

Retraction

Retracted: Visual Feature Evaluation of Shenyang Greenway Landscape Based on Deep Learning

Security and Communication Networks

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

- (1) Discrepancies in scope
- (2) Discrepancies in the description of the research reported
- (3) Discrepancies between the availability of data and the research described
- (4) Inappropriate citations
- (5) Incoherent, meaningless and/or irrelevant content included in the article
- (6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

- [1] T. Pan and M. Jiang, "Visual Feature Evaluation of Shenyang Greenway Landscape Based on Deep Learning," *Security and Communication Networks*, vol. 2022, Article ID 8730399, 11 pages, 2022.

Research Article

Visual Feature Evaluation of Shenyang Greenway Landscape Based on Deep Learning

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At present, the research on the visual characteristics of greenway landscape is mostly focused on the evaluation of beauty degree, landscape preference, and recreation preference and mainly on the overall macroscopic evaluation of a single greenway or typical spatial research in some areas, while less attention is paid to the overall characteristics of urban greenway landscape and the differences in visual characteristics of different types of greenway landscape. The emergence of new data and new technologies such as street view, Baidu map, and deep learning provides the possibility to study the visual characteristics of greenway landscapes in large scale and full sample. The study of greenway landscape based on large deep learning can effectively refine the overall pattern of visual characteristics of greenway landscape and reveal the differences of visual characteristics of different types of greenways and their key factors, so as to provide support for the planning and design of greenway landscape and landscape appearance enhancement.

1. Introduction

In recent years, many problems such as fragmentation of natural ecological pattern, homogeneity of urban landscape, and lack of regional characteristics have gradually emerged. In order to effectively cope with the above problems, Shenyang City prepared and adopted the “Shenyang City Greenway System Construction Plan” as early as 2012, laying out greenways in the urban green space system and positioning them as “an important part of the urban ecosystem, scenic tourism system, and comprehensive transportation system, with leisure and fitness and tourism functions as the main functions, taking into account the transportation and commuting functions. Subsequently, they also issued a document proposing to steadily promote the construction of urban greenways and promote the formation of a green development and lifestyle. Since 2017, Nanjing, Wuhan, Shanghai, Guangdong and many other places have actively promoted the construction of greenways and made positive progress. To further promote the formation of green development and lifestyle, they will clearly continue to improve

the construction standards of greenway projects to further enhance the leading green and healthy living style. The construction of suitable regional characteristics of the greenway landscape has become an important element of the current urban green development.

With the rapid advancement of greenway construction in Shenyang, the visual resources of greenways have been fully utilized while there are also excessive excavation and destruction. Due to the excessive pursuit of visual attraction in the construction of a single greenway, the inconsistency between the new greenway and the existing greenway and the overall landscape of the city is increasingly prominent. At the same time, some of the earlier completed greenways due to the imbalance of management and care and other issues lead to the decline of visual landscape quality, and gradually with the overall appearance of the city, while the repair of the destroyed greenway landscape is also arbitrary, the new repair landscape visual features difficult to integrate into the overall landscape of the greenway landscape. The reason for this is that there is a lack of understanding of the overall features and visual characteristics of the greenway

landscape and the commonalities and differences, and a lack of theoretical guidance in the practice of visual resources mining and utilization, visual attraction elements restoration and enhancement, which leads to the construction of greenway visual landscape construction arbitrarily. In view of the above, there is an urgent need to clarify the commonality and differences of visual characteristics of the current urban greenway landscape, and to clarify the color of the greenway landscape, so as to guide the unity of the landscape construction of the greenway and its coordination with the overall landscape of the city.

Landscape vision is a composite concept, as the conception and formal expression of landscape design, has an important impact on the audience's associative experience and consciousness perception. The current domestic and international research on landscape vision is mostly about the perceptual cognition of physical landscape objects, reflecting people's consensus landscape consciousness. At the same time, the study in [1] believes that through the generalization and refinement of the typical characteristics of specific objects, a single landscape design element that can reflect the local characteristics, reflect the spirit of the region and be understood by the local public can be regarded as a "landscape visual" unit, and the imagery structure is inseparable from the traditional Chinese aesthetic. It is important to understand and construct the structure of imagery in landscape design.

In order to comprehensively evaluate the visual characteristics of greenway landscape, this paper evaluates greenways from multiple levels of greenway landscape characteristics, from point to line to surface, in multiple dimensions. The evaluation analysis is carried out from two aspects of the composition of the visual elements of greenway landscape and the diversity of the composition of the elements to reveal the overall composition characteristics of the visual elements of greenway landscape in Shenyang, the differences in the characteristics of the visual elements of different levels and types of greenway landscape, and the specific composition characteristics of different visual elements in each greenway. The spatial distribution sequence characteristics in different types of greenway landscapes are evaluated from three aspects: green view rate, sky and water bodies, and the number and magnitude of changes of the ups and downs of each visual element in the greenways are compared and analyzed so as to reveal the spatial sequence changes of the visual elements of greenway landscapes. The overall spatial accessibility characteristics of all greenways are studied and correlated with three kinds of positive services, namely, green view rate, landscape vignettes and post buildings, and two kinds of negative interferences, namely, peripheral buildings and peripheral utility pole billboards, to reveal the relationship between the quality of visual services of different types of greenway landscapes and the accessibility of residents, so as to provide reference for the improvement of visual services of greenway landscapes. Based on the above research results, suggestions and strategies for the optimization of greenway landscape enhancement are proposed around the visual elements of greenway landscape and their spatial distribution sequence characteristics and the accessibility of residents' space.

2. Related Work

In recent years, foreign visual landscape research has conducted a number of empirical studies on visual landscape quality, preferences, and impacts using new data and technologies. The visual quality of 20 scenic-eligible roadway landscape features was assessed using color slide photography, combined with design procedures in [2]. The study in [3] investigated the influence of public art on the visual character and affective evaluation of landscapes by having undergraduate and graduate students view landscapes with or without public art in turn and rating the visual character and affective evaluation of each landscape, with results showing that the affective quality of public art had a greater impact on the landscape. The study in [4] assessed the visual quality of landscapes in historic areas using a photo questionnaire method based on a range of indicators, such as landscape visual legibility, consistency, complexity, temporality, continuity, historicity, visual scale, and spatial perception. The study in [5] evaluated the visual quality of landscapes by analyzing the visual preferences of residents through social media Instagram photos, a platform dedicated to uploading and discovering visual content (e.g., photos and videos), which can be a tool for analyzing community preferences and a new approach in the field of landscape. The study in [6] explored the relationship between the visual characteristics of the landscape and the large-scale landscape in Taiping District, Peninsular Malaysia as a study. The landscape characteristics of Taiping, Perak and surrounding areas are evaluated to understand the changes in the landscape.

Chinese scholars started their research on greenway landscape visualization late, and now mainly focus on the study of greenway landscape visual perception and preference. The study in [7] studied the influencing factors of greenway cycling perception from three aspects: social characteristics, behavioral characteristics and landscape element characteristics, and extracted the cycling perception characteristics of different types of greenways by semantic evaluation method and picture analysis method, and found that different types of greenways have different landscape visual structures. The study in [8] reveals the differences of visual characteristics of different cities and their landscape types, and provides a lot of rich research support for urban landscape style camping. The study in [9] proposed that the Guidelines for Greenway Planning and Design were introduced at the national level, but confined to the differences in local characteristics, cities have introduced more detailed and more geographically distinctive standards for greenway landscape construction. For example, the study in [10] evaluated the current situation of greenways in Zengcheng, Guangdong, and divided the composition of greenways into six parts: slow walking system, greening system, service facility system, traffic interchange system, signage system, and lighting system. The study in [11] classified the greenway elements in Shenyang into three categories, namely, mountain elements, water elements, and urban park elements. The study in [12] compared the sustainability performance and visual preference of landscape elements in the

landscape and proposed the design of landscapes with highly sustainable elements and visual preference. The study in [13] took Zijinshan National Forest Park as the research object, and carried out landscape visual evaluation of 15 sites according to subjective and objective evaluation weighting, and analyzed the best and worst landscape visual conditions by combining subjective and objective methods for equal proportional weighting analysis, and this evaluation system is comprehensive and operable in the protection and development of landscape visual resources.

In recent years, with the rapid development of new data and new technologies, the study of visual characteristics of landscape has made new breakthroughs in many aspects, such as research scale, research object, and research methods. The study in [14] conducted a relevant experiment in California, USA, by means of real-time photography, and obtained streetscape photographs of a street intersection in four directions: east, west, north, south, and west, quantitatively calculated the proportion of vegetation in the photographs and used it as the green view rate value of the point for the first time. Subsequently, the study in [15] improved the experiment of [16] by using Google panoramic photos to extend the view of the observer, and their acquisition included more angles of panoramic photos, and the computer automatically extracted the photo bands to obtain the green field of panoramic photos. With the introduction of Google Street View maps, it was found that the richness of information contained in Google panorama maps could bring new possibilities for urban studies. The study in [17–20] performed semantic segmentation and street view element target recognition on Google's street view panoramic photos, identified trees, buildings, sky, and road surface of all photos, and used metrics such as field of view and shape to generalize and quantify the visual quality of the landscape.

In China, the study in [21] extracted the spatial distribution characteristics of street green view rate based on Baidu Street View data and explored the objective perception level of street green space, meanwhile, the actual perceived degree of street green space was studied by overlaying street green view rate and real-time population heat, so as to complete the evaluation of street green space maintenance and enjoyment. Based on street images, the study in [22] presented the application of newly developed deep convolutional neural networks in landscape analysis. Using the trained deep convolutional neural network model, different urban features can be accurately identified from the street images. The study in [23] used Baidu Street View photos and Microsoft machine learning algorithm to measure the street greenway landscape in the central city of Zhoushan Islands as the research object, and summarized the landscape type composition and landscape spatial distribution in the area. [24] introduced the quantitative evaluation method of street space evaluation index, and measured the street evaluation index of Beijing and Shanghai through objective element composition analysis and users' subjective evaluation by using the image data of street microscale. The study in [25] crawled the large-scale streetscape data of Shanghai and extracted the greening visibility based on machine learning

algorithm, and carried out the overlay analysis with the street accessibility based on spatial network analysis. By comparing with the greening rate based on satellite remote sensing images, we found that the greening rate obtained from the calculation based on remote sensing images could not accurately show the greening exposure in citizens' daily life.

Numerous studies have shown that processing streetscape mapping datasets with the help of deep learning is a very effective and objective data work to help planners and urban researchers understand streetscapes from a human perspective. Most of the traditional landscape evaluation studies rely on small sample size surveys and limited data sources, which are not only laborious, expensive, and time-consuming to acquire, but also these data sources can hardly meet the research needs of measuring human perception of landscape on a large scale. With the rapid development of new technologies and data represented by computer technology and multisource urban data, the popularity of street view data represented by Baidu Street View and Google Street View has provided new possibilities for high-precision large-sample street view visual feature research.

3. Methods

The Greenway Planning and Design Guidelines (Jiancheng letter [2016] No. 211) classifies the greenway composition into five categories: greenway trail system, greenway greening, service facilities, municipal facilities, and signage facilities. Among them, the greenway trail system is mainly for walking paths, bicycle paths, comprehensive paths and traffic connection points; service facilities are mainly for buildings, such as stations, visitor service centers, and recreational facilities, such as activity sites, resting places, and environmental health facilities such as garbage bins; municipal facilities are mainly for pipeline networks, ditches, etc.; signage facilities are for signs, interpretation, warnings, and other signs; road greening is mainly for trees and shrubs and herbaceous plants. According to the visual classification of visual landscape, the above greenway composition can be classified as visual landscape of carriageway, pedestrian path, station building, landscape sketches, shrubs, and herbaceous plants. At the same time, a certain amount of water and sky can be seen in the Shenyang greenway recreation view. Therefore, in this study, combining with the actual situation of Wuhan greenway, the landscape elements of the greenway are divided into eight categories: sky, trees and shrubs, carriageway, pedestrian path, herbaceous plants, water body, landscape sketches, and station buildings. In addition, there are other landscape visual elements in the actual streetscape pictures, mainly stairs and billboards in the greenway surroundings, etc. This study identifies these nongreenway landscape elements also as streetscape recognition objects (see Table 1) and analyzes them as greenway landscape visual interference elements.

The general technical route of this paper is shown in Figure 1.

The visual feature extraction network of greenway landscape established in this paper includes a shared

TABLE 1: Classification of greenway landscape elements.

System name	Elements	Greenway Baidu street view element extraction	Greenway landscape visual elements	Visual interference elements
Greenway tour warp system	Pedestrian paths	Carriageway, walkway	Carriageway	Surrounding buildings
	Bicycle paths		Walkway	
Greenway greening	Comprehensive walking and cycling paths	Herbaceous plants of trees and shrubs	Herbaceous plants of trees and shrubs	Surrounding poles
	Traffic connection point		Sky	
Service facilities	Greenway greening	Stagecoach buildings, sky, water bodies, landscape vignettes, cars, surrounding buildings, surrounding poles, surrounding billboards	Water bodies	Surrounding billboards
	Management service facilities		Stagecoach buildings	
Municipal facilities	Supporting commercial facilities	Landscape vignettes	Landscape vignettes	
	Recreation and fitness facilities			
Signage facilities	Science education facilities			
	Safety and security facilities			
	Environmental health facilities			
	Environmental lighting facilities			
	Electricity and telecommunications facilities			
	Water supply and drainage facilities			
	Other			
	Instruction facilities			
	Warning signs			

VGG-like convolutional network coding layer and two decoding layers, which are the feature point detector decoding layer and the descriptor decoding layer, respectively. Referring to Superpoint's network model structure, the parts of the coding layer and descriptor are retained, the activation function is improved, and the detector decoding layer, training process, and loss function are different. The overall network framework is shown in Figure 2.

A VGG-like convolutional backbone network is used as an encoder, which serves to dimensionalize the image and facilitate feature extraction. The encoding layer consists of a convolutional network layer, a pooling layer and a nonlinear activation function. The coding layer uses three maximal pooling layers to change the original image size $H \times W$ to $H_c = H/8, W_c = W/8$. The activation function is a leaky ReLU activation function.

The feature point detector decoder layer performs a two-layer convolution operation on the shared feature map to turn the feature map into $H/8 \times W/8 \times 64$. The feature map is operated by Softmax so that the feature map takes values between 0 and 1, and feature points taking values close to 1 indicate that the location is a real feature point. Then, after dimensional transformation, the feature point map with the same size as the original image is output and used to calculate the loss function of the feature point detection layer.

The descriptor decoding layer up-samples the feature map of descriptors by 3 times of interpolation, and then

normalizes the feature map values to unit length using L2 parametric, and outputs a dense descriptor of $H/8 \times W/8 \times 256$, which is used to compute the loss of descriptors with the feature map output by the feature point detector.

The training of the model is performed based on the single-strain transformation of the image and the noise addition. The single-response change is the mapping relationship from one plane to another, including affine change, perspective transformation. A random single-strain change is applied to the original image I to obtain I_h , and then a loss function is calculated for both to achieve the effect of self-supervised learning.

The loss function is expressed as

$$L(P, PhD, Dh, H) = \lambda_1 L_d + \lambda_2 L_p, \quad (1)$$

where λ_1, λ_2 is the weight parameter, P, Ph are the feature maps of the original I and the transformed I_h maps, D, Dh are the descriptors of the two maps, and L_d, L_p are the descriptors and the loss function of the detector, respectively. After transformation, random noise is added to I, I_h including Gaussian noise, random brightness variation, pretzel noise, and fuzzy treatment to enhance the model performance.

The training principle of feature points is derived from the Expectation Maximization (EM) algorithm, and the main steps are shown in Figure 3. In the training process, the target feature points are processed as follows: ① detects the point K in the original figure I , and projects the point K onto

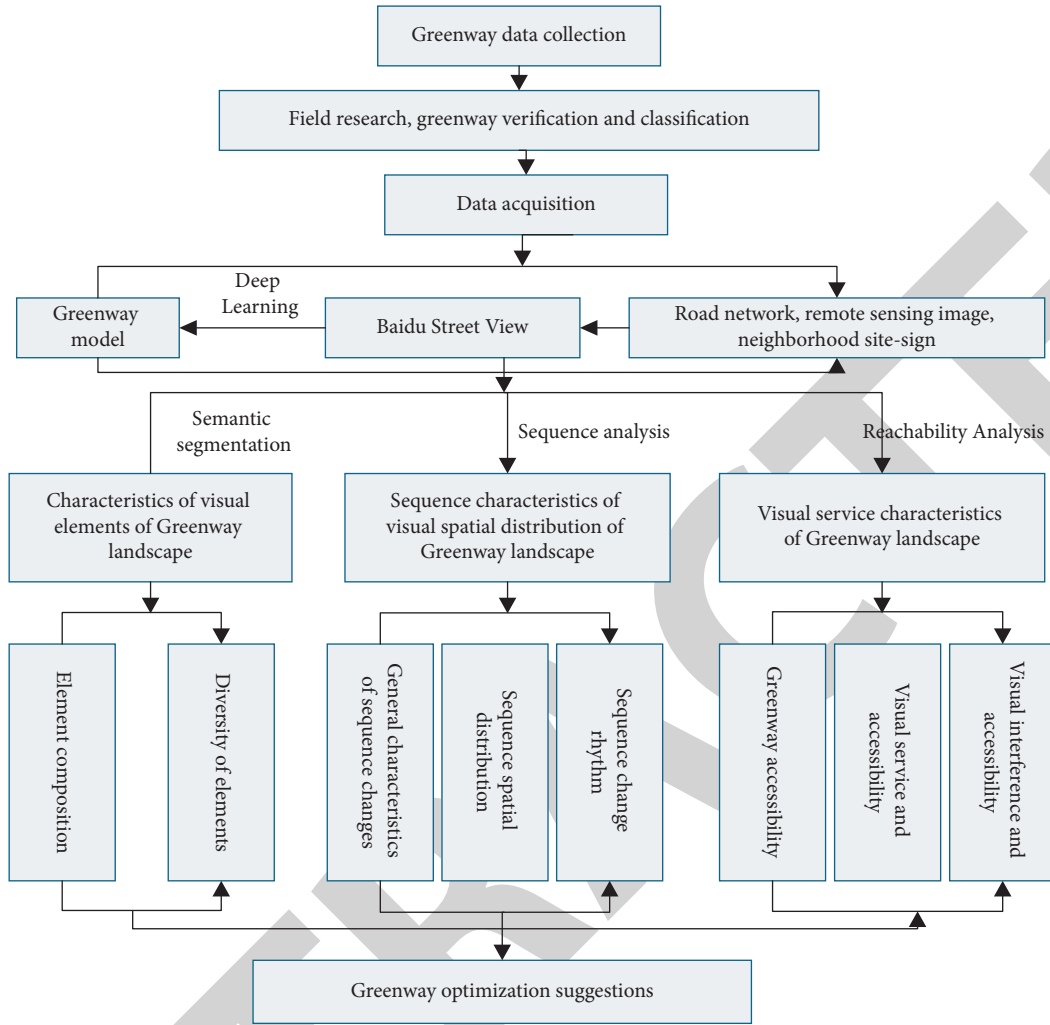


FIGURE 1: Technology roadmap.

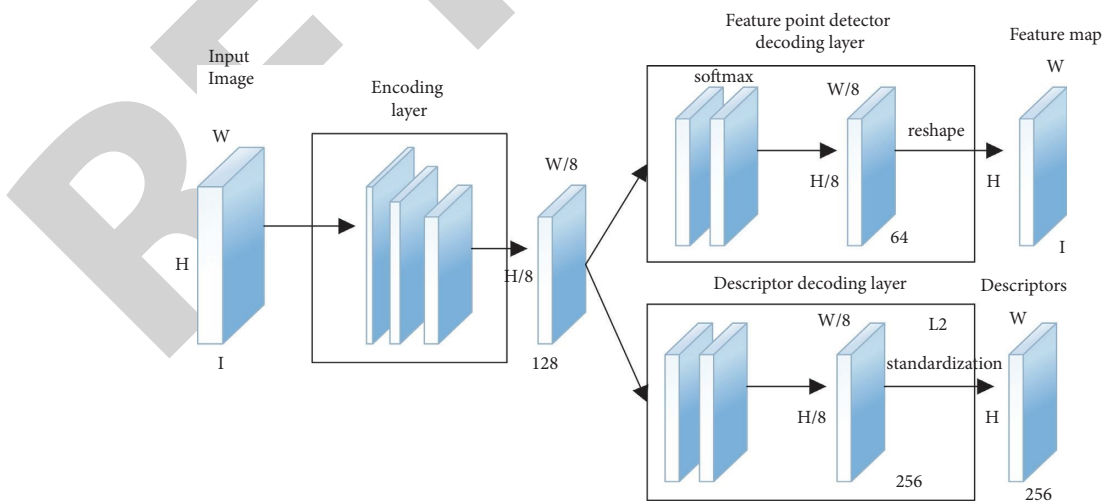


FIGURE 2: Architecture of the feature extraction network.

I_h according to the imposed single-strain transform to form K_{proj} . ② Two ways are used to match the detected points K_h on the transformed points K_{proj} and I_h , which are 2D

coordinates and descriptors, respectively, both using nearest-neighbor matching to form two pairs of matched point sets. ③ Form the target point K'_h by the matched point set,

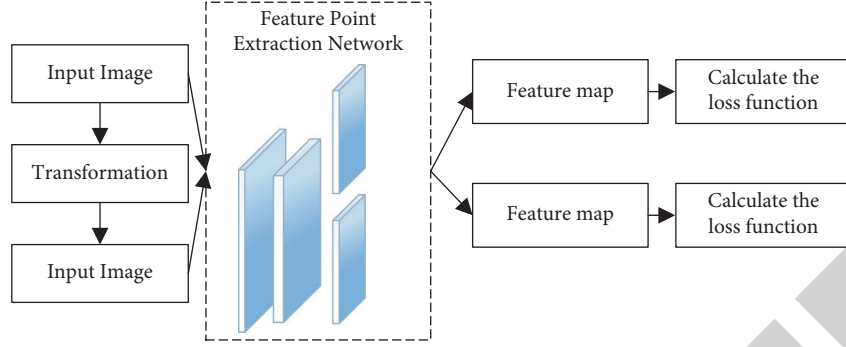


FIGURE 3: Feature training procedures.

and then project it to the original figure I to form K' according to the inverse transformation of the single-response transform, and form a pair of point sets with K'_h for calculating the loss function.

The loss function of the detector part is expressed by applying the negative log-likelihood method as

$$L_p = -\frac{1}{2} (\log P[K'] + \log P_h[K'_h]), \quad (2)$$

where $P[K'], P_h[K'_h]$ denotes the distribution of detected feature points on I, I_h , respectively.

Given the I, I_h two images to be trained, the true feature points K', K'_h are extracted by the following steps:

- (1) The set of feature points K', K'_h is extracted from the images by two different pooling operations, denoted as

$$\begin{aligned} K &= \text{maxpool}_{32 \times 32}(P), \\ K_h &= \text{maxpool}_{16 \times 16}(p_h). \end{aligned} \quad (3)$$

The feature points are selected in two different sizes, 32×32 and 16×16 , so that the feature points can be distributed to cover the whole map but not too dense. The image is pooled to return an array of coordinates of feature points (x_i, y_i) .

- (2) A single-response transformation $K_{\text{proj}} = \overline{KH}$ is performed on K . Points that are beyond the image boundary are discarded, D_{proj}, D_h for the descriptor of K_{proj}, K_h .
- (3) Matching is performed on I_h according to the descriptors and coordinate relations, respectively, denoted as

$$\begin{aligned} \text{dist}_{\text{geom}}, \text{idx}_{\text{geom}} &= \text{match}_{\text{geom}}(K_{\text{proj}}, K_h), \\ \text{idx}_{\text{desc}} &= \text{match}_{\text{desc}}(D_{\text{proj}}, D_h). \end{aligned} \quad (4)$$

The function of $\text{match}_{\text{geom}}$ is to perform nearest-neighbor matching on K_{proj}, K_h based on Euclidean distance, returning the distance between matching points and the index of the point. idx_{geom} gives the index of K_{proj} the most matched point on the descriptor.

- (4) The coordinates of the possible true feature points on I_h are expressed as

$$K'_h = \text{mean}(K_{\text{proj}}(i), K_h[\text{idx}_{\text{geom}}(i)]). \quad (5)$$

From the above equation, it can be seen that the possible true feature points K'_h are obtained by taking the mean value of K_{proj} and the matching K_h , and then this is inverted by the single-strain transformation and projected back onto the original graph to obtain K' . K', K'_h obtained after the above steps is used to calculate the loss function equation (2).

The loss function in the descriptor part consists of two parts, denoted as

$$L_d(D, D_h, K, K_h, H) = L_{\text{desc}} + L_{\text{wrong}}. \quad (6)$$

Let $g_i = D_{\text{proj}}(i)D_h^T(\text{idx}_{\text{geom}}[i])$, the above equation is the dot product between the feature point descriptors matched according to the coordinate Euclidean distance. The descriptors are normalized, so the dot product is equal to the cosine similarity. L_{desc} Maximize the similarity of each pair of feature point descriptors, expressed as

$$L_{\text{desc}} = \frac{1}{N_{\text{desc}}} \sum_j (1 - g_j). \quad (7)$$

L_{wrong} has the opposite effect and aims to minimize the similarity of the mis-matched feature point descriptors, denoted as

$$L_{\text{wrong}} = \frac{1}{N_{\text{wrong}}} \sum_j (1 - g_j). \quad (8)$$

4. Experiments

To analyze the diversity characteristics of the visual element composition of the greenway landscape, this study used the entropy index to calculate the reflection. The entropy index to measure diversity has been widely used in several scenarios, especially in-built environment studies. Its calculation formula is

$$D_i = - \sum_{i=1}^R p_i \times \ln p_i, \quad (9)$$

where D_i is the element diversity of the i th Baidu street-scape, R is the total number of landscape element types, where p_i refers to the proportion of the i th element in the greenway to the total number. The diversity value is between 0 and 1, and the larger it is, the higher the diversity of the greenway is.

In order to analyze the spatial distribution sequence characteristics of visual elements in each greenway, this study takes 500 m as a sequence analysis unit, starts from one end of a greenway (starting point or end point), calculates the average value of visual proportion of all elements in this unit, and uses this to represent the characteristic value of visual elements in this unit section of the greenway.

The formulae for the magnitude of change and frequency of change, respectively, are

$$P = \frac{f + g}{L}, \quad (10)$$

where P is the frequency of sequence change.

$$H = \frac{\sum_{i=1}^n |F_i - F_{i-1}|}{f + g}, \quad (11)$$

where H is the magnitude of the sequence variation, F is the extreme value in the sequence (the value of the crest or trough in the sequence).

To further analyze the accessibility of residents to the visual element services of the greenway landscape, this study first calculates the accessibility of each greenway landscape street spot, and then correlates the accessibility results with the percentage of visual elements to obtain the service efficiency of the visual elements of the greenway, so as to further clarify the key characteristics of the greenway landscape such as high service low accessibility and low service high accessibility. Research shows that 0–1.5 km is a suitable range for residents to use public facilities and green space, so in this paper, to study the relationship between greenway services and accessibility, the number of residential neighborhoods covered within the 1.5 km buffer zone of greenway street points is calculated as a benchmark, and the higher the number of neighborhoods, the higher the accessibility value. The correlation analysis of the visual element services and their accessibility of the greenway landscape is based on the cross-quadrant axis characterized by the Excel software with scattered distribution, where the origin of the quadrant axis is the intersection of the visual element characteristic values and the accessibility mean values.

The results of the statistical analysis of the visual elements of 29 greenway landscapes in Shenyang (Figure 4) show that the sky is the main visual element of the greenway landscape in Shenyang, with the highest percentage of 43%; road trees and shrubs have the second highest percentage, with 17%; pedestrian paths, herbaceous plants, post buildings, landscape artifacts, and water elements have lower

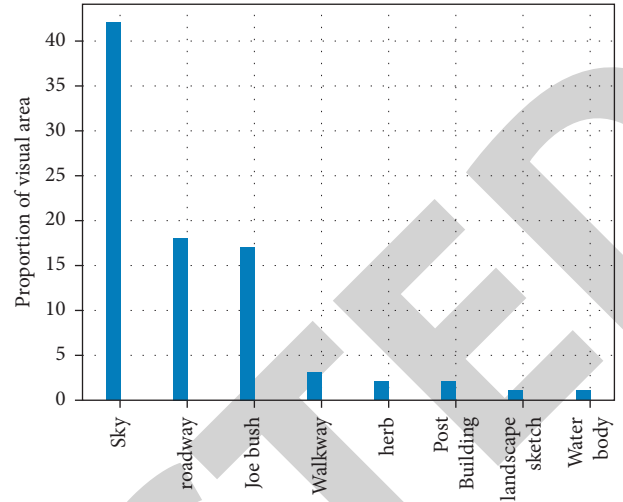


FIGURE 4: Visual proportion of greenway landscape elements.

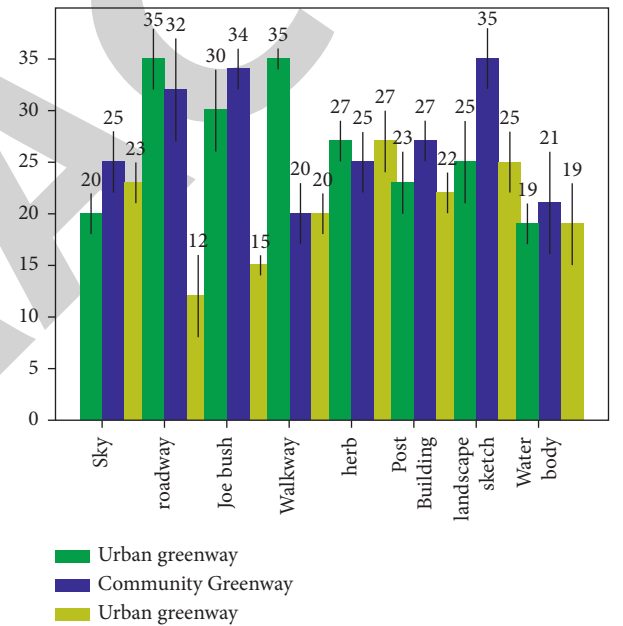


FIGURE 5: Percentage of visual area of greenway landscape elements of different levels.

percentages in turn and are relatively small, with less than 5%.

Looking at the different classes (Figure 5), the visual share of sky in urban greenways, community greenways, and urban greenways increased in order, while the share of trees and shrubs decreased in order, and the share of trees and shrubs in urban greenways was significantly higher than the other two types. The visual proportions of pedestrian paths and stagecoach buildings in urban greenways were higher than those of urban and community greenways, while the visual proportions of vehicular paths in urban greenways were lower than those of the other two types of greenways. The percentage of herbaceous plants in urban greenways is significantly higher than that of community greenways and urban greenways.

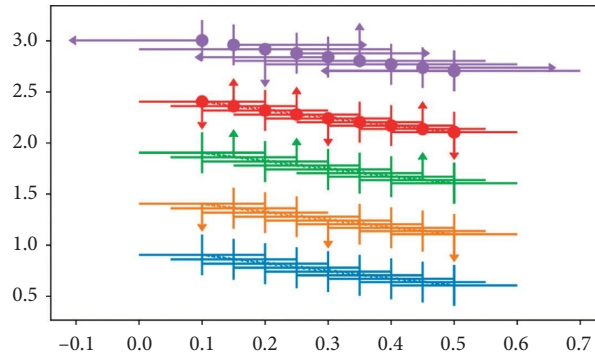


FIGURE 6: The visual proportions of different types of greenway landscape elements.

TABLE 2: Whitehorse road landscape elements index.

Observation type	Number of photos	Number of people	Number of motor vehicles	Building area ratio (%)	Green view rate (%)	Road area ratio (%)	Sky area ratio (%)
Working day-isometric mean	88	0.9	0.18	2.99	39.5	29.29	20.95
Working day-node average	117	0.15	0	5.86	50.25	9.58	24.13
Rest day-isometric mean	88	2.3	0.09	5.33	40.36	20.49	22.55
Rest day-node average	115	0.67	0.03	5.52	53.77	9.24	19.56

TABLE 3: Listening road landscape elements indicators.

Observation type	Number of photos	Number of people	Number of motor vehicles	Building area ratio (%)	Green view rate (%)	Road area ratio (%)	Sky area ratio (%)
Working day-isometric mean	45	1.97	1.35	9.12	45.23	23.49	5.79
Working day-node average	27	1.89	1.91	5.97	48.89	17.79	0
Rest day-isometric mean	41	3.98	0.98	7.62	48.81	17.99	8.36
Rest day-node average	25	4.23	1.55	4.92	57.68	12.30	10.13

TABLE 4: Forest road landscape element indicators.

Observation type	Number of photos	Number of people	Number of motor vehicles	Building area ratio (%)	Green view rate (%)	Road area ratio (%)	Sky area ratio (%)
Working day-isometric mean	182	1.31	0.32	3.34	51.89	20.67	14.89
Working day-node average	206	0.52	0.21	5.77	54.23	14.98	16.03
Rest day-isometric mean	187	2.21	0.6	3.89	51.36	1.97	15.32
Rest day-node average	212	1.13	0.25	4.85	56.03	14.32	15.69

The results of the visual proportion of landscape elements in different types of greenways (Figure 6) show that among the six types of greenways, the visual proportion of sky in mountainous greenways is the highest among all types of greenways, and the opposite is true for trees and shrubs, which are the lowest. The sky visual area share of countryside

and field-type greenways is relatively high, while the sky visual area share of urban, riverfront, and lagoon type greenways is the lowest, but the visual area share of trees and shrubs of lagoon type greenways is the highest among all types of greenways. The percentage of vehicular paths in the field-type greenways is significantly lower than that of other

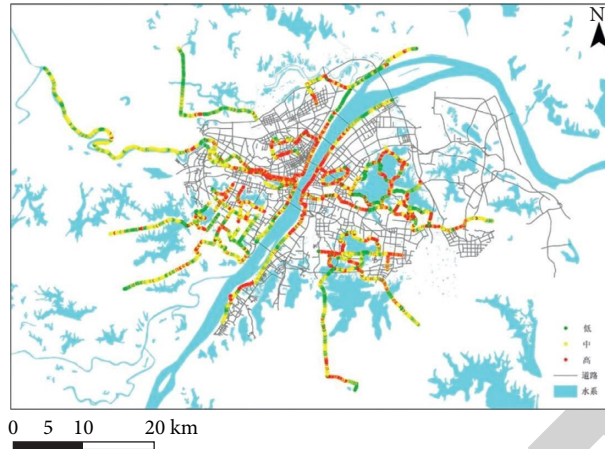


FIGURE 7: Features of visual diversity of greenway landscape.

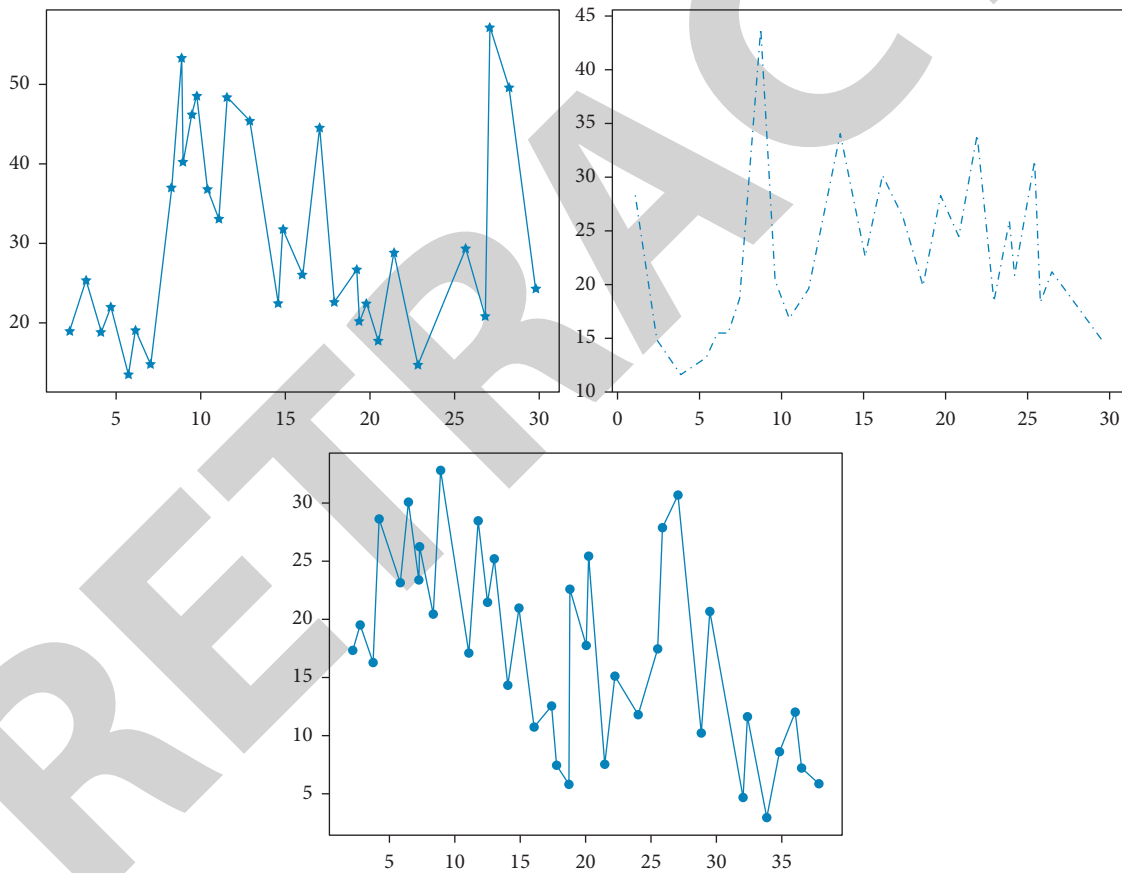


FIGURE 8: Green visibility series of riverside greenways.

greenways, while the visual percentage of pedestrian paths and herbaceous plants is significantly higher than that of other types of greenways. The proportion of stagecoach buildings is significantly higher in riverfront, lake, and urban greenways than in countryside, field, and forest greenways.

With the help of software, the number of people, the number of motor vehicles, and the elemental area rate in the recorded photos can be quantified and analyzed. The

number of people and vehicles can reflect the activity status and motor vehicle interference status of the site (Tables 2–4). The element area rate can reflect the visual structure of the landscape. Also, the comparison of node data and isometric record data can reflect the rider preference.

White Horse Road is a theme road created by artistic design, with a very good location, and has been praised since its opening, among which the Peach Blossom Island and the

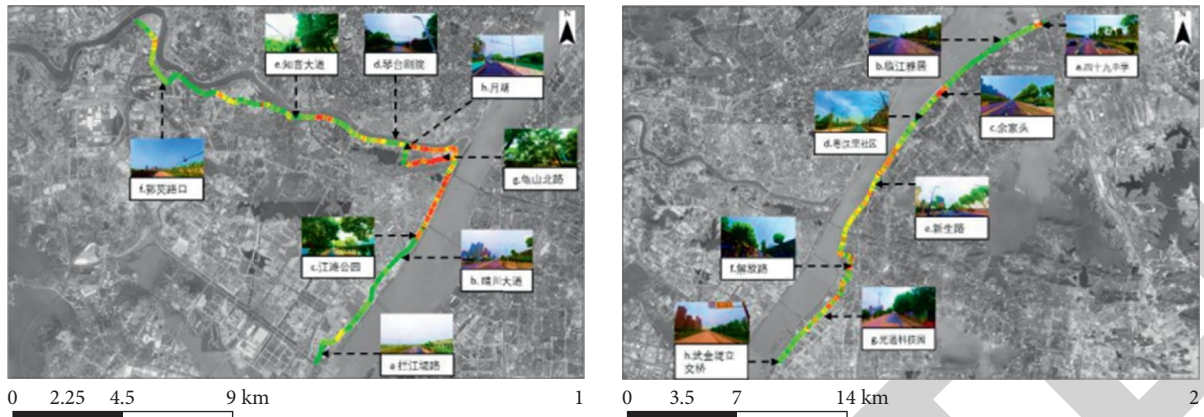


FIGURE 9: Spatial distribution of green visibility of riverside greenways.

Ten Mile Promenade have received more attention. But probably because the construction is not yet complete, the amount of activity is not very large.

Listen to the Tao Road is the earliest section of the East Lake, in line with the scale of pedestrian activity, but is also full of historical and cultural heritage. However, the frequency of motor vehicles in this theme path is high, which may cause some interference to the slow-moving activities, the element area ratio does not vary much between different time periods, nodes, and recorded photos.

Forest Road is the longest path and the most complex system in this study, but also the richest one in landscape. From the data, isometric records and node photos produce large differences in activity. Combined with its landscape element ratio, the overall green view is high, and it is a greenway dominated by natural landscape; in comparison, the proportion of buildings in the nodes is slightly higher.

In order to conduct a hierarchical analysis of the greenway landscape visual element diversity index (Figures 7–9), this study used the natural interruption method to classify the entropy index calculation results into three levels: low (0–0.12), medium (0.12–0.33), and high (0.33–1), and visualized them in GIS software for spatial analysis. The results show that the high values of diversity of visual elements composition of greenway landscape are mainly distributed in the central urban areas along the river and lake, and generally show the characteristics of high in the main urban areas and low in the suburban areas. Specifically, the diversity values of visual elements of greenway landscape along the intersection of Yangtze River and Han River are significantly higher than those of other areas.

The overall variation in the sequence of green views for the riverfront-type greenways (Figure 8) is large and the number of changes is high.

5. Conclusion

In summary, the continuous organization of visual elements is not only the key to enriching the linear landscape space of

the greenway and enhancing the recreational experience, but also an important means to enhance the coordination between the landscape appearance of the greenway and the surrounding environment and to strengthen the sense of organic order. Shrubs, skies, landscape vignettes, etc. are key elements affecting the visual space characteristics of the greenway, determining the visual space of the enclosed and permeable, virtual and real, light and dark characteristics. Space can also be added through the landscape vignette, so that the visual picture of the greenway landscape presents a different scene. You can also control the sequence of water surface changes to increase the diversity and interest of the greenway space.

Data Availability

The experimental data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest regarding this work.

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