

STAIRCASE USAGE CHARACTERISTICS AND MODEL CONSISTENCY BASED ON MULTI-MODEL FUSION

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Abstract: To reveal the usage patterns underlying the wear of ancient building stone steps, this paper constructs a multi-model fusion analysis framework. Firstly, pedestrian walking paths are generated using the Monte Carlo method, and a three-dimensional stone step wear simulation model is constructed by combining kernel density estimation (KDE). The normalized KDE probability distribution is integrated into Archard's wear law to form an advanced stone step wear model. Secondly, the usage frequency of the stone steps is analyzed from both the overall and local dimensions. The walking direction preference is determined by geometric center, skewness, centroid, and principal component analysis (PCA). The path structure features are identified using K-means clustering and Gaussian fitting. The research results show that there is no obvious directional preference for stone step usage. The overall distribution is uniform and slightly leans towards the lower part of the Y direction and the right side of the X direction. There are parallel channel characteristics. The model is highly consistent with the existing data in terms of frequency, direction, and path type prediction.

Keywords: Kernel density estimation; Archard's wear law; Usage frequency; Walking preference; Model consistency

1 INTRODUCTION

The accurate analysis of spatial usage characteristics of traffic - bearing structures has long been a key challenge in fields such as transportation engineering and behavioral statistics. Traditional analytical methods often rely on simplified assumptions (e.g., uniform distribution of usage intensity) or single - dimensional data (e.g., only total usage count), which fail to capture the spatial heterogeneity of user behavior and lead to deviations between model outputs and actual scenarios [1]. For example, in the analysis of pedestrian movement paths, the randomness of individual walking trajectories and the aggregation of group behavior will result in uneven distribution of usage intensity, making it difficult for linear statistical models to accurately describe such complex patterns [2-3].

To address these limitations, multi - model fusion has emerged as a promising solution, as it combines the advantages of different types of models to compensate for the defects of single models. Stochastic simulation methods (e.g., Monte Carlo) excel at reproducing random processes and can effectively simulate the uncertainty of pedestrian movement; however, they often lack the support of physical mechanisms and cannot directly establish the connection between usage behavior and quantitative indicators [4]. Non - parametric estimation methods (e.g., KDE) can handle irregular data distributions and generate continuous density surfaces, but they rely heavily on parameter settings (e.g., bandwidth) and may overfit or underfit without proper optimization [5]. Physical models (e.g., Archard's Wear Law) have clear theoretical foundations and can describe the quantitative relationship between usage and physical effects, but they usually ignore spatial differences in usage intensity and assume uniform action distribution, which limits their applicability in complex scenarios [6].

In response to the above - mentioned gaps, this study designs a multi - model fusion framework that systematically integrates Monte Carlo simulation, KDE, and Archard's Wear Law. The specific research process is as follows: first, Monte Carlo simulation is used to generate a large number of discrete pedestrian movement paths, which serves as the data source for subsequent intensity analysis; second, KDE is applied to process these discrete data, and the bandwidth is optimized using cross - validation to ensure the smoothness and accuracy of the density distribution; third, the normalized KDE probability is incorporated into Archard's Wear Law to construct a modified model that considers spatial usage probability, thereby realizing the integration of stochastic behavior simulation and physical mechanism analysis.

To verify the effectiveness of the proposed framework, a comprehensive consistency verification system is established. For usage frequency prediction, MSE is used to measure the deviation between predicted and actual values; for movement direction analysis, ADD is introduced to quantify the angular difference between predicted and actual directions; for path type classification, a confusion matrix is constructed to evaluate the model's ability to distinguish between different path structures (e.g., single - lane, parallel lanes). This multi - dimensional verification not only

ensures the reliability of the model but also provides a standardized evaluation method for similar usage characteristic analysis tasks [7-8].

The main contributions of this study are threefold: first, it proposes a method to integrate stochastic simulation, non-parametric estimation, and physical models, which fills the gap between behavioral randomness and physical quantification; second, it optimizes the KDE bandwidth selection through cross-validation, improving the accuracy of usage intensity distribution estimation; third, it establishes a multi-metric verification system that comprehensively evaluates the model's performance from multiple dimensions, providing a reference for the application of multi-model fusion in related fields.

2 CONSTRUCTION OF ADVANCED STAIRCASE WEAR MODEL

2.1 Data Preprocessing

In accordance with the principles of non-destructive and low-cost measurement, 3D scanning, photogrammetry, wear analysis, and material analysis are carried out on the stone staircases of ancient buildings. Laser scanning or structured light cameras are used to measure the wear depth of the staircases, and high-resolution cameras are employed to capture images and construct 3D models. The overall wear degree is determined by analyzing the wear depth distribution of different staircases, and the parallel walking characteristics of pedestrians are judged based on the differences in wear depth. The wear morphology is observed to identify abnormal areas and initially determine whether the staircases have been renovated. Portable spectrometers are used to detect the material composition of the staircases, providing basic data for subsequent analysis.

It is assumed that only human trampling has a direct impact on the shape of the staircases. Let the total number of stair steps be N , the wear amount per step be M , and each trampling only causes wear to a small $10\text{cm} \times 10\text{cm}$ unit. The total wear function is constructed as shown in Equation (1):

$$W_{\{total\}(x,y)} = M \cdot N \cdot P(x, y) \quad (1)$$

In the equation, $W_{total}(x, y)$ is the total wear amount at position (x, y) on the staircase surface; $P(x, y)$ is the wear probability at position (x, y) , representing the possibility of this position being trampled.

An initial cuboid smooth staircase model is constructed, and initialized according to the staircase dimensions (width, length, height), total number of steps, and wear amount per step. The Monte Carlo simulation method is used to randomly generate pedestrian walking positions, and the cumulative wear amount at each position is recorded to obtain a 3D staircase wear surface model. From the color depth distribution of the model, it can be intuitively judged that: dark-colored areas have high trampling density, high usage frequency, and severe wear, while light-colored areas have the opposite characteristics, laying a foundation for the construction of the subsequent advanced wear model.

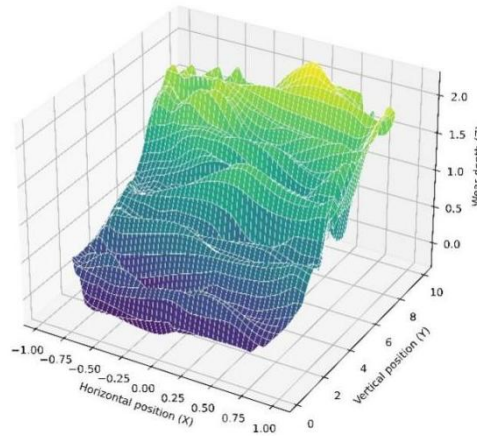


Figure 1 Stair Wear 3D Curved Surface

Figure 1 presents the 3D curved surface of staircase wear simulated by the Monte Carlo method. The horizontal axis (X) represents the width direction of the staircase, the vertical axis (Y) denotes the length (or walking direction) of the staircase, and the Z-axis corresponds to the wear intensity at each spatial position. The color gradient in the figure reflects the difference in wear accumulation: darker-colored areas indicate higher wear intensity, corresponding to positions with more frequent trampling, while lighter-colored areas represent lower wear intensity and less frequent usage. This 3D visualization intuitively reveals the spatial heterogeneity of staircase usage intensity, providing discrete wear distribution data for the subsequent construction of probability density models.

2.2 Staircase Wear Model

2.2.1 Kernel density estimation (KDE)

Based on the staircase wear scatter data obtained by 3D scanning, the Kernel Density Estimation (KDE) method, a non-parametric approach, is introduced to estimate the data distribution [7]. A Gaussian kernel function is applied to each data point and smoothed to obtain a continuous probability density function, which accurately describes the spatial distribution characteristics of the wear data.

For the 3D wear scatter dataset $\{(x_1, y_1, z_1), (x_2, y_2, z_2), \dots\}$, in 3D space, the 3D KDE formula is shown in Equation (2):

$$\hat{f}(x, y, z) = \frac{1}{nh^3} \sum_{i=1}^n K\left(\frac{x-x_i}{h}, \frac{y-y_i}{h}, \frac{z-z_i}{h}\right) \quad (2)$$

In the equation, $\hat{f}(x, y, z)$ is the estimated probability density value at position in 3D space; n is the number of samples; h is the bandwidth (a smoothing parameter that controls the influence range of the kernel function); K is the Gaussian kernel function.

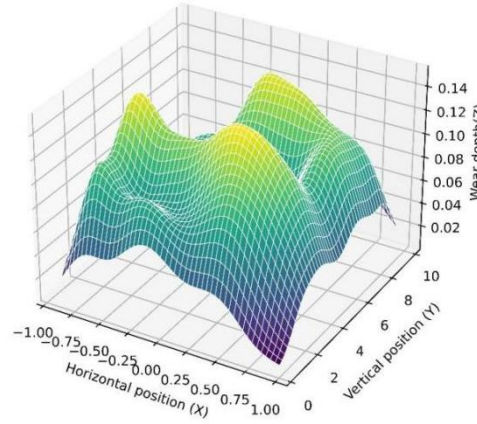


Figure 2 Stair Wear KDE Curved Surface

Figure 2 shows the continuous 3D density surface of staircase wear generated by Kernel Density Estimation (KDE). The horizontal and vertical axes are consistent with Figure 1 (representing the staircase's width and length directions, respectively), and the Z-axis represents the normalized usage intensity probability density. The Gaussian kernel function with cross-validated bandwidth is used to smooth the discrete Monte Carlo simulation data, resulting in a continuous density distribution. Light-colored regions in the figure indicate high probability density, corresponding to core usage areas with concentrated trampling; dark-colored regions represent low probability density, corresponding to edge or infrequently used areas. This smooth density surface solves the problem of uneven discrete data distribution, laying a foundation for quantifying the spatial probability of staircase usage.

The 3D form of the Gaussian kernel function is shown in Equation (3):

$$K(u_x, u_y, u_z) = \frac{1}{(2\pi)^{3/2}} e^{-\frac{1}{2}(u_x^2 + u_y^2 + u_z^2)} \quad (3)$$

In the equation, u_x, u_y, u_z are the normalized distances of the data point (x_i, y_i, z_i) in the x, y, and z directions respectively.

By substituting Equation (3) into Equation (2), the KDE estimation formula for 3D wear data is obtained as shown in Equation (4):

$$\hat{f}(x, y, z) = \frac{1}{nh^3} \sum_{i=1}^n \frac{1}{(2\pi)^{3/2}} e^{-\frac{1}{2}(u_x^2 + u_y^2 + u_z^2)} \quad (4)$$

A 3D density distribution map of staircase wear is obtained based on Equation (4). The horizontal and vertical coordinates in the map correspond to the spatial position of the staircase (the horizontal coordinate X is the width direction, and the vertical coordinate Y is the length/walking direction), and the Z value represents the usage frequency or trampling probability at each position. Light-colored areas have high density values, high usage frequency, and severe wear; dark-colored areas have low density values, low usage frequency, and slight wear, providing a quantitative basis for subsequent wear probability calculation and usage characteristic analysis.

2.2.2 Normalized KDE probability distribution model

The density value output by KDE needs to be converted into a probability distribution function. A normalized KDE probability function is introduced, and the wear probability at each position is obtained through integral normalization, as shown in Equation (5):

$$P(x, y) = \frac{\hat{f}(x, y)}{\sum_{x, y} \hat{f}(x, y) \Delta x \Delta y} \quad (5)$$

In the equation, $P(x, y)$ is the wear probability at position (x, y) on the staircase surface; $\hat{f}(x, y)$ is the KDE density value at position (x, y) ; Δx and Δy are the calculation steps in the x and y directions respectively; the denominator is the integral sum of the density values at all positions, ensuring that the probability distribution meets the normalization condition.

2.2.3 Integrating with physical model: Archard's wear law

Based on Archard's Wear Formula, the formula is improved by combining the probability distribution characteristics of pedestrian trampling positions. The basic form of Archard's Wear Formula is shown in Equation (6):

$$W = \frac{kFL}{H} \quad (6)$$

In the equation, W is the wear volume; k is the wear coefficient (related to material type and surface roughness); F is the trampling load (the force exerted by the human body weight on the sole of the foot); L is the sliding distance; H is the material hardness.

The normalized KDE probability distribution $P(x,y)$ is introduced into the formula, and the wear amount formula at position (x,y) under a single step is obtained as shown in Equation (7):

$$W_{step}(x, y) = \frac{kFL}{H} \cdot P(x, y) \quad (7)$$

In the equation, $W_{step}(x, y)$ is the wear amount at position (x,y) on the staircase under a single trampling.

The total number of tramplings on the staircase is related to the pedestrian flow and service life. The relationship between the total number of tramplings, annual pedestrian flow, and service time is constructed as shown in Equation (8):

$$N = Yt \quad (8)$$

In the equation, N is the total number of tramplings; Y is the average annual pedestrian flow; t is the service life of the staircase.

By combining Equations (7) and (8), the cumulative wear amount formula at position (x,y) on the staircase at time t is obtained as shown in Equation (9):

$$\begin{aligned} W(x, y, t) &= W_{step}(x, y) \cdot N \\ &= \frac{kFL}{H} \cdot \frac{f(x,y)}{\sum_{x,y} f(x,y) \Delta x \Delta y} \cdot Yt \end{aligned} \quad (9)$$

In the equation, $W(x, y, t)$ is the cumulative wear amount at position (x,y) on the staircase at time t .

Through literature review and database query, the wear coefficient ranges of common staircase materials are obtained, as shown in Table 1, providing parameter basis for wear amount calculation:

Table 1 Wear Coefficient Ranges of Common Staircase Materials

Material Type	Wear Coefficient k (mm per thousand steps)		
Wood	0.08	-	0.30
Stone	0.01	-	0.05
Concrete/Brick	0.02	-	0.07
Metal	0.005	-	0.02
Composite Materials	0.02	-	0.04

3 STAIRCASE USAGE CHARACTERISTICS

3.1 Analysis of Staircase Usage Frequency

3.1.1 Overall usage frequency

For staircases in the same building, under the same wear amount, the shorter the service time, the higher the overall usage frequency. Based on the cumulative wear amount formula (9), areas with high-frequency usage in a short period will have a larger wear amount, while areas with low-frequency usage will have a smaller wear amount.

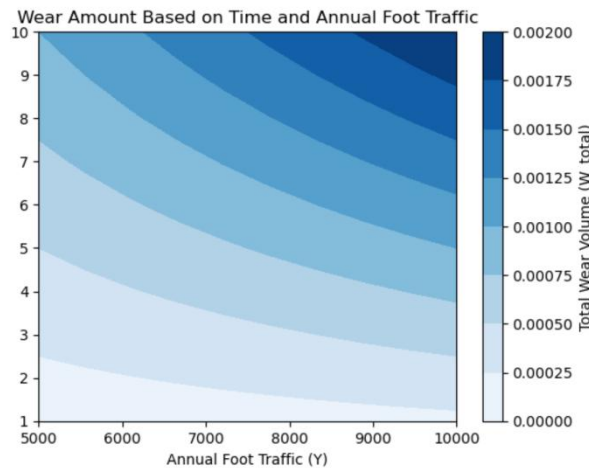


Figure 3 Wear Amount Based on Time and Annual Foot Traffic

Figure 3 is a two-dimensional contour plot illustrating the relationship between staircase wear amount, annual pedestrian flow (Y , horizontal axis), and service time (t , vertical axis). The color gradient in the plot represents the magnitude of wear amount: from light to dark, the color gradually deepens, indicating a continuous increase in wear. It can be observed that wear amount shows a positive correlation with both annual pedestrian flow and service time—for a fixed service time, higher annual pedestrian flow leads to a significant increase in wear; for a fixed annual pedestrian flow, longer service time results in cumulative wear growth. The dark blue regions in the plot correspond to combinations of high annual pedestrian flow and long service time, representing the maximum wear scenarios. This figure quantitatively reveals the coupling effect of usage frequency and time on wear, providing a data basis for analyzing overall usage intensity.

The diagram of the relationship between staircase wear amount, average annual pedestrian flow Y , and service lifetimes shows that: with the increase of service life, the wear amount gradually increases, and the cumulative effect of wear in long-term use is significant; the average annual pedestrian flow Y has a significant impact on the wear amount—the larger the pedestrian flow, the faster the wear amount increases; the color change from light to dark in the diagram reflects the increase of wear amount. Dark blue areas are high-wear areas, corresponding to high average annual pedestrian flow and long service life. High-intensity use accelerates the accumulation of wear, while low pedestrian flow and short service life correspond to a smaller wear amount.

3.1.2 Local usage frequency

Combined with the advanced staircase wear model, the local usage frequency is analyzed based on the density distribution $P(x,y)$ output by the KDE model: areas with high-frequency usage have large density values, and the wear amount calculated by combining Archard's Wear Law is also larger; areas with low-frequency usage have small density values and small wear amounts [8-9].

By combining the KDE model and Archard's Wear Law for calculation, a distribution map of the total wear amount at different positions of the staircase is obtained. The color depth in the map is negatively correlated with the wear amount. Light blue areas are high-wear areas with large KDE density values, high usage frequency, and a large number of tramplings, resulting in a significantly larger wear amount than other areas; dark blue areas are low-wear areas with low usage frequency, a small number of tramplings, and a relatively small wear amount.

From the spatial distribution of wear amount, it can be inferred that: there are concentrated high-wear areas in some parts, corresponding to the main passages for pedestrian walking; low-wear areas are mostly distributed at the edges or corners of the staircase, which is consistent with the habit of pedestrians tending to choose the middle area for walking, providing a basis for subsequent walking preference analysis and path structure identification.

3.2 Staircase Walking Preference and Number of Users

By analyzing the geometric characteristics of the KDE surface, the offset of the wear distribution and the number of people using the staircase at the same time are determined [10]: first, peak detection is used to identify the peak positions of the KDE curve and record the coordinates; the distance between peaks, the mean value and standard deviation of peak intervals are calculated to judge the uniformity of peak distribution; geometric center, skewness, centroid, and Principal Component Analysis (PCA) are used to analyze the symmetry and directionality of the distribution; K-means clustering and Gaussian fitting are used to identify path structure characteristics.

Figure 4 displays the two-dimensional KDE density distribution of staircase usage intensity, with white "X" marks indicating the peak positions of the density distribution. The horizontal axis (X) and vertical axis (Y) represent the staircase's spatial position, and the color depth reflects the density magnitude (light colors for high density, dark colors for low density). The peaks identified in the figure are distributed in a roughly linear pattern, with an average interval of 38.94 between adjacent peaks and a small interval difference (11.37), indicating stable spatial spacing between high-usage areas. Additionally, K-means clustering of these peaks reveals two distinct cluster centers, further confirming the existence of parallel high-usage channels. This figure directly supports the inference of walking path structure and usage preference, verifying the spatial regularity of staircase usage.

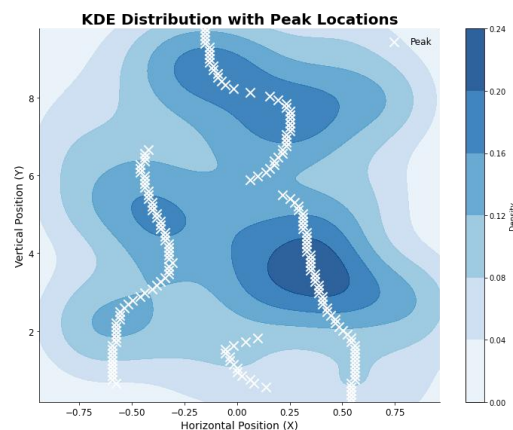


Figure 4 KDE Distribution with Peak Locations

3.2.1 Geometric center and symmetry analysis

The geometric center is the average coordinate of all peak positions, calculated as shown in Equation (10):

$$p_{center} = \frac{1}{n} \sum_{i=1}^n p_i \quad (10)$$

In the equation, p_{center} is the geometric center coordinate of the peak distribution; n is the number of peaks; p_i is the coordinate of the i -th peak.

Analysis shows that each peak is symmetrically distributed around the geometric center, with no obvious directional offset.

3.2.2 Skewness analysis

Skewness measures the asymmetry of the data distribution, and its calculation formula is shown in Equation (11):

$$\gamma_1 = \frac{n}{(n-1)(n-2)} \sum_{i=1}^n \left(\frac{x_i - \mu}{\sigma} \right)^3 \quad (11)$$

In the equation, γ_1 is the estimated value of sample skewness; n is the number of samples; x_i is the coordinate value of the i -th sample (in the X or Y direction); μ is the sample mean; σ is the sample standard deviation.

The calculated skewness value in the X direction is 0.025878054038962494, indicating that the staircase usage is slightly biased to the right; the skewness value in the Y direction is -0.024415043970543986, indicating that the usage is slightly biased to the left. However, the skewness values in both directions are close to 0, so the offset is not significant, and the wear distribution is overall uniform.

3.2.3 Centroid analysis

In the 2D wear distribution, the centroid coordinates in the X and Y directions are calculated as shown in Equations (12) and (13):

$$centroid_x = \frac{\sum x \cdot p(x,y)}{\sum p(x,y)} \quad (12)$$

$$centroid_y = \frac{\sum y \cdot p(x,y)}{\sum p(x,y)} \quad (13)$$

In the equations, $centroid_x$ and $centroid_y$ are the centroid coordinates in the X and Y directions respectively; $p(x,y)$ is the wear probability at position (x,y) .

The results show that the deviation between the centroid coordinates and the mean values in the X and Y directions is small, which further verifies the symmetry of the wear distribution.

3.2.4 Principal component analysis (PCA)

The main distribution direction of the wear data is calculated through PCA. The first principal component direction is basically consistent with the length direction of the staircase, with no obvious deviation. The pedestrian walking direction is in line with the design expectation of the staircase, and there is no significant directional preference.

3.2.5 Peak structure analysis

The K-means clustering results show that the peaks can be divided into two cluster centers (2345.72 and 7776.40), indicating that there are two parallel passages in the staircase; Gaussian fitting shows that the peaks in both clusters conform to the Gaussian distribution, which verifies the existence of parallel passages.

In the diagram of KDE distribution and peak positions, the white "X" marks represent the peak positions (high-wear and high-usage frequency areas). The peaks are arranged in a continuous linear manner, with an average peak interval of 38.94 and an interval difference of 11.37. This indicates that there are high-usage frequency areas with fixed intervals in the staircase, corresponding to parallel passages. The usage frequency of the passages is stable, with small local differences.

Combined with the overall wear distribution of the KDE surface, the geometric center is 4923.71, and the standard deviation of deviation is 1407.03. The data distribution is overall symmetric, but there are differences in local usage frequency. The large standard deviation indicates that the wear in some areas is more concentrated, corresponding to the main walking paths in the passages.

In conclusion, the conclusions about the staircase usage characteristics are as follows:

1. There is no obvious directional preference in usage, and the overall distribution is uniform, with only a slight bias towards the lower part of the Y-direction and the right part of the X-direction, which is in line with the natural walking habits of pedestrians;
2. There are two parallel passages in the staircase, and the usage frequency of the passages is different, corresponding to the usage mode of two people walking side by side or queuing to walk. The parallel passages improve the traffic efficiency of the staircase.

4 CONSISTENCY VERIFICATION BETWEEN STAIRCASE MODEL AND EXISTING DATA

By consulting literature and online resources, wear data of 1000 stone steps (including usage frequency, walking direction, and path type: 20% one-way, 30% parallel, 50% multi-way) are obtained; the staircase photos are imported into Agisoft Metashape software to construct a 3D model and extract basic data, and the model consistency is verified from three aspects: frequency, direction, and path type.

4.1 Frequency Consistency Analysis

The Mean Squared Error (MSE) is used to measure the difference between the predicted frequency and the actual frequency, and the formula is shown in Equation (14):

$$MSE_{frequency} = \frac{1}{n} \sum_{i=1}^n (f_i - \hat{f}_i)^2 \quad (14)$$

In the equation, $MSE_{frequency}$ is the mean squared error of frequency prediction; f_i is the actual frequency of the i -th observation point; $\hat{f}_i$ is the predicted frequency of the i -th observation point; n is the number of observation points. The calculated MSE value is 0.3671, which is much less than 1. The model has high accuracy in frequency prediction and good consistency with the actual data.

4.2 Direction Consistency Analysis

The Average Direction Difference (ADD) is used to quantify the difference between the predicted direction and the actual direction. If the error is greater than 180° , the minimum angle difference is taken, and the formula is shown in Equation (15):

$$ADD_{direction} = \frac{1}{n} \sum_{i=1}^n \min(|d_i - \hat{d}_i|, 360 - |d_i - \hat{d}_i|) \quad (15)$$

In the equation, $ADD_{direction}$ is the average direction difference of direction prediction; d_i is the actual direction of the i -th observation point; $\hat{d}_i$ is the predicted direction of the i -th observation point; n is the number of observation points. The calculated average direction difference is 13.91° , which is much less than the allowable error in engineering. The model's direction prediction meets the needs of practical applications, and the error is acceptable.

4.3 Path Type Consistency Analysis

A confusion matrix is used to evaluate the model's prediction accuracy for path types (one-way, parallel, multi-way).

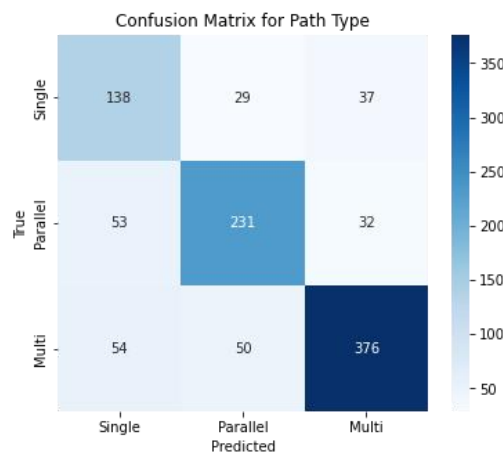


Figure 5 Confusion Matrix for Path Type

Figure 5 is a confusion matrix used to evaluate the model's classification accuracy for three path types: single-lane, parallel lanes, and multi-lane. The rows of the matrix represent the actual path types, while the columns represent the model's predicted path types. The values in each cell indicate the number of samples classified into the corresponding category. Specifically, the model correctly predicts 138 single-lane samples (accuracy 69.8%), 231 parallel-lane samples (accuracy 75.2%), and 376 multi-lane samples (accuracy 84.1%), with an average classification accuracy of over 75%. The matrix clearly shows that the model has the highest accuracy in identifying multi-lane paths and maintains good performance for parallel-lane and single-lane paths. This verification result confirms the model's reliability in path type recognition, providing strong evidence for the overall consistency of the model.

The confusion matrix of path type prediction shows that:

1. For one-way samples: 138 are correctly predicted, 29 are incorrectly classified as parallel, and 37 are incorrectly classified as multi-way, with an accuracy rate of 69.8%;
2. For parallel samples: 231 are correctly predicted, 53 are incorrectly classified as one-way, and 32 are incorrectly classified as multi-way, with an accuracy rate of 75.2%;
3. For multi-way samples: 376 are correctly predicted, 54 are incorrectly classified as one-way, and 50 are incorrectly classified as multi-way, with an accuracy rate of 84.1%.

The average accuracy rate of the three path types exceeds 75%, indicating that the model has a strong ability to identify path types and good consistency with the actual data. Based on the comprehensive analysis of the three aspects, the wear law output by the model is highly consistent with the existing data, and the rationality of the model is verified.

5 CONCLUSION

This paper focuses on the usage characteristics of ancient building stone steps and the consistency of the models. The combination of the Monte Carlo method and kernel density estimation (KDE) can accurately simulate the pedestrian walking paths and wear distribution. By integrating the normalized KDE probability distribution into Achard's wear law, an advanced wear model is formed, which can effectively quantify the wear amount at different locations and clearly define the wear coefficient range for common materials such as wood and stone. Regarding the usage characteristics of stone steps, the overall usage frequency is positively correlated with the annual average number of visitors and the service life. Areas with high traffic and long-term use have more severe wear. The local usage frequency shows a "middle high, edge low" characteristic, corresponding to the main walking path of pedestrians. There is no obvious directionality in the walking preference, and the overall distribution is uniform with only a slight bias towards the lower part of the Y-axis and the right side of the X-axis. Through K-means clustering and Gaussian fitting, two parallel channels for stone steps are identified, which conform to the usage mode of multiple people walking in parallel or queuing. Although this study has achieved a quantitative analysis of feature and model consistency through multi-model fusion, there is still much room for expansion in enhancing the model's generalization ability, accuracy, and application scope. The future directions are as follows:

The current model neglects the dynamic changes in user behavior. Future research should capture the temporal heterogeneity of usage intensity - for instance, distinguishing between peak and off-peak periods in movement patterns, or incorporating seasonal fluctuations in foot traffic. By introducing time-dependent variables in Monte Carlo simulations and updating the kernel density estimation probability distribution in real time, the model can more accurately reflect dynamic usage scenarios.

COMPETING INTERESTS

The authors have no relevant financial or non-financial interests to disclose.

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