Accurate Forecasting of Underground Fading Channel Based on Improved LS-SVM

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Keywords: Channel Forecasting; LS-SVM; Fading Channel; Abnormal Data

Abstract. Aiming at the shortcomings of traditional fading channel forecasting algorithms, least square support vector machine(LS-SVM) is applied to predicting underground fading channel. In light of complicated and changeable underground environment, the measured data may be abnormal. Thus, an improved LS-SVM with abnormal data detection is proposed in this paper to forecast underground fading channels. This algorithm utilizes amplitude of the fading channel as observed values to establish studying model and then implements nonlinear prediction with the help of learning and judgment ability of LS-SVM. The experiment shows that the prediction algorithm based on improved LS-SVM raises the prediction accuracy of fading channels and is an effective and feasible nonlinear fading channel forecasting method.

Introduction

In a communication system, it is crucial for receiver to obtain channel characteristics in advance, which is helpful to achieve adaptive modulation and demodulation and adaptive power control technology. Traditional prediction algorithms of fading channel are mainly based on linear ones [1][2]. However, due to the complicated nonlinear characteristics of the channel, lots of nonlinear algorithms attract much more attention, such as neural network and support vector machine (SVM) [3]. Neural network has slow convergence rate and is easy to fall into the local minimum. LS-SVM is an improved algorithm of standard SVM, which is a machine learning method based on structural risk minimization principle and overcomes the problems of neural network. It has been successfully applied to various fields.

In this paper the LS-SVM is used to construct underground Nakagami fading channel prediction model. And considering the abnormal underground data, LS-SVM is improved during data processing to detect and eliminate the abnormal data. The feasibility and effectiveness of the method are verified by experimental results.

Nakagami Distribution

The underground tunnel differs from indoor multipath environment, with well-observed roughness and many obstacles which lead to severe reflection, diffraction and scattering phenomena. Therefore, the received signal is synthesized by multipath signals. Nakagami distribution, Rayleigh distribution and Rice distribution can be used to describe the multipath fading in high frequency (HF) channel. The Rayleigh distribution is often used to simulate fast fading in HF channel of short distance. In light of long distance channel, it is quite rough to adopt the Rayleigh distribution [4]. Nakagami distribution can describe different characteristics through changing the parameter m. Rayleigh and Rice are special cases for certain values. Therefore it is reasonable to adopt Nakagami distribution to describe the small scale multipath fading in underground mine.

Nakagami distribution is also known as m-distribution whose probability density function is as follows [5]:

$$p(r)=\frac{2m^m r^{2m-1}}{\Gamma(m)\Omega^m}\exp(-\frac{mr^2}{\Omega}) \tag{1}$$

In the equation, $\Gamma(m)=\int_0^\infty x^{m-1}e^{-x}dx$ is Gamma function. Ω=E[r^2] is second-order central moments, average power. $m=E^2[r^2]/Var[r^2]$ represents fading factor, which indicates fading severity of transmitted signal resulted from multipath effects. The smaller the value m is, the more serious the fading; otherwise, the less serious the fading. When m=0.5 and m=1, the distribution transforms into unilateral Gauss distribution and Rayleigh distribution separately. When m＞1, it is very similar to Rician distribution. And the relationship between the two distributions is shown in equation (2).

$$m=\frac{(K+1)^2}{(2K+1)} \tag{2}$$

Among the equation, K is the Rician factor.

Compared to Rayleigh or Rician, Nakagami can describe distributions of different statistic characteristics by changing the value m. Therefore, Nakagami fading channel model is more flexible and convenient to characterize the different degrees of fading of multipath signals under the mine [6].

Improved LS-SVM Based on Abnormal Data Detection

LS-SVM algorithm. LS-SVM introduced least square method into SVM. The corresponding Lagrange function is defined. With the KKT conditions a set of linear equations are achieved and by solving the equations the resolution of the problem is gained

For a given training data set: $(x_i, y_i), i=1,2,\cdots l, x_i\in R^n, y_i\in R$. The training data of original space R^n is mapped to feature space $\phi(x_i)$ by taking advantage of nonlinear mapping function $\phi(\cdot)$. The optimal decision function in the high-dimension feature space is as follows [7]:

$$y(x)=\omega\cdot\phi(x)+b. \tag{3}$$

Thus, nonlinear regression estimation function in original space transformed to linear function in feature space. To search for the parameters ω and b by using structural risk minimization principle is to minimize

$$R=\frac{1}{2}\|\omega\|^2+\gamma\cdot R_{emp}. \tag{4}$$

Among the Eq. 2, $\|\omega\|^2$ is the incredible risk which indicates the complexity of model, R_{emp} is the empirical risk and the value γ is regularization parameter which controls the penalty degree of error sample.

The optimization problem of LS-SVM is presented in Eq. 5.

$$\min J(\omega,\xi)=\frac{1}{2}\|\omega\|^2+\frac{\gamma}{2}\sum_{i=1}^{l}\xi_i^2 \tag{5}$$

s.t. $y_i=w^T\cdot\phi(x_i)+b+\xi_i, i=1,2,\cdots l.$

Lagrange function is defined as Eq. 6[8]:

$$L(\omega,b,e_i,\alpha_i)=\frac{1}{2}\omega^T\omega+\frac{\gamma}{2}\sum_{i=1}^{N}\zeta_i{}^2-\sum_{i=1}^{N}\alpha_i(\omega^T\phi(x_i)+b+\zeta_i-y_i). \tag{6}$$

Among the equation, α_i are the Lagrange factors. According to KKT conditions, partial derivative is calculated:

$$\begin{cases} \dfrac{\partial L}{\partial \omega} = 0 \Rightarrow \ \omega = \sum_{i=1}^{i} \alpha_i \phi(x_i) \\ \dfrac{\partial L}{\partial b} = 0 \ \Rightarrow \ \sum_{i=1}^{i} \alpha_i = 0 \\ \dfrac{\partial L}{\partial \xi_i} = 0 \Rightarrow \ \alpha_i = \gamma \xi_i \\ \dfrac{\partial L}{\partial \alpha_i} = 0 \Rightarrow \ \omega^T \cdot \phi(x_i) + b + \xi_i - y_i = 0 \end{cases} . \tag{7}$$

For $i = 1, 2, \cdots l$, ω and ξ are eliminated and then get

$$\begin{bmatrix} 0 & 1 & \cdots & 1 \\ 1 & K(x_1, x_1) + \dfrac{1}{c} & \cdots & K(x_1, x_n) \\ \vdots & \vdots & \vdots & \vdots \\ 1 & K(x_n, x_1) & \cdots & K(x_n, x_n) + \dfrac{1}{c} \end{bmatrix} \begin{bmatrix} b \\ \alpha_1 \\ \vdots \\ \alpha_n \end{bmatrix} = \begin{bmatrix} 0 \\ y_1 \\ \vdots \\ y_n \end{bmatrix}. \tag{8}$$

Among the Eq. 6, K is a square matrix of which $K_{ij} = \phi(x_i)^T \phi(x_j) = K(x_i, x_j)$ for the element at row i and column j. $K(\cdot,\cdot)$ is the kernel function. α and b can be obtained by least square method and the predicted output is shown in Eq. 9.

$$\begin{aligned} y &= \sum_{i=1}^{l} \alpha_i \phi(x)^T \phi(x_i) + b \\ &= \sum_{i=1}^{l} \alpha_i K(x, x_j) + b. \end{aligned} \tag{9}$$

LS-SVM Prediction with Abnormal Data Detection. In underground environment, electromagnetic wave has refraction, reflection and diffraction phenomenon during propagation [9] and due to the mine equipment, vehicles and personnel, noise jamming could be high. Therefore, the amplitude of the received signal may be greatly changed, resulting in undesirable sampling data. In LS-SVM model, data are divided into support vectors, which are divided into boundary support vectors and non boundary support vectors, and non support vectors. Only part of α_i resolved from Eq. 9 are not zero and their corresponding training samples are support vectors[10]. So, the α_i corresponding to abnormal data meet the conditions that $\alpha_i = \gamma$.

Combined with the analysis of the LS-SVM, the procedure of abnormal data detection is as follows[11].

1) Establish LS-SVM model with the original data.
2) When using the model to regression estimating, find the samples which meet the conditions that $\alpha_i = \gamma$. Calculate the residuals between prediction values and original values. That is to calculate $E_i = |y_i - \hat{y}_i|$, where y_i is original value and $\hat{y}_i$ prediction value.
3) According to the actual needs and accuracy of the data, the constant ε is defined. If $E_i > \varepsilon$, the y_i with the same subscript is an abnormal sample and eliminate y_i. A new estimated value $\tilde{y}_i$ is regained for (x_i, y_i) to replace the abnormal one.
4) Rebuild the LS-SVM model with the revised data, comparing the performance with the former one.

Simulation Experiment and Discussion

In the experiment, the parameters of the Nakagami channel model are set as follows. Carrier frequency is 2.3GHz. Maximum Doppler frequency shift is 106Hz. m parameter of Nakagami distribution is set to 1.5. 400 training samples and 400 test samples are generated on this basis. In order to verify the accuracy of the method in this paper, the abnormal data is added to replace the original samples. The insertion method is as follows.

To avoid the concentration phenomenon of random insertion data, the training set are divided into four groups [1,100], [101,200], [201,300] and [301,400]. Four points are selected randomly to modify in each group and sixteen abnormal data are obtained. The abnormal data of testing set are produced in the same way.

Radial basis function is used and embedded dimension d=3 in LS-SVM model. The wavelet neural network(WNN) regression forecasting method is also applied for comparison. The hidden layer of the network structure contains 6 nodes, and the number of iterations is 100 times. Fig. 1 shows the comparison between prediction curve and original curve when the samples don't contain abnormal data. It can be seen that although WNN has a larger float at some points, the prediction values of two algorithms fit with the original values to a large degree.

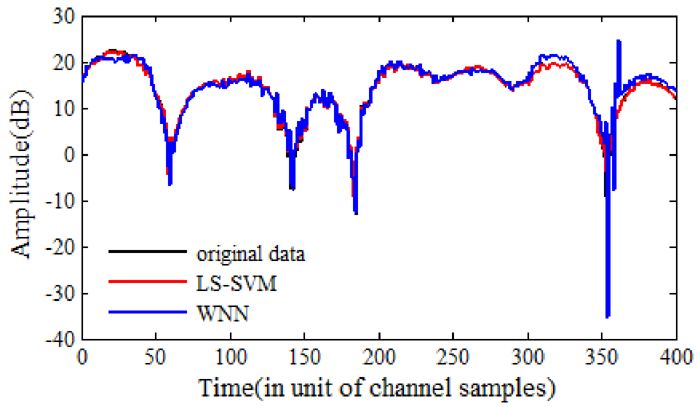

Fig. 1 LS-SVM and WNN prediction without abnormal data

When there are abnormal data in the samples, use the method in this paper to detect and eliminate abnormal data and rebuild LS-SVM model. Fig. 2 shows the comparison between standard LS-SVM and method in this paper with abnormal data. It can be seen that regression curve with LS-SVM is deviated from the original data to some degree but the method in this paper is not affected by abnormal data basically and maintain good prediction accuracy. Fig. 3 shows the comparison between WNN and method in this paper with abnormal data. It indicates that the prediction curve of WNN has a larger offset from original one because of the interference of abnormal data while the method which is that LS-SVM based on abnormal data detection and elimination keep good robustness and is less affected by the random fluctuation. Fig. 4 represents the prediction error curves of standard LS-SVM, WNN and the method in this paper. The prediction error of the other two algorithms is apparently larger than the improved LS-SVM method in this paper.

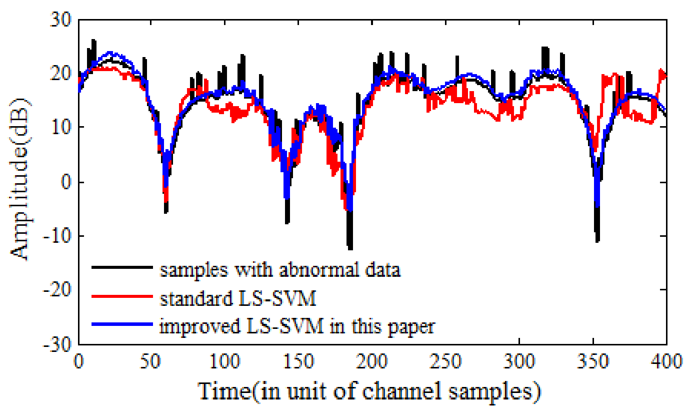

Fig. 2 Comparison between LS-SVM and method in this paper with abnormal data

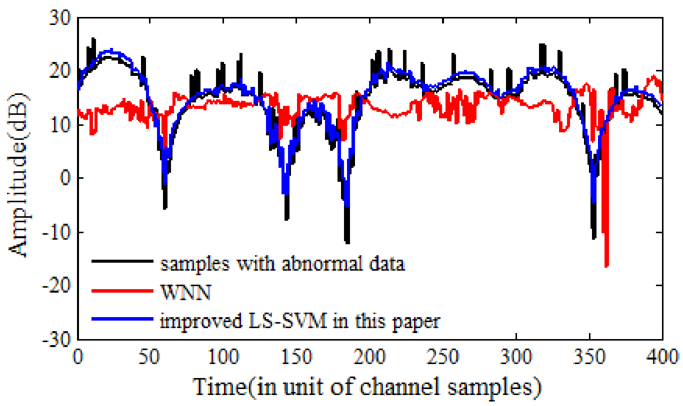

Fig. 3 Comparison between WNN and method in this paper with abnormal data

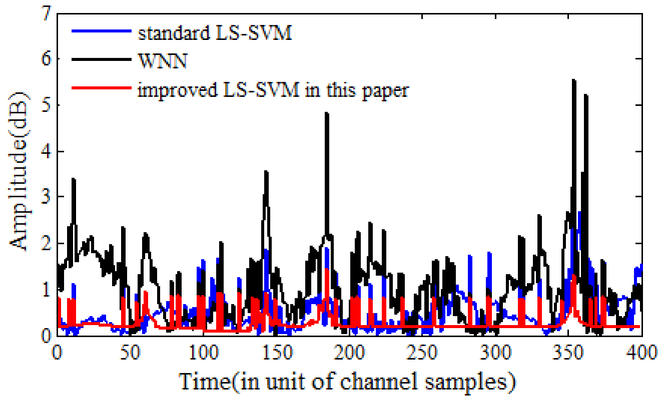

Fig. 4 Prediction error of three algorithms

Performance Analysis of the Model

Three indicators are used to measure the performance of two different models. They are mean absolute error (MAE), root mean square error (RMSE) and correlation coefficient. The MAE between prediction values and original values is defined as follows:

$$\mathrm{MAE} = \frac{1}{N}\sum_{i=1}^{N}\left|y_i - \hat{y}_i\right|. \tag{10}$$

The RMSE is defined as follows:

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}{N}}. \tag{11}$$

And the correlation coefficient is defined as follows:

$$r = \frac{\sum_{i=1}^{N}(y_i - \bar{y})(\hat{y}_i - \bar{\hat{y}})}{\sqrt{\sum_{i=1}^{N}(y_i - \bar{y})^2}\sqrt{\sum_{i=1}^{N}(\hat{y}_i - \bar{\hat{y}})^2}}. \tag{12}$$

Among the equations, y_i is the original value. $\hat{y}_i$ is prediction value. $\bar{y}$ is the average of original values and $\bar{\hat{y}}$ is the average of prediction values. The smaller the MAE and RMSE is, the better the performance is. And *r* shows the similarity degree of original data and prediction data.

Table 1 shows the performance of three algorithms from these three aspects. Compared to standard LS-SVM or WNN, the improved LS-SVM that detects and eliminates abnormal data has a better performance. The MAE and RMSE are smaller than the other two algorithms and the correlation coefficient is larger. The superiority of the proposed method can be displayed in the presence of abnormal data.

Table 1 Performance Comparison of three algorithms

Prediction Method	MAE	RMSE	r
WNN	5.3184	6.6695	0.90853
LS-SVM	2.7589	3.7896	0.919143
Method in this paper	1.3734	1.7983	0.984155

Conclusion

Forecasting of fading channel is vital for mobile communication. In this paper, in light of underground Nakagami fading channel, an improved LS-SVM method that used to detect abnormal data is implemented. From the simulation experiments, the method in this paper can detect the abnormal data and at the same time, the correct regression prediction is carried out which has an important significance for improving nonlinear fading channel forecasting.

Acknowledgement

This research was supported financially by Natural Science Basic Research Plan in Shaanxi Province of China (Program No. S2015YFJM1734).

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