of short term traffic prediction and in urban traffic control system and traffic route guidance.

The advantage of linear regression model method is using a small, simple testing equipment can achieve a prediction model, its invested resources are simple and cheap. But it is poor in adaptability and real time performance, because the linear regression model is predetermined, through the influence factors of the actual measured prediction, the results apply only to certain roads [14]. And when a large deviation appears between the actual traffic conditions and parameter calibration of traffic state, the prediction error will increase, and prediction model can't timely correction error, and it is also difficult to calibrate online multiple linear regression parameters. Moreover, in the process of the quantification of the main factors influencing, the prediction still exists some kinds of uncertainty. We can predict the travel time of the historical data highway vehicles by using linear regression analysis and gray theory model, the two types of speed weighted final prediction speed. Then we can get the predicted travel time by making reoccupy section length divided by prediction speed [15]. Fuzzy regression of highway travel time prediction model considers various factors, when it achieve high accuracy based on applying this model, but the weight allocation method is different. In the methods of travel time prediction, there are still some problems: (1) data sampling difficulty; (2) using the drive and speed ratios to predict time, there is a certain error ratio; (3) various factors impacting drive time, as well as the ratio of parameters; (4) these models can only be adapted to the specific road segment and universality is poor.

The problem this paper focuses on is how to How to build a predicting model of small sample, high precision to realize the vehicle travel time prediction. In view of this paper combines the learning ability MKLR nonlinear prediction processing characteristics [15], logistics planning was proposed based on MKLR vehicle travel time prediction algorithm. So, the researches of vehicle travel time to logistics planning: (1) firstly preprocesses historical data; (2) select the appropriate kernel function and make training of the historical data, and do error analysis; (3) predict the vehicle travel time by using the trained network.

Experimental results show that, through the analysis of using different methods to predict, travel time prediction method, which put forward in this paper, has higher accuracy than the above methods. It also could illustrate the feasibility and effectiveness of the proposed prediction method.

II. OUR PROPOSED SCHEME

To overcome the shortcoming of previous approach, in this part, we will propose a method for problem name. Our proposed algorithm is on the base of the generalized multiple kernel learning. The graphical illustration of our approach for problem name is summarized in Figure. It contains several procedures, (1) data collection; (2) model the data and extract the feature; (3) train the model and perform test.

![Figure 1. The flow chart for the proposed framework](image)

The dataset comes from the monitoring data collection of the high speed intersection on certain section collected by Shanghai traffic management departments, which selected the 68 data as the research object during National Day. These data are used for predictive analytics for travel, travel time, average speed and so on in the logistics plan, which are divided into training set and test set.

A. Generalized Multiple Kernel Learning

Despite of the extensive application of single kernel learning approach, for samples contain heterogeneous information, irregular instance or uneven distributed example in high dimensional feature space, using single kernel to map such database is unreasonable [13]. Consequently, for the above problem, study on kernel combination, i.e., multiple kernel learning, has obtained increasing attention in recent years, and played important role in a lot of problems. This paper introduces a multiple kernel learning approach which breakthroughs the traditional form which is the linear combination of kernel functions, using extending multiple kernels to a more general form.

For kernel function with the form $f(x) = w^T \phi(x) + b$, $k_{d}(x_i, x_j) = \phi(x_i)^T \phi(x_j)$ denotes the inner product over the feature space $\phi$; $d$ is the parameter. This function
could be used for regression or identification according to the characteristics of the function. In support vector machine, the learning goal is to determine $w$ and $b$ from training example $(x_i, y_i)$. Additionally, multiple kernel learning can also solve the kernel parameter $d$. The multiple kernel learning could be extended to:

$$
\frac{1}{2} w^T w + \sum_{i} l(y_i, f(x_i)) + r(d)
$$

where $d \geq 0$; $r$ and the kernel can be arbitrary general function which must be continuous and derivable with respect to $d$; $l$ can be any type of loss function. Here we use the following one for regression.

$$
l = C \max(0, |y_i - f(x_i)| - \varepsilon)
$$

Three conditions need attention. First, we adopt non-convex equation, which is exactly opposite to convex equation $\sum_{i} w_i^T w_i / d_i$, since for the general kernel combinations $w_i^T w_i$ which run not require to tend to 0 with $d_i$ tending to 0. Second, we assume which $r(d)$ has strong objectivity and it also is composed of a set of parameters rather than taking it as a constraint. The final the constraints of function $d \geq 0$ could be relaxed to a more general situation that it is defined positive [5, 10]. If prior knowledge could be got, the constraint can also be enhanced. In both cases, if there is $\nabla_y r$, then gradient descent based optimized is still available [5].

In order to use the existing large-scale optimization, a criterion procedure is used to tune the original two-step nested optimization. In the outer loop, the kernel learning is run through the re-optimization of $d$, while in the inner loop, the kernel is fixed and the support vector machine parameters could be learn. This can be achieved by means of rewriting the original assumption as the following equation for $d \geq 0$.

$$
\min T(d) = \min \frac{1}{2} w^T w + \sum_{i} l(y_i, f(x_i)) + r(d)
$$

B. Solution Using Gradient Descent

If gradient descent is not used in the outer loop, we would like prove the existence of $\nabla_y T$, and efficient compute is needed. When proving the existence of $\nabla_y T$, the dual formulations of $T$ could be used as follows,

$$
W_c(d) = \max \gamma \alpha - \frac{1}{2} \alpha^T Y K Y \alpha + r(d)
$$

$$
W_k(d) = \max \gamma \alpha - \frac{1}{2} \alpha^T K \alpha + r(d) - \gamma \in Y [\alpha]
$$

where $K$ is the kernel matrix, $Y$ is a diagonal matrix whose element is class label.

It can be proved which $W_c$ and $W_k$ can be derived:

$$
\frac{\partial T}{\partial d_i} = \frac{\partial r}{\partial d_i} - \frac{1}{2} \alpha^* \frac{\partial H}{\partial d_i} \alpha^*
$$

In the above formula, it can be used for the regression when $H = K$. Hence, so that utilize gradient, we first require getting $\alpha^*$. As a result of $W_c$ or $W_k$ are equal to their corresponding multiple kernel matrix of single kernel support vector machine, $\alpha^*$ can be obtain using any support vector machine optimization algorithm. In order to ensure the convergence and projection operation, we choose $s^*$ based rules of Armijo. For limiting condition $d \geq 0$, it is so simple like $d \leftarrow \max(0, d)$. If we demand a fast convergence rate, then we can make the appropriate changes rather than through gradient descent so as to conduct the second step of our assumptions successfully.

Note that kernel $K$ is limited to positive and $\nabla_y K$ is limited to be existent and continuous. Therefore we could obtain kernels $K$ meeting the conditions [5]. Moreover, we could convert the kernel parameters to general kernel form, for data,

$$
k_i(x_i, y_i) = (d_0 + \sum_{m} d_m \phi(x_i) \phi(y_i))^s
$$

Or written as

$$
k_i(x_i, y_i) = \exp(-\sum_{m} d_m \phi(x_i) \phi(y_i))
$$

So that to fit $A$, minor adjustments to $d$ is required. We could utilize it for feature.

For $r$, we need to assume it a continuously differentiable function. Because $d$ is limited to the non-negative quadrant, then the distinct forms of $p \geq 1$ falling within this range. In fact, adjusting $l_i$ with $r(d) = \delta^T d$ could be used to determine some common problems. When only a few relevant kernels appear or if $\mu$ and $\sum$ can be got, then $l_i$ can be adjusted through the form of $r(d) = (d - \mu)^T \sum^{-1}(d - \mu)$. Finally, when it is employ for regression, $\log |K_A|$ can be included in $r$.

The step of MKLR is report in Table I.

| Algorithm 1 MKLR | 1: $n \leftarrow 0$
| 2: initialize $d^*$ randomly | 3: Repeat the operation
| 4: $K \leftarrow k(d^*)$ | 5: Choose the support vector machine and employ kernel $K$ and $\alpha^*$
| 6: $d^{n+1} \leftarrow d^* - s^* \left( \frac{\partial r}{\partial d_i} - \frac{1}{2} \alpha^* \frac{\partial H}{\partial d_i} \alpha^* \right)$ | 7: If the restrictions are independent, $d^{n+1}$ will be mapped to the feasible configure
| 8: $n \leftarrow n+1$ | 9: until convergence

III. EXPERIMENTAL RESULTS

This section will empirically assess our proposed MKLR for traffic prediction. The experiment procedures are as follows. First, perform data collection and data
processing. Second, feature extraction using the approach in the above section. Third, train the model and perform test. The experimental steps are summarized in the above figure. This section will sequentially present the dataset, evaluation criterion and experimental results.

A. Experimental Dataset

The data used in this paper is the monitoring data of the highway interaction on certain section collected by Shanghai traffic management departments. It is mainly used for predictive analytics for travel, travel time, average speed and so on in the logistics plan. Dataset in total includes the date of eight sections and nine locations. The data of these factors can be divided into training and identification two phases. The data in the training data is the former 45 groups, while the test data is the remaining 23 groups. The task is to use the MKLR method to predict these factors. Because of the kernel function regression method adopted as above; this paper selected the 68 data as the research object during National Day. The dataset is summarized in Table II.

<table>
<thead>
<tr>
<th>Dataset</th>
<th>Training set</th>
<th>Test set</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>vehicle miles</td>
<td>45</td>
<td>23</td>
<td>68</td>
</tr>
</tbody>
</table>

B. Evaluation Criterion

The mean squared error (MSE) of an estimator is a way to quantify the difference between values implied by an estimator and the true values of the quantity being estimated. MSE is a risk function, corresponding to the expected value of the squared error loss or quadratic loss. MSE measures the average of the squares of the error. The error is the amount by which the value implied by the estimator differs from the quantity to be estimated. The difference occurs because of randomness or because the estimator doesn't account for information that could produce a more accurate estimate.

\[
\hat{Y} = \text{a vector of } n \text{ predictions,}
\]

\[
MSE = \frac{1}{n} \sum_{i=1}^{n} (\hat{Y}_i - Y_i)^2
\]

and \( Y \) is the vector of the true values, then the MSE of the predictor can be expressed as:

\[
MSE = \frac{1}{n} \sum_{i=1}^{n} (\hat{Y}_i - Y_i)^2
\]

The MSE is the second moment (about the origin) of the error, and thus incorporates both the variance of the estimator and its bias. For an unbiased estimator, the MSE is the variance of the estimator. Like the variance, MSE has the same units of measurement as the square of the quantity being estimated. In an analogy to standard deviation, taking the square root of MSE yields the root-mean-square error (RMSE) or root-mean-square deviation (RMSE), which has the same units as the quantity being estimated; for an unbiased estimator, the RMSE is the square root of the variance, known as the standard deviation.

C. Main Results

In the first experiment, it target to verify the superiority and robustness of MKLR method for traffic prediction, in comparison with others. The Shanghai Traffic dataset is collected from the highway interaction of Shanghai and is randomly separate to training set and test set. The dataset is collected from the monitors of the highway interaction by Shanghai traffic management department. It contains 68 groups of data from eight sections and nine locations. We utilize MSE and RMSE as the evaluation standard for evaluation. As summarize in the previous part, the parameters of MKLR is determine by the standard method. The train MKLR is then adopted to conduct identification. The test is performed for multiple rounds, with default set.

<table>
<thead>
<tr>
<th>Experiment</th>
<th>Algorithm</th>
<th>Evaluation standard</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>MSE</td>
</tr>
<tr>
<td>Round 1</td>
<td>SVR</td>
<td>0.229</td>
</tr>
<tr>
<td></td>
<td>MKLR</td>
<td>0.106</td>
</tr>
<tr>
<td>Round 2</td>
<td>SVR</td>
<td>0.199</td>
</tr>
<tr>
<td></td>
<td>MKLR</td>
<td>0.119</td>
</tr>
<tr>
<td>Round 3</td>
<td>SVR</td>
<td>0.238</td>
</tr>
<tr>
<td></td>
<td>MKLR</td>
<td>0.219</td>
</tr>
<tr>
<td>Round 4</td>
<td>SVR</td>
<td>0.226</td>
</tr>
<tr>
<td></td>
<td>MKLR</td>
<td>0.191</td>
</tr>
<tr>
<td>Round 5</td>
<td>SVR</td>
<td>0.209</td>
</tr>
<tr>
<td></td>
<td>MKLR</td>
<td>0.153</td>
</tr>
<tr>
<td>Average</td>
<td>SVR</td>
<td>0.218</td>
</tr>
<tr>
<td></td>
<td>MKLR</td>
<td>0.166</td>
</tr>
</tbody>
</table>

Figure 2. The comparison of experimented algorithm over two standard

The MSE and RMSE is take advantage of as the assessment standard for the traffic prediction. We do the experiment for 20 rounds and present the experimental results of partial trial are in Table III and Figure 2. As report in Figure 2, using our method to learn parameter, MKLR for traffic prediction reach the highest performance of 0.276 under the criterion of MSE, while MKLR achieve the highest performance of 0.345 under the criterion of RMSE. Further, the average MSE of MKLR is 0.166 which outperforms that of (linear square regression) LSR (0.218). The potential reasons for these results are mainly threefold. Firstly, the MKLR has the ability to map the nonlinear data in the low dimensional space to the high dimensional space by a kernel function, which makes the prediction problem easy. Secondly, the
parameter selection algorithm is according to the distribution information of the input data to determine the parameters of the MKLR, which makes the MKLR having better adaptability. Thirdly, the experimental procedure of the proposed algorithm could provide informative features and maximize the discrimination ability.

In the second experiment, we run experiments over Shanghai Traffic dataset. The dataset is collected from the monitors of the high speed interaction by Shanghai traffic management department. It contains 68 groups of data from eight sections and nine locations. This experiment verifies the effectiveness of our proposed MKLR for traffic prediction, and the effectiveness of the optimization method. The experimental strategy is presented in the previous section of this paper. It takes the advantage of a standard algorithm to learn the MKLR using the dataset Shanghai Traffic dataset. In this experiment, MKLR employs the default parameters configure by authors. The verification criterions are MSE and RMSE where mean square error and root mean square error are two typical, popular and robust measures for regression problems.

**TABLE IV. THE RECOGNITION RESULTS OF TRAFFIC PREDICTION USING MKLR**

<table>
<thead>
<tr>
<th>Training samples</th>
<th>Evaluation Standard</th>
<th>Method</th>
<th>MSE</th>
<th>RMSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>30%</td>
<td>Standard</td>
<td>MKLR</td>
<td>0.216</td>
<td>0.314</td>
</tr>
<tr>
<td></td>
<td></td>
<td>LSR</td>
<td>0.352</td>
<td>0.564</td>
</tr>
<tr>
<td>40%</td>
<td>Standard</td>
<td>MKLR</td>
<td>0.181</td>
<td>0.285</td>
</tr>
<tr>
<td></td>
<td></td>
<td>LSR</td>
<td>0.333</td>
<td>0.466</td>
</tr>
<tr>
<td>50%</td>
<td>Standard</td>
<td>MKLR</td>
<td>0.171</td>
<td>0.242</td>
</tr>
<tr>
<td></td>
<td></td>
<td>LSR</td>
<td>0.298</td>
<td>0.375</td>
</tr>
<tr>
<td>60%</td>
<td>Standard</td>
<td>MKLR</td>
<td>0.164</td>
<td>0.226</td>
</tr>
<tr>
<td></td>
<td></td>
<td>LSR</td>
<td>0.273</td>
<td>0.348</td>
</tr>
<tr>
<td>70%</td>
<td>Standard</td>
<td>MKLR</td>
<td>0.151</td>
<td>0.201</td>
</tr>
<tr>
<td></td>
<td></td>
<td>LSR</td>
<td>0.260</td>
<td>0.311</td>
</tr>
</tbody>
</table>

We do experiments over Shanghai Traffic dataset. The dataset is collected from the monitors of the high speed interaction by Shanghai traffic management department. It contains 68 groups of data from eight sections and nine locations. This experiment will verify the superiority of MKLR in traffic prediction, and optimization. It adopts the approach summarize in above section to train MKLR and cross-validation algorithm to choose the parameters. The evaluation criterions are respectively MSE and RMSE where mean square error and root mean square error are two typical, popular and robust measures for regression problems. The test was performed for 10 rounds on this approach, and the overall results of varying experimental setting are presented in and Figure 3. As reported in and Figure 3, the value of MSE is around 0.17, consistently outperforming other compared algorithms. Moreover, in distinct experimental rounds, the MSE of the proposed approach also outperform other compared algorithm. These results are consistent with the previous work, which demonstrate that MSE is a reliable measure for traffic prediction as well as MKLR. The reasons are from the following three aspects. Firstly, The MKLR is capable to adapt and deal with complexly distributed data well, where the adaptability essentially comes from the flexibility of the kernel parameters. Secondly, in comparison with empirical parameter selection algorithm, the selection approach for model parameters can adapt to the dataset. Thirdly, the experimental procedurs of the proposed method could provide informative features and could maximize the discrimination ability.

In the third experiment, we evaluate the abilities of our proposed MKLR approach in traffic prediction, by comparison experiment. Two popular standard MSE and RMSE are adopted for verification. Mean square error and root mean square error are two typical, popular and robust measures for regression problems. The dataset is Shanghai Traffic dataset. The experimental step is presented in above section. Our method MKLR is learnt by the algorithm in above part, where some parameters of MKLR are set to defaults. The test is performed for several rounds over randomly separate dataset.

**TABLE V. THE EXPERIMENTAL RESULTS OF LSR AND MKLR**

<table>
<thead>
<tr>
<th>Experimental round</th>
<th>Algorithm</th>
<th>Evaluation Standard</th>
<th>MSE</th>
<th>RMSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Round 1</td>
<td>LSR</td>
<td>0.228</td>
<td>0.281</td>
<td></td>
</tr>
<tr>
<td></td>
<td>MKLR (ours)</td>
<td>0.106</td>
<td>0.278</td>
<td></td>
</tr>
<tr>
<td>Round 2</td>
<td>LSR</td>
<td>0.190</td>
<td>0.378</td>
<td></td>
</tr>
<tr>
<td></td>
<td>MKLR (ours)</td>
<td>0.119</td>
<td>0.185</td>
<td></td>
</tr>
<tr>
<td>Round 3</td>
<td>LSR</td>
<td>0.201</td>
<td>0.319</td>
<td></td>
</tr>
<tr>
<td></td>
<td>MKLR (ours)</td>
<td>0.219</td>
<td>0.240</td>
<td></td>
</tr>
<tr>
<td>Round 4</td>
<td>LSR</td>
<td>0.153</td>
<td>0.290</td>
<td></td>
</tr>
<tr>
<td></td>
<td>MKLR (ours)</td>
<td>0.191</td>
<td>0.242</td>
<td></td>
</tr>
<tr>
<td>Round 5</td>
<td>LSR</td>
<td>0.205</td>
<td>0.282</td>
<td></td>
</tr>
<tr>
<td></td>
<td>MKLR (ours)</td>
<td>0.153</td>
<td>0.207</td>
<td></td>
</tr>
</tbody>
</table>

The experimental results of our proposed method MKLR and the compared method LSR are respectively shown in Table V and Figure 4. These results are
obtained through the selection method of cross validation method under distinct parameter configuration. Mean square error and root mean square error are two typical, popular and robust measures for regression problems. From the results of Table 4, we could find that, for different experimental rounds, under the verification standard of MSE or RMSE, the proposed approach for traffic prediction is significantly lower than that of the compared LSR, respectively about 0.166-0.197 and 0.235-0.301. The reasons for these results are mainly three aspects. (1) MKLR has the ability to map the nonlinear data in the low dimensional space to the high dimensional space by the kernel function, which makes the prediction problem easy. (2) In comparison with empirical parameter selection method, the selection approach for model parameters can adapt to the dataset. (3) The framework of the proposed approach contains a set of comprehensive step which sequentially maximize the recognition ability.

IV. CONCLUSION

This paper adopts the method of LMKR to realize the vehicle travel time prediction of logistics planning, this process mainly includes the following steps: (1) preprocessing the historical data, in need of conducting normalization processing to the data of different dimensions, the unity in the interval [0, 1]. (2) Choosing the proper kernel function, because the different kernel functions for prediction ability will produce different effects. By comparing other forms of several kinds of kernel function, this paper selects the RBF kernel function form, because the kernel function in the case of large sample has good learning ability. (3) Real time prediction. In this paper, through the training of sample, the trained network can be gained, and using the network, logistics vehicle travel time can be predicted. The trained network parameter remains invariant.

Finally the experimental results show that:(1) Respectively by using the proposed algorithm MKLR, SVR and LSR to planning logistics vehicle travel time sample training, by the time the result comparison, it can be seen that the mentioned method has smaller error, the algorithm can be used to predict. (2) Using MKL-Rt to predict logistics vehicle planning travel time, the prediction results have higher credibility. When we use MKLR to predict the vehicle logistics planning travel time, the comparing between real time index and predictive value shows that the method significantly improves the prediction precision, shows that the proposed logistics travel time prediction method is feasible and effective. However, because of the inherent contradiction of the MKLR, in the next work, we focus on the improvement of the MKLR and the integrated application of other methods.

REFERENCE


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