Rain Attenuation Prediction Models of 60GHz Based on Neural Network and Least Squares-Support Vector Machine

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Abstract Although 60 GHz mmWave (millimeter-wave) has attractive features and promising applications, it is affected seriously by rain attenuation. Based on the neural networks and SVM (support vector machine), two novel rain attenuation prediction models for 60 GHz millimeter-wave are proposed in this paper. We respectively applied the BP (back-propagation) neural network and LS-SVM (least squares-support vector machine) to simulate the non-linear relationship between rainfall intensity and rain attenuation, then the two models are compared with general ITU-R model. Experimental results showed that both of the proposed prediction models are indeed superior to the existing ITU-R model for rain attenuation prediction in the sense of both accuracy and stability while LS-SVM is the most promising model for the prediction of rain attenuation.

Keywords 60 GHz mmWave • Back-propagation neural network • Least squares-support vector machine • Rain attenuation

1 Introduction

With attractive features and broad unlicensed bandwidth, 60 GHz mmWave is becoming one of the most promising candidates for multigigabit wireless communication system. Despite of advantages of 60 GHz mmWave, a lot of technical challenges still need to be overcome before its fully deployed. Rain attenuation effect, one of technical challenges, limits the practical use of 60 GHz mmWave for longer terrestrial links and Earth-space urban communication [1].

Rain attenuation effect [2] is caused by the absorption and scattering of raindrops and it can result in attenuation and depolarization of electromagnetic wave. In 2003,

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a study was performed by QinetiQ to investigate bastatic scattering at 60 GHz. This study concluded that even for modest rainfall rates r ($r < 10$ mm/h), rain attenuation is often evident [3]. The study also highlighted the need for the development of theoretical models.

In order to predict rain attenuation of 60 GHz mmWave according to the rainfall intensity, ITU-R recommended a popular model which established a non-linear relationship between rain attenuation factor γ_R and rain intensity R (mm/h). The ITU-R model [4] can be described $\gamma_R = k \times R^{\alpha}$, where k and α are correlation coefficients that depend on the raindrop size, frequency, electromagnetic wave polarization and can be estimated by statistical regression and curving fitting.

Despite the ITU-R model has been widely used for calculating rain attenuation, some problems still exist and attract widespread attention. On one hand, the traditional ITU-R model can only satisfy accuracy requirement when frequency is below 55 GHz, but it can not fully meet the high accuracy requirement of 60 GHz mmWave. On the other hand, rain attenuation coefficients depend on complex factors such as radio parameters which are difficult to be evaluated accurately. Therefore, it is natural to find the evident difference between measured values of rain attenuation and the ITU-R calculated ones.

Motivated by the considerations above, we utilize two efficient and robust models for rain attenuation prediction inspired by the promising BP neural network [5] and the LS-SVM [6] algorithm. Experimental results show that both of the proposed prediction models are indeed superior to the existing ITU-R model for rain attenuation prediction in the sense of both accuracy and stability.

The rest of this paper is structured as follows. The principles of BP neural network and LS-SVM algorithm are depicted in Sects. 2 and 3, respectively. Subsequently, two kinds of rain attenuation models are established according to the measured rainfall intensity samples in Sect. 4. In Sect. 5, we compare the performance of ITU-R model, BP neural network model and LS-SVM model in the sense of accuracy and stability. Finally, we conclude the whole investigation in Sect. 6.

2 BP Neural Network [5]

Artificial neural network (ANN) is a large-scale parallelism nonlinear dynamical system, consisting of a series of simple nodes and the links between nodes. Neural network processes the input knowledge by learning and analyzing samples parallelly and possesses characteristic of high speed calculation, abundant association, great robustness, potentiality of self-adaptive, self-organization and self-learning.

BP neural network, a type of article neural network, is a multilayer feed-forward neural network based on back propagation algorithm. It has been proven by CHENT to be able to approximate continuous nonlinear function which makes the neural network widely-used in nonlinear system modeling. A typical BP neural network is given as Fig. 1 shows.

We suppose a BP neural network composed of M layers and N nodes. The sum input and output of the j-th neuron of M-th layer are expressed as I_{jk}^{M}, O_{jk}^{M} which can be calculated as formulas (1) and (2). In these formulas, W_{ij} represents the weight between the i-th neuron of $(M - 1)$-th layer and the j-th neuron of M-th layer.

$$I_{jk}^{M} = \sum_{i=1}^{n} W_{ij} O_{jk}^{M-1} \tag{1}$$

$$O_{jk}^{M} = f(I_{jk}^{M}) \tag{2}$$

When it comes to back propagation, we define E_k as object function which represents the error between expected output d_k and actual output y_k by the formula (3). Then, the overall error value of these S samples can be calculated as formula (4).

$$E_k = \frac{1}{2} \sum_{j=1}^{m} (d_{jk} - y_{jk})^2 \tag{3}$$

$$E = \frac{1}{2S} \sum_{k=1}^{S} E_k \tag{4}$$

The learning processing of BP neural network is equivalent to unconstrained optimization problem. By optimizing the weights between nodes continuously, the overall error value E will drop below some pre-determined threshold. After the learning process, the "well enough" BP neural network can be applied to predict the output according to input data.

3 LS-SVM Algorithm [6]

Standard SVM algorithm can convert an original sample space into a higher-dimension or even infinite-dimension space through nonlinear mapping. By the conversion, the nonlinear problems can be solved through the linear learning machine in higher-dimension feature space. Compared with the SVM algorithm, Suykens proposed LS-SVM algorithm. LS-SVM is the least squares version of support vector machines (SVM), which is a set of related supervised learning methods that analyze data and recognize patterns, and is used for classification and regression analysis widely. By LS-SVM, we can find the solution by solving a set of linear equations instead of a convex quadratic programming (QP) problem for classical SVMs.

For a given set of training data set $S = \{(x_1, y_1), (x_2, y_2), \ldots, (x_n, y_n)\} \in R_n \times R_n$, regression analysis is to find a function f after training. Then, if we give a new

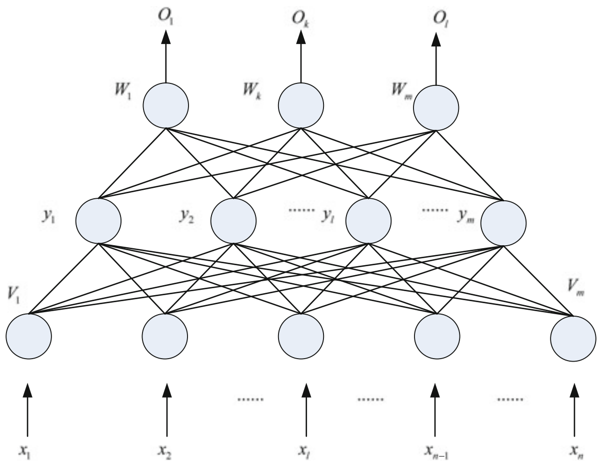

Fig. 1 BP neural network topology diagram. The BP neural network includes input layer, hidden layer and output layer. *X* represents the input data while the *O* represents the output data

sample, we can get a corresponding output which has the minimum deviation from the true value according to the trained function. According to the LS-SVM algorithm, we can map the sample set into a higher-dimension feature space by the following linear function:

$$f(x) = \mu^T \phi(x) + t \tag{5}$$

In the above formula, $\phi(x)$ represents the nonlinear mapping results from original feature space to higher-dimension feature space, μ is the coefficient vector in feature space while t is the offset. According to the structural risk minimization principle, the risk bound is minimized by the following minimization problem:

$$min\{\frac{1}{2}\mu^T \mu + \frac{\lambda}{2}\sum_{i=1}^{l} e_i^2\} \tag{6}$$

Subject to the equality constraints:

$$y_i = \mu^T \phi(x_i) + t + e_i \qquad i = (1 \sim l) \tag{7}$$

Hence, the solution of LS-SVM regressor will be obtained after we construct the Lagrangian function:

$$L = \frac{1}{2}\mu^T \mu + \frac{\lambda}{2}\sum_{i=1}^{l} \alpha_i[\mu^T \phi(x_i + t) + e_i - y_i] \tag{8}$$

where $\alpha_i \in R$ are the Lagrange multipliers and the conditions for optimality are:

$$\begin{cases} \dfrac{\partial L}{\partial \mu} = 0 \quad \longrightarrow \quad \mu = \sum_{i=1}^{l} \alpha_i \phi(x_i) \\ \dfrac{\partial L}{\partial t} = 0 \quad \longrightarrow \quad \sum_{i=1}^{l} \alpha_i = 0 \\ \dfrac{\partial L}{\partial e_i} = 0 \quad \longrightarrow \quad \alpha_i = \gamma e_i \\ \dfrac{\partial L}{\partial \alpha_i} = 0 \quad \longrightarrow \quad \mu^T phi(x_i) + e_i + t - y_i = 0. \end{cases} \tag{9}$$

Elimination of μ and e_i will yield a linear system instead of a quadratic programming problem:

$$\begin{bmatrix} 0 & e_i^T \\ e_i & Q + I/\gamma \end{bmatrix} \begin{bmatrix} t \\ \alpha \end{bmatrix} = \begin{bmatrix} 0 \\ y \end{bmatrix} \tag{10}$$

with $e_i = [1, \ldots, l]^T,\ \alpha = [\alpha_1, \ldots, \alpha_l]^T,\ y = [y_1, \ldots, y_l]^T,\ Q = \phi(x_i)^T \phi(x_i)$.

Radial basis function are chosen as kernel function, then LS-SVM regression function can be obtained based on the least square method:

$$f(x) = \sum_{i=1}^{l} k(x_i, x_j) + t \tag{11}$$

Seen from the above formulas, the optimization problems can be converted to linear equation according to the LS-SVM algorithm. Meanwhile, LS-SVM accelerates the speed of modeling by reducing the search dimension.

4 Two Kinds Rain Attenuation Models

In order to study the external factors which affect the rain attenuation model in 60 GHz, Vaclav Kvicera and Martin experimented in Prague for 5 years. The experimental results show that the factors which affect the rain attenuation model include the distance s between transmitter and receiver, frequency f, rainfall intensity r, raindrop temperature t, humidity n, pressure P, wind velocity v, wind direction d and visibility k [7]. Therefore, the prediction function of rain attenuation model can be summarized as:

$$A = f(s, f, r, t, n, P, v, d, k) \tag{12}$$

However, rain intensity is the key factor which has greatest influence on rain attenuation. Over a 5-year period, cumulative distributions of rain intensity and rain attenuation were measured exactly and the experimental samples proved to be helpful as reference for further study. In this paper, we select the experimental samples randomly from their experimental results and establish the model between rain intensity r and rain attenuation A without considering the other factors by the formula (13)

$$A = kf(r) \tag{13}$$

4.1 BP Neural Network Model

In order to establish BP neural network model which represents the relationship between rain intensity r and rain attenuation A, learning process should be conducted first. In this paper, 78 samples of rain intensity are selected randomly as example cases and the learning process works in small iterative steps. Firstly, one of rain intensity samples is applied to network, and the network produces the corresponding rain attenuation value based on the current state of its synaptic weights. Then the mean-squared error signal is calculated. Next the error value is propagated backwards through the network, and small changes are made to the weights to reduce the error signals in each layer. The whole process is repeated for each of the 78 example cases, then back to the first case again, and so on. The cycle is repeated until the overall error value drops below pre-determined threshold. Through several simulations, we choose to establish a "well enough" BP neural network which composes the input layer with one node, a single hidden layer with 13 nodes and the output layer with one node. The selected transfer function of hidden layer and output layer is "logsig" and "purelin", respectively.

4.2 LS-SVM Model

Similarly, we can set up the LS-SVM model between rain intensity r and rain attenuation A basing on the nonlinear combination principle of LS-SVM. Supposing 78 samples of rain intensity and rain attenuation values constitute the LS-SVM training model $\{(X_t, Y_t), X_t \in R^m\}_{t=1}^{l}$, then the optimal linear regression function can be obtained in higher-dimension feature space according to the formula (5).

After setting up mapping relationship, the problem of solving combinatorial prediction function by LS-SVM is equivalent to constrained optimization problem. Through several mathematical formula transformations, we can establish the fitting function successfully. In order to get the function which can represent the mapping between rain intensity and rain attenuation, we adopt Python27 for optimization, while the optimized parameter is c = 4,096, g = 1, p = 1.

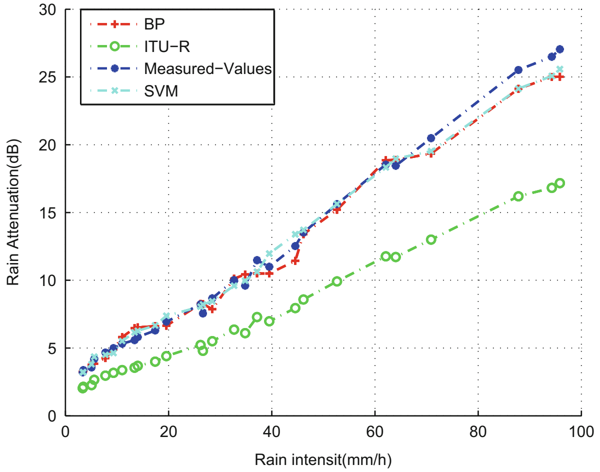

Fig. 2 Predictive values of different models. The predictive values based on BP neural networks model and LS-SVM model have smaller deviations from actual measurement whereas the ITU-R model can not always get the correct prediction

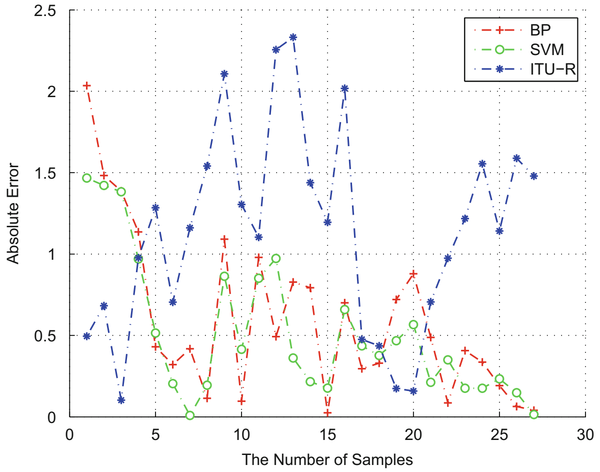

Fig. 3 Absolute error of different models. The absolute errors of proposed models are apparently smaller than ITU-R model

5 Performance Comparison

In accordance with the principles above, BP neural network model and LS-SVM model for the prediction of rain attenuation have been set up successfully. To examine the performance of models, 27 rain intensity samples are selected as test samples which can be used to get the corresponding rain attenuation values based on BP neural network model, LS-SVM model and ITU-R model. Figure 2 shows the contrast between the predictive values and the measured values. In parallel, Figs. 3 and 4 give the absolute error and square error, respectively.

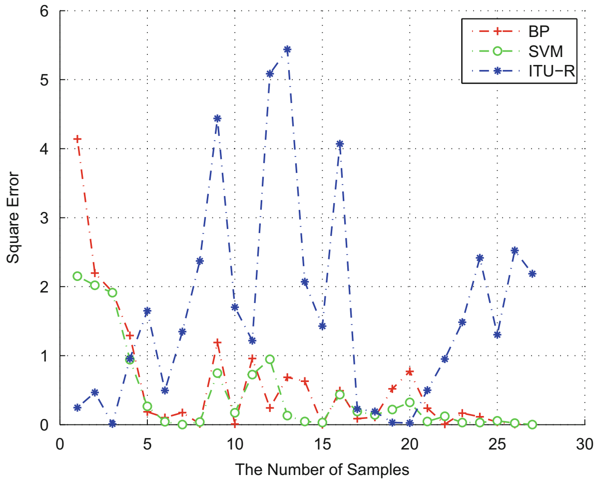

Fig. 4 Square errors of different models. The square errors of our proposed models are apparently smaller than ITU-R model

Table 1 MAE, MSE, MAX of different models

Prediction models	MAE	MSE	MAX
ITU-R model	1.1337	1.6605	2.3320
BP model	0.5988	0.6036	2.0348
LS-SVM model	0.5123	0.4362	1.4668

In order to evaluate the performance of these models fully, the following three indicators including mean absolute error (*MAE*), maximum error (*MAX*) and mean square error (*MSE*) are adopted to compare the performance of models in this paper just by the formulas (14)–(16), where t_i represents predictive value of the three models, k_i represents the measured value and N is the number of test samples.

$$MAE = \sum_{i=1}^{N} \frac{t_i - k_i}{N} \tag{14}$$

$$MAX = max(|t_i - k_i|) \tag{15}$$

$$MSE = \sum_{i=1}^{N} \frac{(t_i - k_i)^2}{N} \tag{16}$$

According to the formulas, we calculate MAE, MSE and MAX of the three rain attenuation models just as Table 1 shows.

In summary, BP neural network model and LS-SVM model are indeed superior to the existing ITU-R model in the sense of both accuracy and stability. In addition, because of LS-SVM model based on the principle of structural risk minimization, it has the unique global optimum solution. So it is superior to the BP model.

6 Conclusion

Comparing with the popular model recommended by ITU-R, we proposed two novel rain attenuation prediction models for 60 GHz mmWave based on the BP neural networks and LS-SVM algorithm in this article. The experimental results show that BP neural networks model is superior to the popular ITU-R model in the sense of accuracy and stability. Meanwhile, LS-SVM model can predict the rain attenuation with a better performance regardless of accuracy or stability compared with the other models and that make it an ideal and promising model for rain attenuation prediction at 60 GHz.

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