Quantitative Measurement and Preference Research of Urban Landscape Environmental Image Based on Computer Vision

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***Abstract*—At present, research on landscape preferences mostly uses traditional questionnaire surveys to obtain public aesthetic attitudes, and the analysis method still relies on manual coding with small sample sizes. However, the research on landscape preference of applying network big data and computer vision technology is rare, and the research content and algorithm application are limited. In order to improve the research effect of quantitative measurement and preference of urban landscape environment image, the algorithm proposed in this paper combines two-dimensional analysis modules, two-dimensional visual domain analysis and three-dimensional visual analysis, and makes full use of the advantages of the two analysis modules, and analyzes the scale from large scale to medium and micro scale based on different accuracy urban digital models. Through image classification and content recognition, image semantic segmentation and image color quantification, the landscape feature information in pictures is mined, and the dimension of landscape image is put forward based on this. In addition, this paper combines experimental analysis to verify that the method proposed in this paper has certain results. It is not only suitable for visual analysis of landmark buildings and landmark structures in cities, but also can analyze the visual characteristics of natural landscapes as urban images in cities. Therefore, the quantitative method of urban visual landscape analysis proposed in this paper can provide reliable data support for the follow-up urban design work.**

Keywords*—Computer vision; urban landscape; environmental image; quantification; measure

I. INTRODUCTION

With the development of the times, people's living standards are constantly improving, and the public's aesthetic concept is also constantly improving. More and more people are beginning to pay attention to the spiritual ascension. Moreover, some once neglected art forms, such as abstraction and performance art, are increasingly recognized by people through deformation and exaggeration. Although more information can be obtained through the domestic literature retrieval system at present, it is still found that many researches on image modeling mainly focus on the field of art, such as traditional Chinese painting, oil painting and sculpture. At the same time, although the development of graphic design, product design and other design fields has made some achievements, most design works still focus on specific artistic design, and there is little research on the specific environment in urban public space.

Image is the bridge of two-way communication between people and landscape, and any experience in landscape places is related to images. Landscape image experience focuses on the spiritual communication relationship between landscape quality and people, including memory, imagination, thinking and accompanying positive emotions. Kevin Lynch first put forward the concept of urban image. After analysis, he concluded that environmental image should consist of three parts: personality, structure and implication. Although his concept of environmental image is put forward at the macro level of the city, it is undeniable that these three characteristics are also the basis of forming landscape image [1].

The personality of landscape image refers to the distinguishability and recognizability as a landscape place. Nowadays, driven by the rapid and urgent production environment of globalization and economic interests, the newly built squares are the same, the landscape avenues are the same, and even the street lamps and signs are in a unified mode. Similar pedestrian commercial streets, similar architectural forms, similar residential landscapes and similar pocket parks make cities and landscapes similar. Because landscape designers don't fully tap the physical and humanistic characteristics of the site, the potential energy of the site can't be revealed and its uniqueness can't be created. The personality of the urban landscape disappears, and the cultural threads of the urban landscape also break. In this case, the landscape loses its narrative (information component) and its poetic experience (rich expression) [2].

In order to improve the research effect of quantitative measurement and preference of urban landscape environmental image, the algorithm proposed in this paper combines two-dimensional analysis modules: two-dimensional visual domain analysis and three-dimensional visual analysis. In addition, this paper combines experimental analysis to verify that the method proposed in this paper has certain results. It is not only suitable for visual analysis of landmark buildings and landmark structures in cities, but also can analyze the visual characteristics of natural landscapes as urban images in cities. Therefore, the quantitative method of urban visual landscape analysis proposed in this paper can provide reliable data support for the follow-up urban design work.

II. RELATED WORKS

Landscape imagery is a landscape imagery pattern gradually formed by people in the process of landscape cognition, which refers to the interactive relationship and perceptual experience between subjects and objects. It includes both the presentation based on the "image" of the landscape object and the perception based on the "meaning" of the viewing subject. The coastal landscape imagery is a mapping of the public's perception of coastal landscapes and the cognitive evaluation of different sea areas, including the landscape projection imagery created by relevant propaganda agencies through abstracting urban landscape elements and the landscape perception imagery formed by the public based on their understanding and evaluation of destination urban landscape elements [3]. Previous studies have shown that landscape perception imagery is an important theoretical support for landscape style renewal and creation, and plays an important role in enhancing landscape attractiveness. It has the characteristics of personalization, locality, and sociality [4]. At present, domestic and foreign scholars mainly focus on exploring the constituent elements, spatial distribution, perceptual characteristics, and formation mechanisms of landscape perception imagery, as well as analyzing the perceptual differences of landscape imagery from different perspectives. In addition, some scholars have conducted quantitative evaluations by constructing a landscape image related evaluation system [5].

The public's perception of landscapes often stems from the material carriers and social interaction activities in the natural environment. Traditional research on landscape perception imagery is mostly based on cognitive maps and combined with methods such as questionnaire surveys, participatory surveys, and interviews. There are significant limitations on research time and sample size. With the continuous development of Internet technology and the popularization of artificial intelligence applications, network data based on mass media has become one of the media of landscape image cognition, and it has the advantages of high accuracy, wide source, fast update, large volume and convenient data acquisition [6]. In this context, different scholars have gradually shifted their research on landscape perception imagery to the mining and content analysis of online data. Network data includes travel commentary text data and landscape photography photo data, among which text data has been widely used in the study of landscape perception imagery. For example, some scholars have explored tourists' cognitive preferences for destination landscapes by filtering Weibo texts, or quantitatively evaluated landscape perception images based on the emotions expressed in the texts. At the same time, with the popularization of social media software and the iterative updating of photography equipment, people often spontaneously upload landscape images taken through smartphones and cameras during tourism or sightseeing to social media, photo sharing platforms, and tourism websites. As the public's condensation of local culture and landscape features, these network images contain a large amount of image information and geographical coordinates, as well as other social metadata, which provide extensive and real data for the research of landscape perception images [7]. However, these photo data, as intuitive analysis materials for visual content, are more suitable for application in research. Existing research often relies on manual encoding and other processing methods when processing image data, which has limitations such as strong subjectivity and small research scale. However, the introduction of computer vision algorithms has made up for this deficiency. Currently, research is mostly based on image semantic segmentation technology to identify objects such as people, animals, plants, buildings, and signs in images. The research will be applied to fields such as landscape ecosystem cultural services, landscape aesthetics, urban street scenes, and campus green spaces [8].

In terms of multi-objective adaptive landscape, multi-objective optimization differs from single objective optimization mainly in two aspects. The first point is the objective layer, where each conflicting objective is composed of multiple fitness functions, rather than traditional single fitness functions. The second point is the solution layer. Compared to a single optimal solution in a single objective scenario, the Pareto optimal solution set in a multi-objective scenario is the optimal solution balanced by multiple fitness functions [9]. The author in [10] applied standard fitness landscape analysis techniques to erroneous landscapes. The research content includes the impact of search space boundaries on landscape analysis, the impact of regularization on error surfaces, the impact of architectural settings on landscape morphology, and the impact of different loss functions on attractive basins. With the development of adaptive landscape models, many models for specific scenarios have been further developed, such as those for numerical optimization or discrete optimization, as well as for co-evolution, constraint optimization, multi-objective optimization, and other directions. The Local Optimal Networks (LONs) model has been further developed and has become one of the most widely used landscape analysis techniques today. Meanwhile, the local optimal network is regarded as a composite landscape model that specifically captures the number and distribution of local optimal values in the fitness landscape, and these landscape features have a significant impact on the search heuristic performance [11]. In addition, LONs are mainly applied in discrete optimization and are designed for discrete search spaces. Given the global structure of the landscape that affects search behavior, LONs can be generated for a series of problems to compare algorithm success and failure or the global structure of the search space [12].

Nowadays, social media text data mainly comes from sources such as Weibo, Twitter, and online travelogues. Compared to traditional text data (such as interviews and surveys), it has advantages such as strong real-time performance, rich content, large production volume, and clear semantics. Moreover, it can reflect human behavioral characteristics at a smaller granularity unit. At the same time, social media text data has been applied in tourism geography, such as perceiving tourist destination imagery, analyzing tourist behavior, studying tourist preference characteristics, analyzing tourist attraction popularity, urban social perception, etc. [13]. The consistency between the projected and perceived images of the target image is determined by principal component analysis using online commentary text data [14]. Text data has strong subjectivity, relatively low spatial coupling, high dependence of text semantics on context, and insufficient depiction of common spatial details and backgrounds. However, network photo data has high accuracy, wide geographical coverage, and a large amount of information, which can not only reflect people's subjective feelings, but also comprehensively depict the overall image of tourist destinations from multiple dimensions [15]. Compared to text, images can better record what tourists see in real time, providing visually impactful and realistic information for other potential tourists, and making intangible tourism experiences tangible. Image data is intuitive and easy to understand, with rich visual semantic information, which can objectively depict what tourists see [16]. In addition, tourism managers also actively create the image of tourist destinations by taking beautiful photos. The people, objects, and scenery in the photos are cognitive elements of tourists, and they are all carriers of tourist destination imagery. At present, the main sources of image data include street view data, social media image data, and media promotional image data [17]. Images are a data source with high application value in the future and an important supplement to existing research data. Tourism photos are an important component of tourism activities. Tourists share their travel process in the form of photos, which is a common means of disseminating tourism experiences and destination images. Tourism photos have the function of image dissemination, which enables domestic and foreign scholars to use them as a data source to study the role of tourism photos in the dissemination of destination images [18]. The tourism gaze theory suggests that potential tourists can have psychological imagination and travel motivation when browsing travel photos [19]. At the same time, photos can attract potential tourists to generate imagination and desire to participate in travel activities, and through the analysis of photo content, tourists can understand their interests, preferences, travel behavior, and spatial distribution characteristics in different destinations [20].

With the development of remote sensing technology, some scholars have applied it to landscape pattern analysis. Common landscape classification methods include unsupervised classification and supervised classification. Meftaul et al. [21] have shown through experiments that using mixed classification (i.e. a combination of supervised and unsupervised classification) to classify images can achieve higher classification accuracy, and with the rise of neural networks, some scholars have already used backpropagation (BP) neural networks (BP) for classification.

RAL network classifies images and obtains better results. Based on this discovery, Liu et al. [22] proposed a landscape measurement calculation method, which is widely used in urban landscape pattern analysis, such as vegetation pattern, urban growth and other disciplines. Landscape measurement can quantitatively describe and monitor the changes in landscape spatial structure over time, but cannot specifically reflect the direction and rationality of landscape changes.

Deng et al. [23] proposed an "inverse S-shaped function" to represent the density of urban land, which can identify the size of urban built-up area, measure the compactness and expansion intensity of urban land. However, it only discusses the spatial distribution of urban land use and does not analyze the changes in land use structure during urban development.

At present, there are two problems in the research of landscape pattern. The unclear interpretation characteristics of images of different landscape types have led to the prevalence of the phenomenon of "same spectrum foreign objects and same objects but different universality". These analyses are mostly based on landscape metrics, which are relatively simple research methods and cannot reflect the complexity of landscape pattern changes during the rapid development of cities.

III. Quantitative Measurement Method of Urban Landscape Environment Image

A. Research Methods

The urban visual landscape analysis framework proposed in this paper includes two analysis routes: the traditional model and the point cloud-solid hybrid model, includes two-dimensional and three-dimensional analysis processes, and mainly expounds the visual analysis based on traditional model. Traditional models mainly include urban digital surface model (UDSM) and urban 3D solid model (urban 3D solid model).

The sight urban visual landscape analysis framework proposed in this paper mainly consists of three parts: urban digital model construction, visibility analysis and visual feature extraction. The analysis framework is shown in Fig. 1. The method proposed in this paper combines two-dimensional analysis modules of two-dimensional visual domain analysis and three-dimensional visual analysis, makes full use of the advantages of the two analysis modules, and analyzes the scale from large scale to medium and micro scale on the basis of urban digital models with different accuracy. Models with different accuracy can support visibility analysis results with different degrees of fineness, and the calculation time and model construction cost also increases with the improvement of accuracy. In the analysis model of this paper, the viewing points and the viewed landscape objects will be discretized in the digital model, and the spatial points with elevation attributes will be taken as representatives to participate in the calculation.

For an urban space without strict design control, in addition to the information accumulated in daily life, there may also be some missing public spaces where the target urban landscape can be observed, and visual domain analysis can help research and judge these areas that may be ignored by existing planning and design but have ornamental potential (as shown in Fig. 2).

Potential viewing points are extracted from the visual public space and carried out forward operation in the visual domain analysis, that is, these viewing points V_V are analyzed as viewpoints in the visual domain analysis, and the viewshed of viewpoints in the city can be obtained. The visible area VA_{TO} of target objects from open spaces in the city can be obtained by superimposing the obtained urban visible range and the overall range of the target object. It is worth noting that there is the following relationship of VA_{TO} , A_T and V_V :

$$VA_{TO} = A_T \cap V_V \tag{1}$$

If and only if that entire extent of the target object is visible to the public space,

$$VA_{TO} = A_T \in V_V \tag{2}$$

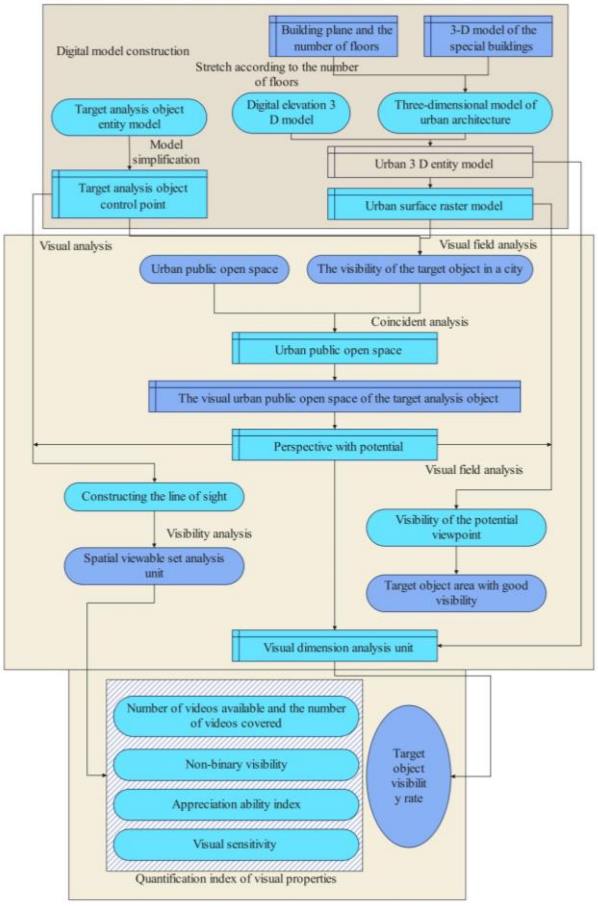
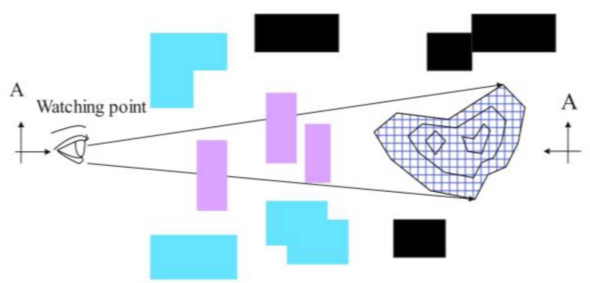
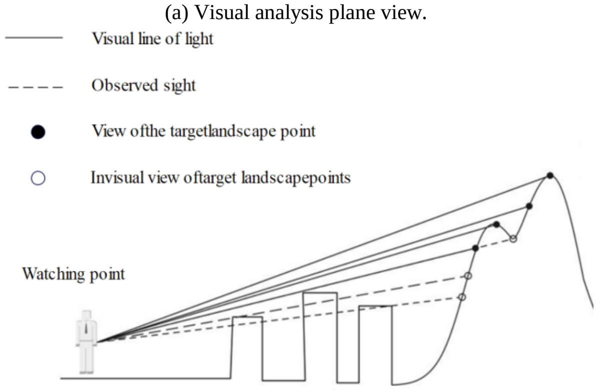


Fig. 1. Flowchart of sight-oriented urban visual landscape analysis.



(a) Visual analysis plane view.



(b) Visibility analysis of sight-oriented.

Fig. 2. Visual domain analysis.

The analysis results of this step can preliminarily test the visibility of the viewing target object, and make more in-depth exploration of areas with relatively high cumulative visibility, that is, areas with high viewing probability in urban space.

The principle of human eye imaging is similar to that of convex lens imaging. If the size of an object remains the same, the closer the object is to the human eye, the larger the image it forms on the retina will gradually become, and the better the visibility of the object will be, and vice versa. That is, the well-known phenomenon of "near big and far small", as shown in Fig. 3.

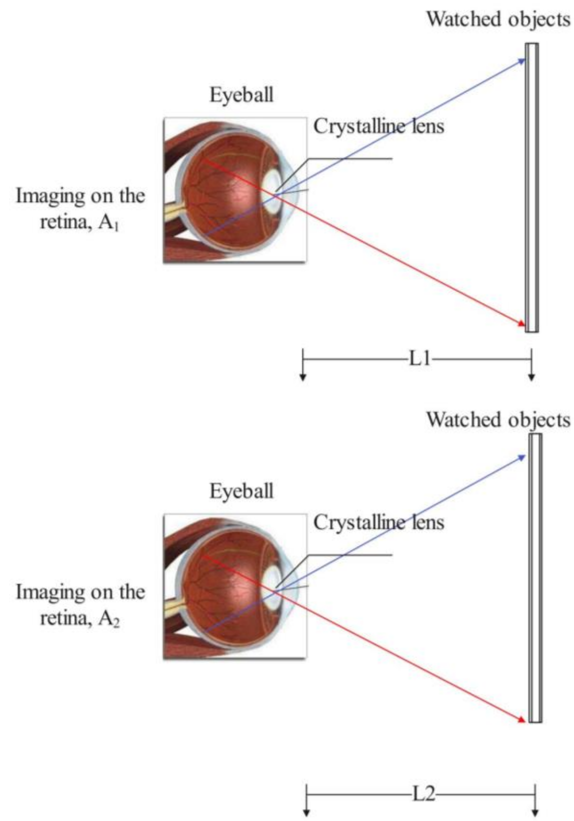


Fig. 3. Imaging size of human eye under different visual distances.

The visibility V_{ij} between the i -th viewpoint and the j -th target point is as follows:

$$V_{ij} = \begin{cases} 0, \text{Line of sight obstruction or } L_{ij} > L_{max} \\ 1, L_{ij} \le D_0 \\ k_{ij} = \dfrac{L_{max} - L_{ij} + D_0}{L_{max}}, D_0 < L_{ij} < L_{max} \end{cases} \tag{3}$$

Among them, D_0 is the optimal line of sight, k_{ij} is the distance attenuation coefficient, L_{max} is the theoretical maximum visual range, that is, the farthest distance that the human eye can see the object clearly, and L_{ij} is the distance between the i-th viewpoint and the j-th target point.

The value range of the optimal sight distance D_0 should be selected according to the height and volume of the target object. The field of view where a clear landscape image and a relatively complete composition effect can be obtained without turning the head is 45 ° ~ 60 ° horizontal angle α and 26 ° ~ 30 ° vertical viewing angle β. Beyond this range, the head must be observed up and down, and the overall composition impression of the scene is not complete enough. It is assumed that the horizontal length of the target scene is W, the vertical height is H, and the human eye height is h. According to the calculation, the sight distance D_{OW} that can obtain the best horizontal field of view is about (0.9 ~ 1.2), as shown in Fig. 4. For the convenience of calculation, $D_{OW} = W$ and $D_{OH} = 4(H-h)$ can be obtained by taking the median of the two.

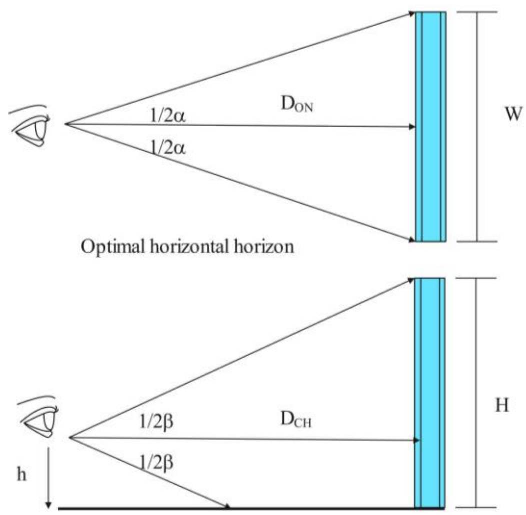


Fig. 4. Schematic diagram of optimal sight distance in horizontal and vertical field of view.

The correction formulas for curvature and atmospheric refraction are as follows:

$$Z = \frac{\left[Z_0 + D^2(R-1)\right]}{d} \quad (4)$$

Among them, Z is the corrected elevation, Z_0 is the surface elevation, D is the horizontal distance, d is the diameter of the earth (12740 km), and R is the refractive index of light (0.13 in standard atmospheric cases). ArcGIS's through-vision sight analysis is based on the analysis and calculation of three-dimensional line segments (rays between the viewpoint and the target point), which retains spatial visual information to the greatest extent, such as the spatial position of sight obstacle points (Fig. 5).

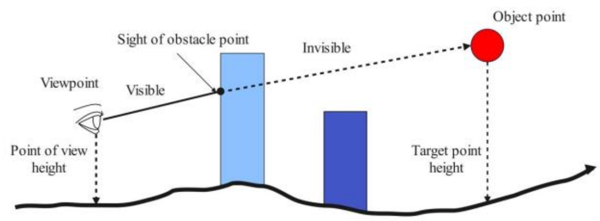


Fig. 5. Analysis of visual sight.

The spatial relationship of sight accessibility is shown in Fig. 6. Taking the target object as a natural mountain as an example, the angle θ_{ij} between the line of sight and the normal vector of the mountain plane where the target point is located determines the proportion of the target mountain displayed in the eyes of the observer. On the other hand, the distance influence can be expressed in non-binary visibility to consider the visual influence of "near is large and far is small".

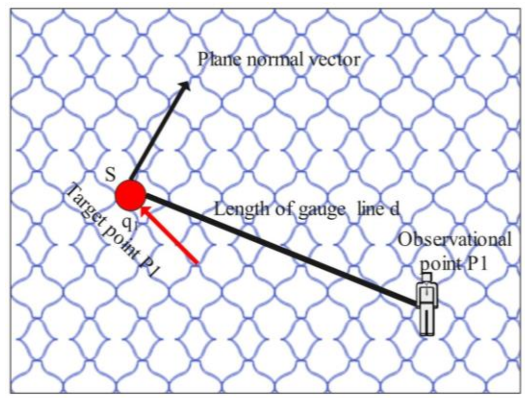


Fig. 6. Schematic diagram of sight accessibility.

It is assumed that there are the i-th viewpoint $P_i(x_i, y_i, z_i)$, the j-th target point $P_j(x_j, y_j, z_j)$ and the plane S_j where P_j are visible to each other, and the cosine of the angle θ_{ij} between the through sight line $\vec{P_J P_I}$ and the plane S_j is:

$$\sin\theta_{ij} = \frac{\vec{n}_J \cdot \vec{P_J P_I}}{\left|\vec{P_J P_I}\right|} \quad (5)$$

Among them, $\vec{n}_J$ is the unit normal vector of plane S_j. The sight accessibility between the plane S_j represented by the target point and the viewpoint P_i is:

$$ASL_{ij} = V_{ij} \cdot \sin\theta_{ij} \quad (6)$$

In the formula, V_{ij} is the non-binary visibility between the observation point and the target point.

If it is assumed that there are n visible target object points for the i-th viewing point P_i in the analysis, the calculation formula of the viewing ability index VAI of P_i is as follows:

$$VAI = \sum_{j=1}^{n} ASL_{ij} \tag{7}$$

Among them, V_{ij} is the sight accessibility between the i-th viewpoint and the j-th target object point. Since the viewpoint and target point of the through-sight line are selected, $0 < V_{ij} \le 1$.

The average viewing ability index measures the average viewing ability of a certain viewpoint to the visible target point. The larger the value, the closer the distance between the viewpoint and the target viewing object, and the better viewing effect can be obtained, and the distance has less influence on it. The smaller the value, the farther the viewpoint is from the target viewing object, and the viewing effect is worse because of the greater influence of the distance on it.

$$VAI_{avg} = \frac{1}{n} \times VAI \tag{8}$$

Visual exposure of target objects (VE) describes the degree of attention of a certain target point in the urban visual landscape environment. Small changes in areas with high visual exposure will be keenly perceived by the observer, while the observer will be slow to change in areas with low visual exposure.

If there are m viewpoints $(P_1, P_2, ..., P_m)$ visible to the target point P_T, that is, the number of videos of the target point is m, the visual exposure of P_T is defined as:

$$VE = \sum_{j=1}^{m} LOSA_{ij} \tag{9}$$

Among them, $LOSA_{ij}$ is the sight accessibility between the i-th viewpoint and the j-th target object point that are visible to each other. Visual exposure reveals the overall gaze degree of mountain points on a selected series of viewing spots. The higher the value, it means that the area represented by the target point is easier to appreciate the whole picture for the selected viewing spots. Otherwise, it means that the area represented by the target point is less exposed in the viewing spots and cannot fully display its whole picture.

The average visual exposure of line of sight measures the average gaze degree of a visible target mountain point in urban space. A low average visual exposure indicates that the average projected area of the point in the viewing spot is small, and the average gaze degree is low. The average visual exposure of the mountain point is:

$$VE_{avg} = \frac{1}{m} \times VE \tag{10}$$

The visible percentage of target objects (VP) refers to the area extraction of the components of the obtained digital image under the condition of simulating the visual picture and calculating the proportion of the target analysis object in the picture. Then, the visibility of the target object observed for the viewpoint i is:

$$VP = \frac{A_T}{A_i} \times 100\% \tag{11}$$

Among them, A_i is the total area of the picture obtained by the viewpoint i, and A_T is the area of the target object in the picture.

B. Experimental Study

This paper takes the landscape of urban lakes and parks as an example. This study uses image data from social media to analyze the public's landscape perception preference characteristics. In order to reduce the influence of a single social media user's preference on the results, this study selects the comment pictures on the social media platform of mainstream travel websites with high audience, wide coverage and large amount of evaluation data as the data source. The web crawler is used to retrieve and crawl all tourist comment pictures in 20 lakes and parks on the Internet. Because the sources of the obtained pictures are complex, it is necessary to clean the picture data, check the obtained social media pictures, and eliminate blurred pictures.

Through image classification and content recognition, image semantic segmentation and image color quantification of image data, the landscape feature information in pictures is mined. Based on this, three dimensions of landscape image are proposed: landscape composition, landscape proportion and landscape color, in which landscape composition can be decomposed into landscape type, spatial scale and landscape elements, landscape proportion includes green vision, sky visibility and architectural visibility, and landscape color is described by HSV color features, and a multi-dimensional landscape image quantitative measurement framework based on public perception is constructed (Fig. 7).

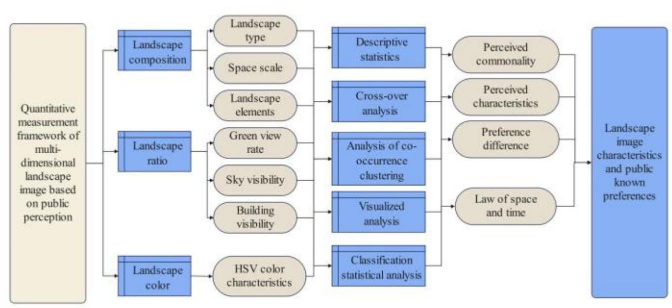


Fig. 7. Quantitative measurement framework of multi-dimensional landscape image based on public perception.

1) Image label analysis data set: The screened landscape pictures are stratified according to different parks, and simple random sampling is carried out in each layer through stratified ratio. A total of 500 pictures are sampled for image label analysis.

2) Model training data set: The screened landscape pictures are stratified according to different parks. Firstly, simple random sampling is carried out in each layer through stratified ratio, and a total of 1,200 pictures are sampled for preliminary model training and adjustment. Secondly, the training data set is adjusted according to the validity of model evaluation, and image data is added to labels with poor recognition effect. Finally, it is adjusted to 1,500 pictures for building Auto ML models.

C. Results

The number of pictures in the training set, validation set and test set of the landscape feature classification AutoML (Automated Machine Learning) model is 1197, 151 and 152, respectively. Through model evaluation, it can be obtained that the average accuracy AP value of the AutoML model for landscape feature classification is 0.933, and when the confidence threshold is 0.5, the accuracy P is 88.36%, the recall R is 84.87%, and the F1 value is 0.866. The P-R curve is shown in Fig. 8. Generally speaking, the accuracy of the model is high, and all indexes are greater than 0.8. It is considered that the model can be used to classify image landscape elements.

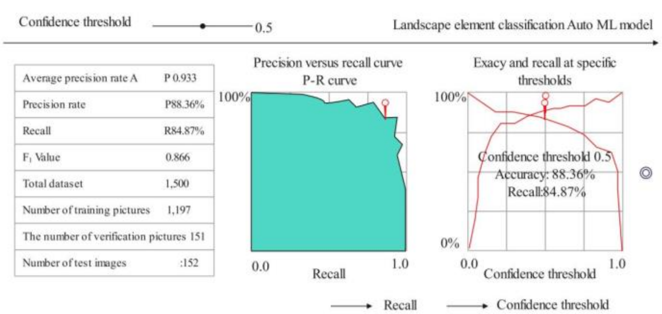


Fig. 8. P-R curve of Auto ML model for landscape feature classification.

The AP values, precision, recall, and F1 values of each label are shown in Table I, and the P-R curve of each label is plotted according to precision and recall, as shown in Fig. 9.

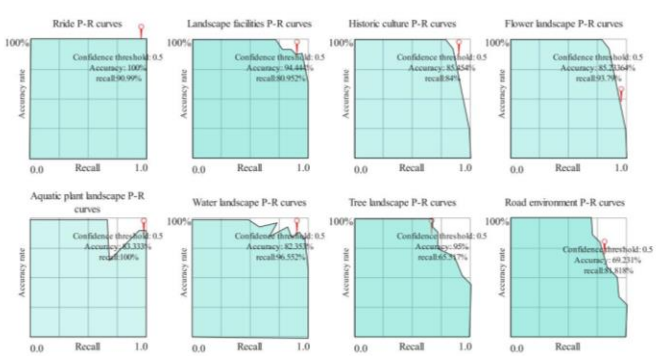


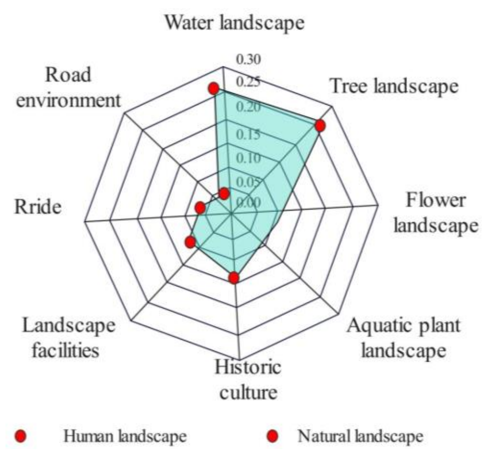
Fig. 9. P-R curves of various landscape types.

TABLE I. EVALUATION INDICATORS OF AUTO ML MODEL FOR LANDSCAPE ELEMENT CLASSIFICATION

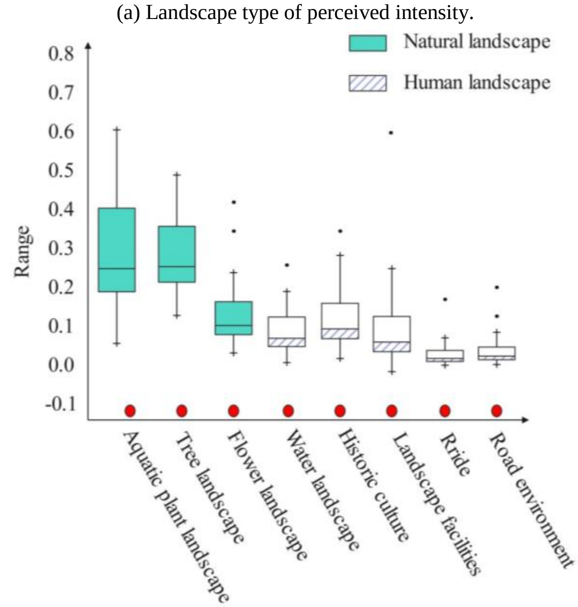
Landscape Type	AP	Precision	Recall	F1-score
Amusement facilities	1	99.00%	90.00%	0.942
Landscape facilities	0.971	93.50%	80.14%	0.863
History and culture	0.959	94.51%	83.16%	0.885
Flower landscape	0.944	87.36%	92.81%	0.900
Aquatic plant landscape	0.936	82.50%	99.00%	0.900
Water landscape	0.933	81.53%	95.58%	0.880
Forest landscape	0.901	94.05%	64.86%	0.768
Road environment	0.895	68.54%	81.00%	0.743

Note: The values of Precision, Recall, and F1-score are the results when the confidence threshold is 0.5.

After sorting out, the statistical results of perception frequency of each landscape type in lake park are obtained (Table II), and the perception results of landscape types are shown in Fig. 10.



(a) Landscape type of perceived intensity.



(b) Boxplots of landscape type perception frequency.

Fig. 10. Landscape type perception results.

TABLE II. STATISTICAL RESULTS OF PERCEPTION FREQUENCY OF LANDSCAPE TYPES IN LAKE PARKS

Landscape Type	Natural landscape				
	Water landscape	Forest landscape	Flower landscape	Aquatic plant landscape	Summary
Number/N	8180	8075	3324	2605	22185
Perceived frequency/%	25.28%	24.97%	10.28%	8.05%	68.58%
Perceived frequency Min	5.73%	11.13%	0.82%	0.34%	35.70%
Perceived frequency Max	57.68%	45.95%	41.11%	21.26%	86.78%
Standard deviation	0.1303	0.0895	0.1036	0.0609	0.1347
Landscape Type	Human landscape				
	History culture	Landscape facilities	amusement facilities	road environment	Summary
Numbe/N	3819	3130	1722	1168	9840
Perceived frequency/%	11.81%	9.67%	5.33%	3.61%	30.42%
Perceived frequency Min	0.00%	3.83%	0.00%	0.82%	12.22%
Perceived frequency Max	31.67%	60.67%	17.32%	15.72%	63.30%
Standard deviation	0.1055	0.1238	0.0383	0.0384	0.1347

D. Analysis and Discussion

By examining the false and negative cases predicted in road environment, water landscape and forest landscape, it is found that the reason for the confusion is that the pictures of the two groups of landscape types contain overlapping or similar landscape contents. For example, a picture taken with a water plank road as the main scene contains a large area of water at the same time, which may cause the model to encounter difficulties in classifying road environment and water landscape, or a picture taken with street trees as the main scene will also cause the model to deviate when classifying forest landscape and road environment. Considering the complexity of the landscape and the manual recognition will also have a certain degree of error, this part of the error can be considered as a normal result. Generally speaking, the trained AutoML model of landscape element classification has high validity, and can be applied to batch prediction of landscape images and identify the types of landscape elements.

The landscape composition of lake park can be divided into three aspects: landscape type, spatial scale and landscape element. This paper focuses on the analysis of the perception commonality and perception characteristics of landscape composition, discusses the public preference orientation and its reasons, obtains the various landscape composition and combination patterns that people prefer, and reveals the seasonal preference differences of landscape composition.

According to the perception intensity of each landscape type [Fig. 10(a)], the perception of natural landscape in lake park is significantly higher than that of human landscape, the perception frequency of water landscape and forest landscape in natural landscape is higher, and the perception frequency of historical culture and landscape facilities in human landscape is higher. On the whole, water landscape, forest landscape and historical culture are the most perceived landscape types in lake parks, accounting for more than 60%. Therefore, these three types of landscapes can be considered as the representative and core landscape types of lake parks. It can be seen from Fig. 10(b) that the perceived changes of natural landscapes are more diverse than those of human landscapes, indicating that the differences in natural landscape characteristics in different parks are more significant.

Therefore, the waterscape in lake park, as the most important landscape element, is also the most popular landscape element, which also reflects that people's hydrophilic psychology and yearning for natural scenery greatly affect their perception preference. Forest landscape is the basic component of urban green space, and its landscape quality directly affects the overall landscape quality of garden green space. It covers all aspects of the landscape environment, making it easier for tourists to be highly perceived. In addition, the reason why history and culture are highly perceived is that it represents the important landscape features of the city, and the cultural landscapes of many tourist destinations in the city show strong tradition and historical customs, which arouse the strong perception of tourists.

The research shows that natural landscape is the core landscape image of urban landscape, and people's hydrophilic psychology and yearning for natural landscape greatly affect their perception preference. Therefore, in the construction and optimization of urban landscape, the naturalness of the landscape should be improved and the authenticity of the natural landscape should be maintained. Besides preserving and protecting the original landscape, it is also very important to restore and reproduce the natural features of the surface by artificial means. According to the natural landscape characteristics and public preference orientation of the study site, the optimization of the natural landscape quality of Wuhan's urban landscape can be considered from the following points. Firstly, the transformation of ecological natural revetment can take the form of lawns and aquatic plants, or natural stone and wood bottom protection. Moreover, the landscape design integrates sponge city ecological technology, reflects the characteristics of lakes and wetlands in Wuhan, and meets the dual needs of ecology and beauty. Secondly, it is necessary to build an open waterfront space, improve the hydrophilicity of waterfront space, and create a recreational landscape place that can be close to nature. Third, it is necessary to plant characteristic plant communities to form a rich plant landscape, pay attention to the construction and development of flower gardens and various flower shows, and attract people to watch and play.

It is necessary to pay attention to the balanced development of landscape construction at macro, meso and micro scales, and create landscapes with reasonable sense of scale, diverse changes in spatial scale, distinct spatial sequence levels and significant differences in visual perception, so as to enrich tourists' emotional experience. Specifically, it can be optimized from the following points. First, it is necessary to coordinate the sense of scale of landscape elements. When creating different landscape spaces, it is necessary to meet the functionality of different landscape elements and their own specific scale attributes, such as the close-range viewing function of sculpture or art installation landscape, which limits its spatial scale from being too large, and requires attention to the design of landscape details. Moreover, it is necessary to highlight the eye-catching image and control function of physical scenery elements in landscape space. Second, it is necessary to create diversified landscape spatial scales. The spatial scale of the landscape within a certain range should not be static, but should be different from the adjacent space, so as to ensure the spatial integrity and richness of the landscape environment and create a variety of environmental atmospheres. Thirdly, it is necessary to construct a distinct hierarchical landscape spatial sequence. Moreover, the macro, medium and micro-scale landscape nodes should be reasonably arranged on the tour route, so as to provide tourists with a variety of spaces for distribution, communication and privacy, enhance the sense of viewing hierarchy of the landscape along the route, and meet people's needs for diversified spatial scales, so as to optimize the utilization of landscape space.

IV. CONCLUSION

This paper presents a sight-oriented quantitative analysis method of urban visual landscape, which is designed on the basis of the whole three-dimensional model of the city and combines the advantages of two-dimensional and three-dimensional spatial visual analysis. It is not only suitable for the visual analysis of landmark buildings and structures in the city, but also can analyze the visual characteristics of natural landscape as the image of the city in the city. Therefore, the quantitative method of urban visual landscape analysis proposed in this paper can provide reliable data support for the follow-up urban design work.

Because the traditional model analysis lacks consideration of vegetation, on the basis of it, the point cloud model can be further used to consider the visual analysis of vegetation. In the quantitative analysis framework of urban visual landscape proposed in this paper, the analysis process among two-dimensional model, three-dimensional traditional solid model and point cloud mixed model is progressive.

This paper crawls the comment pictures on social media platforms, uses a variety of computer vision algorithms to parameterize the pictures, extracts and quantifies the landscape features in the pictures, and based on this, proposes three dimensions of landscape images: landscape composition, landscape proportion and landscape color, constructs a multi-dimensional landscape image quantitative measurement framework based on public perception, quantitatively analyzes the commonalities and differences of landscape images, and explores public perception preferences.

The data query efficiency of the model in this paper is low, so in future research, methods such as voxels will be used to segment point cloud data or seek more efficient big data query strategies to improve computational efficiency and accuracy.

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