Loss Model of VHF Wireless Communication on Sea Surface Based on BP Neural Network

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Abstract

The establishment of a reasonable VHF wireless communication transmission model on the sea is the basis for further research on VHF broadband data communication on the sea. The traditional empirical model relies too much on parameters and specific environment to accurately describe the transmission loss of VHF electromagnetic wave on the sea surface. In this paper, a transmission loss model based on BP neural network is proposed, which has the ability of autonomous learning according to different environments, can improve the calculation accuracy, and is more suitable for the Marine transmission environment. The experimental results show that the calculation results of the transmission loss model based on BP neural network are closer to the real value and have certain practical value.

Keywords

VHF, autonomous learning, transmission loss, feature information.

1. Introduction

Offshore VHF broadband data communication requires high bit error rate standards for communication systems. Electromagnetic wave is transmitted on the sea surface, and it will produce loss of varying degrees due to the influence of many factors, which will directly affect the effect of receiving VHF signals by ships.Therefore, the establishment of a reasonable VHF wireless communication transmission model is the basis for further VHF broadband data communication at sea.The propagation loss model of electromagnetic wave based on BP neural network proposed in this paper has the ability of self-learning and can calculate the propagation loss of VHF electromagnetic wave in the sea more accurately.

2. VHF Communication Transmission Loss Calculation Model

There are two classical VHF wireless signal propagation models: okumura-hata model, free space transmission loss model and lognormal masking model.

2.1 Okumura－Hata Model

Okumura-hata model is one of the most commonly used path loss models. Its characteristics are as follows: taking the median path loss of field intensity in metropolitan areas with quasi-flat terrain as the benchmark, correcting factors such as different propagation environments and terrain conditions [1-3] with correction factors are applied to VHF.The median formula of urban path loss is:

$$L_{mid} = 69.55 + 26.16\lg f - 13.82\lg h_t - a(h_r) + (44.9 - 6.55\lg h_t)(\lg d') \quad (1)$$

Where, f is the communication frequency (in MHz); h_r is the transmitting antenna height of the base station, h_r the antenna height of the mobile station (unit: m), and is the transmission distance (unit: km);A (h_r) is the correction factor of the effective height of the antenna of the mobile station;

$$a(h_r) = (1.1\lg f - 0.7)h_r - 1.56\lg f + 0.8 \quad (2)$$

γ is the distance correction factor, which expands the applicable range of the formula.When $d \le 20$, $\gamma = 1$; when $d > 20$,

$$\gamma = 1 + (0.14 + 1.87\times 10^{-4} f + 1.07\times 10^{-3} H_t)(\lg\frac{d}{20})^{0.8} \quad (3)$$

in the open sea surface area, the path loss of the electromagnetic wave can be expressed as:

$$L_b = L_{mid} - 4.78[\lg(f)]^2 + 18.33\lg f - 40.98 \quad (4)$$

Where, is the median of urban loss prediction.

2.2 Free Space Transmission Loss Model

VHF signals on the sea surface can be regarded as free space transmission. For the free space transmission model, it is necessary to assume that there is an ideal transmission environment, that is, there is only an unobstructed straight path between the transmitting antenna and the receiving antenna.The transmission loss of free space at sea is:

$$L = 32.45 + 20\lg f + 20\lg d \quad (5)$$

in formula (3) : f is the working frequency of the signal. According to the offshore VHF working frequency band, f both values are 157MHz, d is the maximum range of the transceiver antenna. According to the characteristics of VHF short-range transmission, the maximum value of d is 50km.

3. BP Neural Network Loss Model

Network training is the key to obtain the optimal weight of BP neural network [4], and its learning process includes the forward transmission of signal and the reverse transmission of error.When the signal is transmitted forward, the signal flows directly into the network from the input layer, and after being processed by several hidden layers, it finally flows out from the output layer.The error reverse transmission is to spread the error of the output layer to the input layer through the hidden layer, and distribute the error to all elements of each layer to obtain the error signal of each unit, and then use the error signal as the basis of the correct unit [5].

3.1 Proposed Model

BP neural network loss model (BPNNLM) was established with the transmission distance as the input layer and the corresponding loss value as the output layer.After repeated tests and comparisons, tangent function tansig was used for hidden layer and logsig was used for output layer.At this time, the training times are the least and the error also meets the requirements.

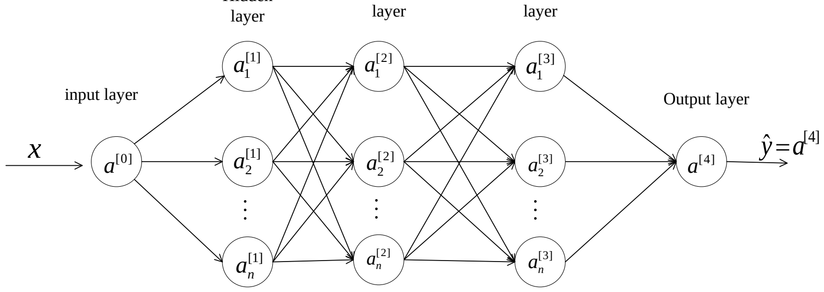

Fig. 1 loss model of BP neural network

As shown in Fig.1, input the sample of electromagnetic wave loss into the first node in the hidden layer and obtain:

$$\mathbf{z}^{(l)} = \mathbf{W}^{(l)} \cdot \mathbf{a}^{(l-1)} + \mathbf{b}^{(l)} \tag{6}$$

$$\mathbf{a}^{(l)} = f_l(\mathbf{z}^{(l)}) \tag{7}$$

$$\mathbf{a}^{(l)} = f_l(\mathbf{W}^{(l)} \cdot \mathbf{a}^{(l-1)} + \mathbf{b}^{(l)}) \tag{8}$$

$$f_l(x) = \frac{1}{1+e^{-x}} \tag{9}$$

Where, L represents the number of layers of the neural network, $f_l(\cdot)$ represents the activation function of neurons in the l layer, $\mathbf{W}^{(l)}$ represents weight matrix from layer l-1 to layer l, $\mathbf{b}^{(l)}$ represents the bias from layer l-1 to layer l, $\mathbf{z}^{(l)}$ represents the input of layer l neurons, $\mathbf{a}^{(l)}$ represents the output of layer l neurons. In this way, the neural network can get the final output $\mathbf{a}^{(L)}$ through the information transmission layer by layer. The whole network can be regarded as a composite function:

$$\mathbf{a}^{(L)} = \varphi(\mathbf{x}; \mathbf{W}, \mathbf{b}) \tag{10}$$

Where, $\mathbf{W}$, B represents the connection weight and bias of all layers in the network. The transmission distance $\mathrm{x}_i = (x_1 \quad x_2 \quad \cdots \quad x_n)$ is taken as a set of input vectors of BPNNLM, the output of the L layer $\mathbf{a}^{(L)}$ is taken as the output of the whole function, and the estimated loss value calculated by BP neural network model is $\hat{\mathrm{y}}=\mathrm{a}^{[L]}$.

3.2 Parameter learning

Loss function is used to estimate the inconsistency between the predicted value $f(x^{(i)}; \mathbf{W}, \mathbf{b})$ of the model and the real value of $y^{(i)}$ [8], which is usually expressed by $\mathcal{L}(\hat{y}, y)$. The purpose of parameter learning is to minimize the loss function, and the loss function is expressed as:

$$\mathcal{L}(y, y) = \frac{1}{m}\sum_{i=1}^{m}(f(x^{(i)}; \mathbf{W}, \mathbf{b}), y^{(i)})^2 \tag{11}$$

Assuming a sample (x, y) is given and input into the neural network model, the network output is $\hat{y}$ and the loss function is $\mathcal{L}(\hat{y}, y)$. To carry out parameter learning, it is necessary to calculate the derivative of the loss function with respect to each parameter, and calculate the partial derivative with respect to the parameters $\mathbf{W}^{(l)}$ and $\mathbf{b}^{(l)}$ in the l layer.So let's take the partial derivative $\frac{\partial \mathcal{L}(y, \hat{y})}{\partial \mathbf{W}_{ij}^{(l)}}$ by the chain rule

$$\frac{\partial \mathcal{L}(y, \hat{y})}{\partial \mathbf{W}_{ij}^{(l)}} = \left(\frac{\partial \mathbf{z}^{(l)}}{\partial \mathbf{W}_{ij}^{(l)}}\right)^{\mathrm{T}} \frac{\partial \mathcal{L}(y, \hat{y})}{\partial \mathbf{z}^{(l)}} \tag{12}$$

$$\frac{\partial \mathcal{L}(y, \hat{y})}{\partial \mathbf{b}^{(l)}} = \left(\frac{\partial \mathbf{z}^{(l)}}{\partial \mathbf{b}^{(l)}}\right)^{\mathrm{T}} \frac{\partial \mathcal{L}(y, \hat{y})}{\partial \mathbf{z}^{(l)}} \tag{13}$$

The second term in formula (9) and (10) is the partial derivative of the target function with respect to the neuron $\mathbf{z}^{(l)}$ at the l layer, which is called error term. The three partial derivatives $\frac{\partial \mathbf{z}^{(l)}}{\partial \mathbf{W}_{ij}^{(l)}}$, $\frac{\partial \mathbf{z}^{(l)}}{\partial \mathbf{b}^{(l)}}$ and $\frac{\partial \mathcal{L}(y, \hat{y})}{\partial \mathbf{z}^{(l)}}$ are calculated respectively.

$$\frac{\partial \mathbf{z}^{(l)}}{\partial \mathbf{W}_{ij}^{(l)}} = \frac{\partial(\mathbf{W}^{(l)} \cdot \mathbf{a}^{(l-1)} + \mathbf{b}^{(l)})}{\partial \mathbf{W}_{ij}^{(l)}} \tag{14}$$

$$= \begin{bmatrix} \frac{\partial(\mathbf{W}_{1:}^{(l)} \cdot \mathbf{a}^{(l-1)} + \mathbf{b}^{(l)})}{\partial \mathbf{W}_{ij}^{(l)}} \\ \vdots \\ \frac{\partial(\mathbf{W}_{i:}^{(l)} \cdot \mathbf{a}^{(l-1)} + \mathbf{b}^{(l)})}{\partial \mathbf{W}_{ij}^{(l)}} \\ \vdots \\ \frac{\partial(\mathbf{W}_{m:}^{(l)} \cdot \mathbf{a}^{(l-1)} + \mathbf{b}^{(l)})}{\partial \mathbf{W}_{ij}^{(l)}} \end{bmatrix} = \begin{bmatrix} 0 \\ \vdots \\ \mathbf{a}_{ij}^{(l)} \\ \vdots \\ 0 \end{bmatrix} \leftarrow \text{line } i \tag{15}$$

$$\triangleq \mathrm{II}_j(\mathbf{a}^{(l-1)}) \tag{16}$$

Where, $\mathbf{W}_{i:}^{(l)}$ is the ith row of the weight matrix $\mathbf{W}^{(l)}$.

$$\frac{\partial \mathbf{z}^{(l)}}{\partial \mathbf{b}^{(l)}} = \mathbf{I}_{m^{(l)}} \tag{17}$$

$\mathbf{I}_{m^{(l)}}$ is the identity matrix of $m^{(l)} \times m^{(l)}$, and $\delta^{(l)}$ is used to define the error term of the l-layer neuron and to represent the influence of the l-layer neuron on the final error.

$$\delta^{(l)} = \frac{\partial \mathcal{L}(y, \hat{y})}{\partial \mathbf{z}^{(l)}} \in \mathbb{R}^{m^{(l)}} \tag{18}$$

According to $\mathbf{z}^{(l+1)} = \mathbf{W}^{(l+1)} \cdot \mathbf{a}^{(l)} + \mathbf{b}^{(l+1)}$,get

$$\frac{\partial \mathbf{z}^{(l+1)}}{\partial \mathbf{a}^{(l)}} = (\mathbf{W}^{(l+1)})^{\mathrm{T}} \tag{19}$$

According to $\mathrm{a}^{(l)} = f_l(\mathbf{z}^{(l)})$,so get

$$\frac{\partial \mathbf{a}^{(l)}}{\partial \mathbf{z}^{(l)}} = \frac{\partial f_l(\mathbf{z}^{(l)})}{\partial \mathbf{z}^{(l)}} \tag{20}$$

$$= \mathrm{diag}(f_l'(\mathbf{z}^{(l)})) \tag{21}$$

So, according to the chain rule, the error term for the l-layer is

$$\delta^{(l)} = \frac{\partial \mathcal{L}(y, \hat{y})}{\partial \mathbf{z}^{(l)}} \tag{22}$$

$$= \frac{\partial \mathbf{a}^{(l)}}{\partial \mathbf{z}^{(l)}} \cdot \frac{\partial \mathbf{z}^{(l+1)}}{\partial \mathbf{a}^{(l)}} \cdot \frac{\partial \mathcal{L}(y, \hat{y})}{\partial \mathbf{z}^{(l+1)}} \tag{23}$$

$$= \mathrm{diag}(f_l'(\mathbf{z}^{(l)})) \cdot (\mathbf{W}^{(l+1)})^{\mathrm{T}} \cdot \delta^{(l+1)} \tag{24}$$

$$= (f_l'(\mathbf{z}^{(l)})) \odot ((\mathbf{W}^{(l+1)})^{\mathrm{T}} \cdot \delta^{(l+1)}) \tag{25}$$

It can be seen from formula (22) that the error term of the l-layer can be calculated by the error term of the $l+1$ layer, and formula (9) can be written as

$$\frac{\partial \mathcal{L}(y, \hat{y})}{\partial \mathbf{W}_{ij}^{(l)}} = \mathrm{II}_j(\mathbf{a}^{(l-1)})^{\mathrm{T}} \cdot \delta^{(l)} = \delta_i^{(l)} \cdot (\mathbf{a}_j^{(l-1)}) \tag{26}$$

Further, the gradient of $\partial \mathcal{L}(y, \hat{y})$ with respect to the weight of the l-layer $\mathbf{W}^{(l)}$ is

$$dw = \frac{\partial \mathcal{L}(y, \hat{y})}{\partial \mathbf{W}^{(l)}} = \delta^{(l)} \cdot (\mathbf{a}^{(l-1)})^{\mathrm{T}} \tag{27}$$

Similarly, the gradient of $\partial \mathcal{L}(y, \hat{y})$ with respect to the l-layer offset $\mathbf{b}^{(l)}$ is

$$db = \frac{\partial \mathcal{L}(y, \hat{y})}{\partial \mathbf{b}^{(l)}} = \delta^{(l)} \tag{28}$$

4. Experimental Environment

First, the receiving power is collected at different distances, and the corresponding transmission loss data is calculated. Divide the data into training data and test data. Then, training data was used to train the BPNLM model until the loss function was no longer down. Finally, the test data is used to evaluate the generalized ability of the BPNLM model, and the calculation results of the okumura-hata model, the free space loss model and the BPNNLM model are relative to the accuracy of the measurement data.

According to the requirements of itu-m.1842-1, the transmitter power is 50w. the effective height of the transmitting antenna is 75mm, and the receiving antenna gain is 8dbi and 2dbi. the 1100khz(4 adjacent 25khz) bandwidth of 157mhz (157mhz) is the longest distance from the antenna.

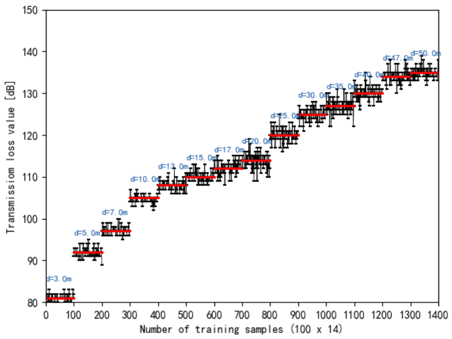

Fig. 2 train data

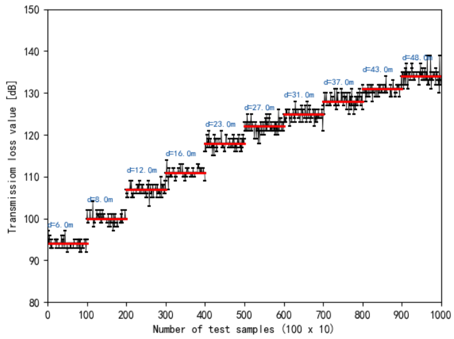

Fig. 3 train data

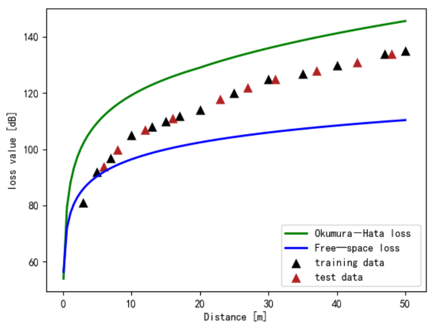

Fig. 3 data distribution

It can be seen from the data distribution curve (Fig. 3) that the okumura-hata model and the free space transmission loss model can basically describe the corresponding relationship between the transmission loss value and the transmission distance of VHF electromagnetic wave, but there is a big error between the estimated value of these models and the actual measured value.The model trained by BP neural network is closer to the real value.

5. Conclusion

In this paper, an electromagnetic wave transmission loss model based on BP neural network is proposed. The experimental results show that the calculation accuracy of BP neural network loss model is higher than that of free space loss model and okumura-hata model, which can be better applied to the Marine transmission environment

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References

[1] Popoola, S.I., A.A. Atayero, and O.A. Popoola, Comparative assessment of data obtained using empirical models for path loss predictions in a university campus environment. Data in Brief, 2018. 18: p. 380-393.

[2] Anusha, V.S., G.K. Nithya, and S.N. Rao. A comprehensive survey of electromagnetic propagation models. in International Conference on Communication & Signal Processing. 2018.

[3] Yoshua, B., C. Aaron, and V. Pascal, Representation learning: a review and new perspectives. IEEE Transactions on Pattern Analysis & Machine Intelligence, 2013. 35(8): p. 1798-1828.

[4] Luo wei and wu zhipan, a fingerprint recognition technology based on BP neural network. Modern computer, 2017(20): p.62-67.

[5] Chen, X., et al. , A Ranging Model Based on BP Neural Network. Intelligent Automation & Soft Computing, 2015. 22(2): p. 325-329.