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Asphalt Pavement Friction Coefficient Prediction Method Based on Genetic-Algorithm-Improved Neural Network (GAI-NN) Model

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Abstract: To overcome the limitations of pavement skid resistance prediction using the friction coefficient, a Genetic-Algorithm-Improved Neural Network (GAI-NN) was developed in this study. First, three-dimensional (3D) point-cloud data of an asphalt pavement surface were obtained using a smart sensor (Gocator 3110). The friction coefficient of the pavement was then obtained using a pendulum friction tester. The 3D point-cloud dataset was then analyzed to recover missing data and perform denoising. In particular, these data were filled using cubic-spline interpolation. Parameters for texture characterization were defined, and methods for computing the parameters were developed. Finally, the GAI-NN model was developed via modification of the weights and thresholds. The test results indicated that using pavement surface texture 3D data, the GAI-NN was capable of predicting the pavement friction coefficient with sufficient accuracy, with an error of 12.1%.

Keywords: pavement engineering, skid resistance, friction coefficient prediction, 3D point-cloud data, genetic neural network

1. Introduction

Modern road pavements must satisfy certain safety, economic, and comfort requirements. Asphalt pavement with high skid resistance is a precondition for ensuring driving safety. The skid resistance of asphalt pavement depends on factors such as the pavement texture structure, tire–pavement contact, and pavement wetness(Mataei et al. 2016). However, there are major problems with the measurement and assessment of pavement skid resistance: ① diverse measurement methods without consistent assessment criteria; ② diverse measurement devices without standard measurement procedures; ③ measurement devices with different accuracies and different application scopes(Xiong et al. 2017; Chai et al. 2013; Dong et al. 2012); ④ difficulties in obtaining a stable friction coefficient without a common index for pavement skid-resistance assessment, as the measurement is affected by factors such as the type of measurement device, wetness of the pavement, and measurement method (dynamic or static).Error! Reference source not found.Error! Reference source not found.

Research indicates that the skid resistance of asphalt pavement mainly depends on the surface texture(Fwa et al. 2003). The pavement surface skid resistance is an important factor affecting the pavement performance, and its measurement affects the rationality and accuracy of pavement evaluation. The friction coefficient has been widely used as a skid-resistance evaluation index(Kane et al. 2018). With the development of three-dimensional (3D) imaging techniques, advances have been achieved in the analysis of the surface texture and skid resistance using 3D scanning and treatment. Gendy et al.(Gendy et al. 2011) obtained pavement surface texture 3D data using the photometric stereo technique and determined the texture using power spectrum estimation (PSE). Their results indicated that the PSE is significantly affected by the mean profile depth and root-mean-square (RMS) roughness. Zelelew et al.(Zelelew et al. 2014)measured the 3D surface texture of asphalt pavements using a circular texture meter and decomposed the results into six wavelet levels: d1–d6. Their results indicated that the texture properties of smooth pavements are mainly affected by levels d1–d4 (both fine and coarse aggregates), whereas those of rough pavements are mainly affected by levels d3 and d4 (coarse aggregates). Zhang et al.(Zhang et al. 2014)analyzed the texture using 3D techniques and determined its 3D properties using two-dimensional parameters such as the fractal dimension, peak angle, and slope. Their results indicated that the asphalt gradation and aggregate properties significantly affect the asphalt pavement skid resistance; grinding and kneading reduce the fractal dimension, mean texture depth (MTD), number of peaks, and friction coefficient. Liu and Shalaby(Liu et al. 2019)examined the 3D texture parameters, skid resistance, and noise of a Portland cement concrete pavement with 13 different textures. Their results indicated that the surface texture properties of pavement are related to its noise and skid resistance and that the amplitude, direction, and density of a texture significantly affect the

noise and skid resistance of the surface. Hu et al.(Hu et al. 2016)obtained texture data of asphalt pavements using a handheld laser scanner and measured the dynamic friction coefficient of the pavements using a dynamic friction tester. They proposed statistical methods for analyzing the relationship between the texture properties and the dynamic friction coefficient of the pavements. Their results indicated that at different test speeds, the texture depth and friction coefficient were not strongly correlated, and that the peak density and arithmetic mean peak curvature of the 3D textures significantly affected the dynamic friction coefficient. Using discrete wavelet transformation, Liu et al.(Liu et al. 2017)analyzed the surface texture 3D data of a pavement to characterize the relationship between its texture parameters and skid resistance. Their results indicated that the 3D MTD, as well as the 3D RMS deviation and skewness, significantly affected the skid resistance of the pavement.

Neural-network models have been used in pavement performance evaluation and prediction. Bianchini et al.(Bianchini et al. 2010)proposed a neuro-fuzzy model for predicting the performance of flexible pavements using the parameters routinely collected by agencies to characterize the condition of existing pavement. Zhang et al.(Zhang et al. 2017)proposed an efficient architecture based on a convolutional neural network to detect pavement cracks using 3D asphalt surfaces with the explicit objective of ensuring pixel-perfect accuracy. Isied et al.(Isied et al. 2019)created an artificial neural network predictive model to determine the endurance-limit strain values for conventional asphalt concrete pavements using beam fatigue test data. Jiang et al.(Jiang et al. 2019) developed a primary delay recovery predictor model based on artificial neural networks, using train operation records from the Wuhan-Guangzhou high-speed railway. Rifai et al.(Rifai et al. 2020) proposed a convolutional neural-network model to evaluate the surface roughness directly using digital surface-texture images.

The aforementioned studies focused on the relationship between the surface texture 3D properties and the skid resistance of asphalt pavements. However, models for describing the relationship between the texture properties and the friction coefficient have not established(Tsai et al. 2012; Sun Z.Y. et al. 2015). In the present study, a model was developed for predicting the relationship between the texture properties and skid resistance of pavements using a backpropagation (BP) neural network(Rumelhart et al. 1986; Holland et al. 1975) improved with a genetic algorithm.

2. Sample preparation and friction coefficient measurement in laboratory

2.1 Sample preparation in laboratory

In this study, 48 asphalt-mixture specimens were used. A total of 30 AC specimens were created using limestone and basis bitumen, and 18 OGFC specimens were created using limestone and modified asphalt. A total of 126 dataset were

acquired by randomly selecting and marking measurement points on the specimens. The granular material used was divided into grades (particle sizes) of 26.5, 19, 16, 13.2, 9.5, 4.75, 2.36, 1.18, 0.6, 0.3, 0.15, 0.075 mm with standard sieve. According to the designed gradation table, the actual amount of aggregate particles and mineral powder of each grade was weighed. AC-13C and OGFC-16 were taken as examples to analyze the composition and dosage of the mineral mixture (Technical specification for highway asphalt pavement construction[M].2015; Standard Test Methods of Bitumen and Bituminous Mixtures for Highway Engineering[M].2011). Figures 1(a) and (b) show the gradation curves of the AC-13C and OGFC-16 mixtures, respectively.

2.2 Friction-coefficient measurement

The surface friction coefficients of the specimens were measured using a pendulum friction tester (Regulations of the Ministry of Communications.2009). The total weight of the pendulum along with the joint of the pendulum apparatus was 1500 ± 30 g. The vertical distance between the rotation axis of the pendulum and the center of gravity of the friction head of the pendulum was 410 ± 5 mm. The positive pressure induced by the friction block on the specimen was 22.2 ± 0.5 N. According to the operation specifications of the pendulum tribometer, the friction coefficient of the marked area of the asphalt-mixture specimen was measured. Each area was measured three times, and the average value was obtained.

3. Acquisition of pavement surface texture 3D point-cloud data

A smart 3D sensor (Gocator 3110) was used to obtain 3D point-cloud data on pavement surface texture. The data-acquisition system is a package of 3D point-cloud acquisition and measurement tools. It includes two cameras: a front camera and a rear camera. There are two imaging modes: stereoscopic correlation measurement and independent triangulation measurement. ① When the detected point can be captured by the two cameras simultaneously, the system operates in the stereoscopic correlation measurement mode, in which it can capture the same point from different views using the two cameras. Because the exact distance and view angle of the two cameras are known, the point can be measured precisely. ② If the measured object is complex or has special characteristics and if the point can be captured by only one camera, the system operates in the independent triangulation measurement mode. An exact measurement result can still be obtained because the sensor system is calibrated during the manufacturing process. Table 1 presents the performance parameters of the system.

In the entire XY plane within the measurement range, the resolution decreased with the increasing distance from the camera. At the far end of the measurement range, the camera had the widest field view and lowest resolution, and at the near end, the camera had the narrowest field view and highest resolution. After the testing, the camera was installed in a

fixed position, as shown in Fig. 1(a), and the resolution did not change during the measurement. In this paper, “x” indicates the column, and “y” indicates the row.

The Gocator 3110 yields an image via the following steps. Step 1: The projector emits a blue light-emitting diode (LED) structured light to illuminate the surface of the target object. Step 2: The front and rear cameras of the sensor capture the blue light reflected by the target object. Step 3: The sensor obtains 3D point clouds of the measured surface. Figures 2(a) and (b) presents a schematic and photograph, respectively, of the Gocator 3110 system.

4. Quality improvement of asphalt pavement surface texture 3D point-cloud data

4.1 Causes of missing data in pavement surface texture 3D point-cloud data

The Gocator 3110 system computes pavement surface height information using the visual differences between the blue LED structured light reflected by the test object captured by the two fixed-position cameras. When the sensor scans the surface texture of a pavement, some of the blue LED structured light reflected by the pavement may not be captured by the cameras if the texture varies substantially. Therefore, the 3D acquisition system cannot compute the height information, which results in missing data in the 3D point-cloud measurement. This significantly reduces the accuracy of the pavement surface texture measurement. Therefore, it is necessary to recover the missing data.

4.2 Interpolation and filtering of pavement surface texture 3D point-cloud data

In this study, missing data from the 3D point-cloud measurement were filled in via interpolation (She T.W. et al. 2017; ISO 16610-21:2011). The interpolation was performed using cubic splines in both the row and column directions. Specifically, an interpolation was performed for each row of a 3D point-cloud dataset and then for each column of the dataset. The mean value of the two interpolation operations was taken as the final value for a missing datum. Figures 3(a)–(c) show the interpolation for filling in the missing data of the asphalt pavement surface texture measurement.

Figure 3(a) presents the original pavement data. Figure 3(b) presents the pavement data after interpolation, indicating that the missing 3D point-cloud data can be recovered. For illustrating the interpolation effect clearly, the data of the 100th row are taken as an example in Fig. 3(c). The red line represents the contour of the 100th row in the original data, and the black line represents the corresponding data after interpolation. Owing to the lack of data, the original contour exhibited a step change, which was addressed via the interpolation. The experimental results indicate that the missing data can be recovered effectively using the cubic-spline interpolation algorithm to ensure the integrity and accuracy of the surface texture.

Owing to factors related to the 3D acquisition system and environment, noise was present in the 3D point-cloud data of the pavement surface textures. The 3D point-cloud data were filtered to minimize the impact of noise on the pavement surface texture measurement. This filtering was performed using an algorithm combining median filtering, which yields the median of the point-cloud data by scanning the data with a filtering window of 5×5 , and double-phase standard deviation filtering, which determines the deviation of the data (Sun Z.Y. et al. 2015). The algorithm is described as follows:

1) The matrix of a 3D point-cloud dataset is denoted as $Z_{m \times n}$, where m and n represent the numbers of columns and rows, respectively. The size of the matrix of the filtering window is denoted as l ($l = 5$ for the example presented below).

2) The data are indexed by row and scanned top-down to obtain the mean $\bar{R}_{ij}$, standard deviation S_{ij} , and median ζ_{ij} of the filtering window area using the following equations:

$$\bar{R}_{ij} = \frac{1}{l * l} \sum_{s=i-2}^{i+2} \sum_{t=j-2}^{j+2} z_{st}, \quad (i = 3, \dots, m-3; j = 3, \dots, n-3), \quad (1)$$

$$S_{ij} = \sqrt{\frac{\sum_{s=i-2}^{i+2} \sum_{t=j-2}^{j+2} (z_{st} - \bar{R}_{ij})^2}{l * l}}, \quad (2)$$

$$\zeta_{ij} = \text{median}(z_{st}), \quad (3)$$

where z_{st} represents the datum in the s^{th} row and t^{th} column of the matrix, and $\text{median}(z_{st})$ represents the median in the filtering window ($s = i-2, \dots, i+2; t = j-2, \dots, j+2$).

3) Each row was assessed for the presence of noise using Equation (4). If the datum satisfies Equation (4), it is considered as noise and is replaced with the mean of the row; if it does not satisfy the equation, no treatment is necessary. Here, k is the filtering coefficient and is usually assigned a value of 1–3.

$$\left| \frac{z_{ij} - \bar{R}_{ij}}{S_{ij}} \right| > k \quad (4)$$

4) The point-cloud data obtained after the median filtering are designated as Z .

Figures 3(d)–(f) show the pavement data after median filtering, improved median filtering, and noise filtering, respectively. The improved median filtering (Fig. 3(e)) retained more details than the traditional median filtering did (Fig. 3(d)).

5. 3D Characterization of asphalt pavement surface texture

5.1 Pavement-texture 3D characterization

According to the texture data obtained using a Gaussian filter, the following texture roughness parameters were used to characterize the roughness of an asphalt pavement profile:

(1) Arithmetic mean profile deviation Ra

$$Ra = \frac{1}{M \times N} \sum_{i=1}^N \sum_{j=1}^M |z(x_i, y_j)|, \quad (5)$$

where M and N represent the numbers of sampling points in the x and y directions, respectively, and $Z(x_i, y_j)$ represents the amplitude.

(2) RMS profile deviation Rq

$$Rq = \sqrt{\frac{1}{M \times N} \sum_{i=1}^N \sum_{j=1}^M [z(x_i, y_j)]^2}, \quad (6)$$

where the symbols are as defined in (5).

(3) MTD

$$MTD = \frac{1}{M \times N} \sum_{i=1}^N \sum_{j=1}^M [z_p(x, y) - z(x_i, y_j)] \quad (7)$$

Here, $z_p(x, y)$ represents the top line of the profile. The other symbols are as defined in (5).

(4) Profile skewness Sk

$$Sk = \frac{1}{Rq^3} \frac{1}{M \times N} \sum_{i=1}^N \sum_{j=1}^M z^3(x_i, y_j), \quad (8)$$

(5) Profile steepness Rku

$$Rku = \frac{1}{Rq^4} \frac{1}{M \times N} \sum_{i=1}^N \sum_{j=1}^M z^4(x_i, y_j), \quad (9)$$

(6) Mean spacing of profile irregularities Sm

$$Sm = \frac{1}{n} \sum_{j=1}^n Sm_j \quad (10)$$

Here, n represents the number of inter-irregularity spaces, and Sm_j represents the j^{th} inter-irregularity space, as shown in Fig. 4.

(7) Mean spacing of local peaks of the profile S

$$S = \frac{1}{m} \sum_{j=1}^m S_j \quad (11)$$

Here, S_j represents the j^{th} horizontal distance between two adjacent peaks, as shown in Fig. 4.

(8) RMS profile wavelength λq

$$\lambda q = 2\pi \frac{Rq}{\Delta q} \quad (12)$$

$$\Delta q = \sqrt{\frac{1}{(M-1) \times (N-1)} \sum_{i=1}^{N-1} \sum_{j=1}^{M-1} \left[\left(\frac{z(x_{i+1}, y_j) - z(x_i, y_j)}{\Delta x} \right)^2 + \left(\frac{z(x_i, y_{j+1}) - z(x_i, y_j)}{\Delta y} \right)^2 \right]} \quad (13)$$

Here, Δx and Δy represent the horizontal spacing in the x and y directions, respectively. The other symbols are as defined in (5).

(9) Percentage of rough areas R

$$R = \frac{A_1}{A_2} \quad (14)$$

$$A_1 = (\Delta x \Delta y) \sum_{i=1}^{N-1} \sum_{j=1}^{M-1} \sqrt{1 + \left[\left(\frac{z(x_{i+1}, y_j) - z(x_i, y_j)}{\Delta x} \right)^2 + \left(\frac{z(x_i, y_{j+1}) - z(x_i, y_j)}{\Delta y} \right)^2 \right]} \quad (15)$$

Here, R represents the roughness of the surface. A_1 represents the actual area of the surface, and A_2 represents the projected area on the horizontal of the surface. Δx and Δy represent the horizontal spacing in the x and y directions, respectively. The other symbols are as defined in (5).

5.2 Relationship between pavement texture properties and friction coefficient

Some of the 3D characteristic data extracted from the road surface texture point-cloud data are presented in Table 2.

To satisfy the requirements for subsequent neural-network model design and optimization, the Pearson correlation coefficient is adopted to analyze the correlation between the obtained friction coefficient and the extracted 3D features. The calculation formula for the correlation coefficient is as follows:

$$p = \frac{\sum_{i=1}^N (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^N (x_i - \bar{x})^2 \sum_{i=1}^N (y_i - \bar{y})^2}}, \quad (16)$$

where N represents the number of samples. x_i and y_i are variables with mean values of $\bar{x}$ and $\bar{y}$, respectively. The calculation results are presented in Table 3.

The results indicate that the friction coefficient f is strongly correlated with the arithmetic mean profile deviation (Ra), RMS profile deviation (Rq), MTD, and percentage of rough areas $\mathbb{R}$. It is also weakly correlated with the mean spacing of profile irregularities (Sm) and profile steepness (Rku). A correlation exists between Ra, Rq, and MTD for the macroscopic texture 3D features.

6. Genetic neural-network model for predicting friction coefficients of asphalt pavement

6.1 BP neural-network model

A BP neural network consists of an input layer, a hidden layer, and an output layer. The input layer imports sample data into the network. The hidden layer processes the data in the input layer. The output layer exports the results of the network. Assume that N , H , and M are the numbers of nodes in the input, hidden, and output layers, respectively; i refers to the i^{th} node in the input layer; h refers to the h^{th} node in the hidden layer; and j refers to the j^{th} node in the output layer; W_{hi} represents the weight of the i^{th} node in the input layer relative to the h^{th} node in the hidden layer; W_{jh} represents the weight of the j^{th} node in the hidden layer relative to the j^{th} node in the output layer; b_h represents the threshold of the h^{th} node in the hidden layer; b_j represents the threshold of the j^{th} node in the output layer; and η represents the learning rate.

The input of the network is expressed as $X_k = (x_1, x_2, \dots, x_n)$; the output of the network is expressed as $Y_k = (y_1, y_2, \dots, y_m)$; the true value is expressed as $T_k = (t_1, t_2, \dots, t_m)$; and f_1 and f_2 represent the activation functions for the hidden and output layers, respectively. The BP neural network was trained through both forward propagation and backpropagation.

(1) Forward propagation

The output of the h^{th} neuron in the hidden layer is expressed as follows:

$$I_h = \sum_{i=1}^r w_{hi} x_i + b_h$$

$$Y_h = f_1(I_h)$$
(17)

The output of the j^{th} neuron in the output layer is expressed as follows:

$$I_j = \sum_{h=1}^n w_{jh} Y_h + b_j$$

$$Y_j = f_2(I_j)$$
(18)

(2) Backpropagation

The sample error is expressed as follows:

$$E = \frac{1}{2} \sum_{j=1}^m (t_j - Y_j)^2$$
(19)

The weights and thresholds of the output and hidden layers are updated using the following equations:

$$w'_{jh} = w_{jh} + \Delta w_{jh} = w_{jh} + \eta \delta_j^M Y_h$$
(20)

$$w'_{hi} = w_{hi} + \Delta w_{hi} = w_{hi} + \eta \delta_h^H Y_i$$
(21)

$$b'_h = b_h + \Delta b_h = b_h + \eta \delta_j^M$$
(22)

$$b'_j = b_j + \Delta b_j = b_j + \eta \delta_h^H$$
(23)

where δ_j^M represents the gradient of the output layer and is expressed as $\delta_j^M = Y_j(1 - Y_j)(t_j - Y_j)$, and δ_h^H represents the gradient of the hidden layer and is expressed as $\delta_h^H = f'(I_h) \sum_{j=1}^M \delta_j^M w_{jh}$.

6.2 Improved BP neural network based on genetic algorithm for pavement skid-resistance prediction

Genetic algorithms solve optimization problems by imitating biological evolution processes, e.g., heredity, mutation, selection, and crossover. Random initialization of the weights and thresholds of a BP neural network may cause large variations in the performance of the prediction model. In this study, the weights and thresholds of the BP neural network were improved using a genetic algorithm, which increased the convergence speed of the neural network and minimized interference of local optimal solutions. Figure 5 shows a flowchart of the genetic-algorithm-improved BP neural network.

(1) Population initialization

Using floating-point coding, the weights of the input layer relative to the hidden layer, the thresholds of the hidden layer, the weights of the hidden layer relative to the output layer, and the thresholds of the output layer were connected as individuals in a population. The real-number coding of the individuals is expressed as follows:

$$w_{11}w_{21}\dots w_{n1}w_{12}w_{22}\dots w_{n2}w_{2l}\dots w_{nl}a_1\dots a_lw'_{11}\dots w'_{n1}b_1.$$

(2) Fitness function

The genetic algorithm evaluated the fitness of the individuals in the population using fitness functions, through a process inspired by natural selection. Fitness functions are developed according to the problem in question. In this study, the fitness of individuals was evaluated using the sum of the absolute values of the friction coefficient predicted using the BP neural network and the measured friction coefficient. The fitness function is expressed as follows:

$$f = \sum_{i=1}^n \text{abs}(y_i - o_i), \quad (24)$$

where y_i represents the predicted friction coefficient; o_i represents the true friction coefficient; and n represents the number of samples.

(3) Selection operation

The selection of individuals was performed using the roulette method. The fitness of an individual in the population determined the probability of the individual being selected during the selection operation. The selected individuals were subjected to mutation and crossover operations to generate new individuals, and the non-selected individuals were deleted.

$$p_i = F_i / \sum_{i=1}^c F_i \quad (25)$$

(4) Crossover operation

The crossover operation randomly selected the crossover points of pairs of parent chromosomes and exchanged the chromosomal segments at the crossover point of each pair. The genetic crossover operation for individuals k_1 and k_2 at the j^{th} position was expressed as follows:

$$\left. \begin{aligned} g_{k_1j} &= g_{k_1j}r + g_{k_2j}(1-r) \\ g_{k_2j} &= g_{k_2j}r + g_{k_1j}(1-r) \end{aligned} \right\} \quad (26)$$

where g_{klj} and j_{k2j} represent the genes of individuals k_1 and k_2 in the j^{th} position, respectively, and r represents a random number in the range of $[0,1]$.

(5) Mutation operation

The mutation operation altered the values of randomly selected individuals. The mutation of the i^{th} individual at the j^{th} position, i.e., g_{ij} , was expressed as follows:

$$g_{ij} = \begin{cases} g_{ij}r + (g_{ij} - g_{\max})r_1(1 - s/s_{\max}), & r_2 \geq 0.5 \\ g_{ij}r + (g_{\min} - g_{ij})r_1(1 - s/s_{\max}), & r_2 < 0.5 \end{cases} \quad (27)$$

where $g_{\max}$ and $g_{\min}$ represent the upper and lower limits, respectively, of the gene; s represents the current number of iteration steps; $s_{\max}$ represents the maximum number of evolutions; and r_1 and r_2 are random numbers.

6.3 Analysis of BP neural-network models for friction coefficient prediction

A total of 126 testing datasets were obtained. Among them, 100 datasets were used to train the GAI-NN, and the remaining 26 datasets were used for testing. The trained neural network was then ready for predicting the friction coefficient of asphalt pavements. To verify the influence of the genetic algorithm on the BP neural-network model, the performance of the GAI-NN was analyzed with regard to two aspects: the crossover probability and mutation probability.

6.3.1 Effect of genetic-algorithm crossover probability on network performance

The crossover probabilities were set as 0.7, 0.8, and 0.9 (it is typically 0.7–1.0), and the neural-network model error curve and fitness model were trained under different crossover probability conditions. Figures 6(a), (c), and (e) present the GAI-NN error curves for the crossover probabilities of 0.7, 0.8, and 0.9, respectively; these figures show that the network model converged well under the three conditions. Figures 6(b), (d), and (f) present the fitness curves corresponding to Figures 6(a), (c), and (e), respectively. As shown, the network converged fastest when the crossover probability was 0.9. In the genetic algorithm, only four generations of evolution were needed to obtain the optimal population. Thus, the GAI-NN model achieved the best weight and threshold when predicting the friction coefficient of asphalt pavement. When the crossover probabilities were 0.7 and 0.8, 8 and 16 generations were needed, respectively. As indicated in Table 4, the RMS error (RMSE), mean absolute error (MAE), and mean absolute percentage error (MAPE) of the network were the smallest when the crossover probability was 0.9. The GAI-NN predicted the anti-skid performance of the road surface most accurately in this case.

6.3.2 Effect of genetic-algorithm variation probability on network performance

The variation probabilities were set as 0.05, 0.075, and 0.1, and the model of the genetic-algorithm optimization BP network was trained accordingly.

The network-error curves and fitness curves with different variation probabilities are shown in Figure 7. The network convergence was the fastest when the crossover probability was 0.05; the optimal population was obtained after four generations of population evolution, whereas when the variation probability was 0.075 and 0.1, six and eight generations were needed, respectively. As indicated in Table 4, the error indices were the smallest when the crossover probability was 0.05, indicating that the neural-network model had the best performance at this value.

6.3.3 Effect of number of hidden-layer nodes on network performance

To investigate the effect of the number of hidden-layer nodes on the GAI-NN, the number was adjusted to 7, 8, and 9, and the corresponding network was obtained by training the model. As indicated by Figure 8 and Table 4, when the number of nodes in the hidden layer was 8, the error of the model was minimized, and the curve was smooth. Additionally, the number of iterations needed to obtain the optimal population, as well as the evaluation indices, were the smallest.

According to the foregoing analysis, the GAI-NN achieves the optimal performance when the number of nodes in the hidden layer is 8, the crossover probability is 0.9, and the variation probability is 0.1.

Comparisons between the measured friction coefficient and the predictions of the BP neural network and GAI-NN are presented in Figures 9(a) and (b), respectively. The friction coefficient fitting results between the predictions and the measurements are shown in Figures 9(c) and (d).

The values of the determination coefficient (R^2) were 0.5701 and 0.688 for the BP neural network and GAI-NN, respectively, indicating that the predicted friction coefficients were strongly correlated with the measured ones. The GAI-NN reflected the relationship between the 3D point-cloud characteristics and the friction coefficient of the asphalt pavement more accurately.

To analyze the performance of the two prediction models in greater detail, the RMSE, MAE, and MAEP were calculated. The results are presented in Table 5.

The RMSE, MAE, and MAEP were smaller for the GAI-NN than for the BP neural network, indicating that the GAI-NN is a feasible model and can predict the road friction coefficient more accurately.

7. Conclusions

(1) The relationship between the pavement texture properties and the friction coefficient was analyzed. The friction coefficient f is strongly correlated with the RMS profile deviation (Rq), MTD , and percentage of rough areas (R) and is weakly correlated with the mean spacing of profile irregularities (Sm) and profile steepness (Rku).

(2) A GAI-NN model was developed for predicting the pavement friction coefficient. The friction coefficients predicted using the model agreed well with the measured friction coefficients.

(3) This study was based on data obtained from specimens of asphalt pavements. Thus, for real-world engineering applications, the model for friction coefficient prediction must be trained further with data corresponding to real-world pavements.

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Tables:

- Table 1.** Performance parameters of Gocator 3110
- Table 2.** 3D characteristic data extracted from road surface texture point-cloud data
- Table 3.** Correlation analysis of macroscopic texture 3D features
- Table 4.** Comparison of GAI-NN results obtained with different parameters
- Table 5.** Friction coefficient prediction performance comparison

Figures:

- (a) Gradation curve of AC-13C

(b) Gradation curve of OGFC-16
- Fig. 1.** Gradation curves
- (a) Schematic

(b) Photograph
- Fig. 2.** Gocator 3110 system
- (a) Original pavement data

(b) Pavement data after interpolation

(c) Interpolated pavement row data
- (d) Pavement data after median filtering

(e) Pavement data after improved median filtering

(f) Filtered noise data
- Fig. 3.** Interpolation and filtering of pavement surface data
- Fig. 4.** Schematic of the mean spacing of profile irregularities and local peaks
- Fig. 5.** Flowchart of the genetic neural network for pavement friction coefficient prediction

- (a) Error curve with crossover probability of 0.7

(b) Fitness curve with crossover probability of 0.7
- (c) Error curve with crossover probability of 0.8

(d) Fitness curve with crossover probability of 0.8

(e) Error curve with crossover probability of 0.9 (f) Fitness curve with crossover probability of 0.9

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(a) Error curve with mutation probability of 0.05 (b) Fitness curve with mutation probability of 0.05
 (c) Error curve with mutation probability of 0.075 (d) Fitness curve with mutation probability of 0.075
 (e) Error curve with mutation probability of 0.1 (f) Fitness curve with mutation probability of 0.1

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Fig. 8. GAI-NN training results for different numbers of hidden-layer nodes

(a) Measured friction coefficient and prediction results of BP network (b) Measured friction coefficient and prediction results of GAI-NN
 (c) Fitting curve of measured friction coefficient and prediction results of BP network (d) Fitting curve of measured friction coefficient and prediction results of GAI-NN

Fig. 9. Friction coefficient prediction results: comparisons and fitting curves

Figures

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Tables

Table 1. Performance parameters of Gocator 3110

Parameter	Value
Clearance distance (mm)	150
Measurement range (mm)	100
Near field of view (mm)	60×105
Far field of view (mm)	90×160
Resolution Z (+/-mm)	0.035–0.108
Resolution XY (+/-mm)	0.090×0.100 to 0.150×0.160

Table 2. 3D characteristic data extracted from road surface texture point-cloud data

Ra	Rq	MTD	Sm	S	λq	R	Rsk	Rku	Δq
0.529	0.743	1.011	0.262	0.383	10.143	1.092	-2.108	5.884	0.461
0.416	0.576	0.993	0.289	0.442	7.931	1.089	-1.754	6.738	0.456
0.407	0.530	0.840	0.248	0.424	8.345	1.077	-1.371	4.467	0.399
0.543	0.772	1.110	0.240	0.436	8.861	1.114	-1.993	5.292	0.547
0.675	0.983	1.194	0.207	0.305	12.308	1.104	-2.050	5.041	0.502
0.574	0.806	2.753	0.288	0.453	9.897	1.109	1.910	4.610	0.512
0.726	0.883	3.387	0.244	0.348	12.208	1.090	0.356	2.853	0.455
0.541	0.822	3.345	0.216	0.458	10.293	1.108	2.334	6.814	0.502
0.537	0.948	1.229	0.247	0.409	9.588	1.143	-3.406	15.420	0.621
0.290	0.359	1.085	0.219	0.458	6.410	1.055	-0.664	2.582	0.352
0.231	0.308	0.577	0.248	0.460	6.073	1.046	-1.564	4.099	0.318
0.500	0.807	0.978	0.254	0.413	9.243	1.106	-2.470	7.552	0.549
0.421	0.561	2.785	0.287	0.416	7.489	1.095	1.423	5.125	0.471
0.666	0.833	1.182	0.064	0.066	11.913	1.082	-1.699	3.650	0.439
0.271	0.352	0.736	0.243	0.459	5.912	1.064	-1.338	4.682	0.374
0.411	0.545	0.890	0.274	0.436	7.652	1.090	-1.670	4.072	0.447

Table 3. Correlation analysis of macroscopic texture 3D features

p	f	Ra	Rq	MTD	Sm	S	λq	R	Sk	Rku	Δq
f	1.000	0.431	0.385	0.452	0.165	0.317	0.370	0.416	0.253	0.109	0.274
Ra	0.431	1.000	0.978	0.522	-0.066	-0.287	0.749	0.745	0.086	-0.391	0.736
Rq	0.385	0.978	1.000	0.512	-0.049	-0.312	0.740	0.782	-0.035	-0.241	0.778
MTD	0.452	0.522	0.512	1.000	0.078	0.031	0.264	0.527	0.528	-0.203	0.509
Sm	0.165	-0.066	-0.049	0.078	1.000	0.445	-0.303	0.243	0.085	0.151	0.243
S	0.317	-0.287	-0.312	0.031	0.445	1.000	-0.387	-0.095	0.436	0.029	-0.094
λq	0.370	0.749	0.740	0.264	-0.303	-0.387	1.000	0.220	-0.016	-0.287	0.207
R	0.416	0.745	0.782	0.527	0.243	-0.095	0.220	1.000	-0.033	-0.077	0.993
Sk	0.253	0.086	-0.035	0.528	0.085	0.436	-0.016	-0.033	1.000	-0.528	-0.055
Rku	0.109	-0.391	-0.241	-0.203	0.151	0.029	-0.287	-0.077	-0.528	1.000	-0.054
Δq	0.274	0.736	0.778	0.509	0.243	-0.094	0.207	0.993	-0.055	-0.054	1.000

Table 4. Comparison of GAI-NN results obtained with different parameters

Input node No.	Hidden node No.	Mutation probability	Crossover probability	RMSE	MAE	MAEP
			0.7	0.110	0.085	16.8%
			0.8	0.084	0.062	12.9%
			0.9	0.062	0.056	12.1%
		0.05		0.062	0.068	12.1%
7	8	0.075	0.9	0.095	0.068	14.7%
		0.1		0.092	0.074	16.2%
	7			0.084	0.066	14.1%
	8	0.05	0.9	0.062	0.056	12.1%
7	9			0.134	0.097	21.0%

Table 5. Friction coefficient prediction performance comparison

Network type	RMSE	MAE	MAEP
BP network	0.094	0.07	15.5%
GAI-NN	0.062	0.068	12.1%

Figures

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