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Plant Configuration Method of Landscape Architecture Based on Neural Network

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Plant characteristics and color quantification are not considered in the configuration of plants in a landscape, resulting in poor rationality and less aesthetic appeal. Therefore, to address these two issues, in this paper, a landscape plant configuration method is proposed based on a neural network. This method involves: determining the principle of landscape plant configuration, extracting the green plant characteristics in landscape plant configuration using the scale-invariant feature transform (SIFT) algorithm, determining the floral characteristics by means of a cluster shape index, and combining the characteristics of the green plants and flowers in order to derive the plant characteristics of landscape plant configuration. The color of the plant landscape is divided using the SBE (Beauty analysis method) method, and the quantitative indexes of plant color are determined; these are: plant landscape hue index, color saturation, color lightness index and plant color uniformity. The quantitative index is calculated to determine the plant color in a landscaped garden. Through the pre-training of data on landscape garden plant configuration, the plant data in each layer of neurons are updated. Using MMD measurement, the overall mean value of two different fields is calculated to determine the loss function. Then, the landscape garden plant configuration model is constructed with the help of a neural network, and the source domain and target domain are further modified to achieve the final landscape garden plant configuration. The experimental results show that the proposed method can effectively improve the rationality of plant configuration and enhance the aesthetic appeal of the landscape.

Keywords: neural network, landscape architecture, plant configuration, SIFT algorithm, SBE method, color quantization.

1. INTRODUCTION

Landscape architecture design is an important element of urban construction and development, as it contributes to the basic appearance, livability, and sustainable development potential of a city. Plant configuration is an important issue associated with landscape design, and requires advanced modern technology and adherence to complex ecological principles [1]. There are several significant problems in the configuration of domestic landscape plants, which restricts the potential of landscape plants to beautify the environment and improve the interactive space of residents. Plant configuration has a long history in China. From the early Zhou and Qin Dynasties to the present, with the development and change of the garden itself, the plant configuration has also changed [2].

Landscape garden plant configuration refers to the collocation relationship between various plants in the garden, such as trees, shrubs, climbing plants, aquatic plants, flower plants and ground cover, or the collocation position between these plants in the garden and the local mountains, water, rocks, buildings and roads [3].

Today, the problem of man interacting with nature is the focus of research on the development of ecological gardens. The need for symbiotic and harmonious coexistence of man and nature has been recognized by countries all over the world [4]. As the current urban environmental problems are becoming increasingly prominent, people are also beginning to pay more attention to environmental protection, and urban greening construction has gradually attracted people's attention. Garden plants, as an important part of urban ecological landscape design, can give full play to the ecological function of plants and effectively reduce urban pollution. Of course,

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the fundamental goal of urban landscape plant allocation is to improve the urban environment, so as to improve the quality of life of urban residents [5]. When choosing urban ecological garden plants allocation, the planting of trees, flowers and lawn grass can effectively expand the urban green area and increase the benefits gained from the ecological effect of green vegetation. Photosynthesis, transpiration and adsorption of plants can effectively regulate the climate, purify urban water and air, reduce urban noise, absorb and transform harmful substances in the atmosphere and, generally, improve the urban environment [6]. This can be achieved by combining traditional culture with modern technological advancements, extracting the scientific part of geomantic omen theory, and combining it with garden plant configuration to form an effective and sustainable system. On the one hand, modern landscape designers should have a sound understanding of Chinese traditional culture and traditional gardening ideas, and have a systematic reference index. On the other hand, they can also integrate the design principle of the unity of heaven and man into the actual project design. In this way, gardening thought is connected with modern landscape design, addressing any shortcomings, and provides guidelines for the development of the modern landscape industry [7]. Refining the scientific value of Feng Shui theory, we can find that the origin of Feng Shui is deeply rooted in classical gardens. The inclusion of the Feng Shui concept in the plant configuration of current landscape gardens will help to achieve a harmonious environment, more suitable for garden plant configuration in China. This meets modern landscapers' need for both appropriate materials and cultural spirit, both of which are of great significance to the development of domestic gardens [8]. Therefore, relevant researchers have designed many landscape plant configurations based on existing methods, and achieved some notable results.

Sun et al. [9] designed an adaptive urban plant allocation method to deal with climate change. This method is an effective means of dealing with climate change, protecting urban biodiversity and stabilizing the urban ecosystem. They proposed an adaptive urban plant allocation method which provides a sustainable ecosystem that is stable despite climate change. Taking southern Jiangsu as an example, firstly, the characteristics and adaptability of various plant species are studied and coded, and then configured according to the plants' resistance to external factors, stability, structural diversity, cultural and aesthetic properties, and cost. It Sun et al. [9] suggest new ways for urban plant communities to deal with climate change and improve the ecosystem function of urban plant communities. This method has a certain theoretical basis, but the quantitative results are not evident in the actual configuration method, which needs further improvement. Peng and Yang [10] designed a plant optimal allocation system based on sunlight adaptability. To address the problems of poor optimization and lengthy time required by the traditional plant optimal allocation system, a plant optimal allocation system based on sunshine adaptability is proposed and designed. The hardware of the system comprises an administrator module, data collection and sorting module, database module and data query module. The system software is designed with the support of system hardware. The multi-objective optimization model of plant configuration is constructed, the constraint conditions and sunshine parameters are determined, and the membership functions of benefit parameters, cost parameters and sunshine parameters are constructed. The multi-objective optimization model is decomposed into multiple

sub-models by using the membership function, and each sub-model is solved respectively to obtain an optimal solution for plant configuration. The system can be implemented at low cost is and the configuration effect is good, but the characteristics of different plant landscapes are not given much consideration in practical application, resulting in a configuration that is not widely applicable.

In view of the shortcomings of the above landscape plant configurations, this paper proposes a method based on the artificial intelligence algorithm of a neural network. The landscape plant configuration model is constructed with the help of a neural network after determining the landscape plant features and effectively evaluating the plant colors. The determined plant features and color features are input into the model, and the configuration results are output to obtain the landscape plant configuration based on a neural network. The proposed research method involves the steps described below.

Step 1: Determine the principle of landscape plant configuration, extract the green plant characteristics in landscape plant configuration with the help of the SIFT algorithm, determine the flower characteristics through the cluster shape index, and combine the green plant and flower characteristics to derive the plant characteristics of landscape plant configuration.

Step 2: Divide the plant landscape color using the SBE method, and determine the quantitative index of plant color, including: plant landscape hue index, color saturation, color lightness index and plant color uniformity. Calculate the quantitative index to complete the quantitative study of plant color in the landscape garden.

Step 3: Through the pre-training of landscape plant configuration data, the plant data in each layer of neurons are updated. With the help of MMD measurement, the overall mean value of two different fields is calculated to determine the loss function. On this basis, the landscape plant configuration model is constructed with the help of neural network, and the source domain and target domain are further corrected to achieve the optimal landscape plant configuration.

Step 4: Experimental analysis.

Step 5: Conclusion.

2. PLANT CONFIGURATION PRINCIPLE AND PLANT FEATURE EXTRACTION IN LANDSCAPE ARCHITECTURE

2.1 The Principles of Plant Allocation in Landscape Architecture

2.1.1 Protection of the Original Landscape and Artificial Restoration Ecology

The large-scale plant landscape of landscape architecture is significant and plays an important role in improving the urban living environment. The ecological benefits produced by the plant cycle and energy exchange of plants combine to establish a sustainable ecological environment. The ecological benefits depend on the amount of green, which is directly proportional to the total leaf area of plants [11]. Therefore, in a limited urban green space, the creation of as many plant communities as possible, together with large-scale urban greening, is a necessary means of improving the ecological environment and developing a garden city. Hence, the landscape garden plays a key role in the improvement of the urban environment.

2.1.2 Economy of Landscape Plant Allocation

Urban construction consumes a great amount of human, material and financial resources. As one of the important links in urban construction, the urban landscape configuration should be based on the concept of "cost saving", This will save a lot of costs for urban construction, thus promoting the healthy development of urban construction. As the main element in the landscape construction of urban public is green space, the selection and configuration of plants are based on the principle of economical and economic construction. Firstly, attention should be paid to the local tree species to be included in the plant configuration [12]. This is because the native tree species are already well-adapted to the local environment, create a stable and lasting landscape, and are highly resistant to diseases and insect pests. Moreover, apart from the costs associated with the importation and transport of foreign tree species, local trees have a lower rate of mortality and require less maintenance. Second, plants should be used in place of lawn. From the perspective of long-term development and management of the landscape, the maintenance cost of lawn is high, and a large area of lawn is not conducive to sustainable ecological development. Therefore, in the design, land should not be planted with lawn, but should be configured with other plants to form a landscape, which not only saves the later management cost, but also offers greater ecological benefits. Third, plant allocation should be considered from the perspective of a long-term ecological landscape. The complex structure of the community landscape which includes trees, shrubs, vines, herbs, flowers and other plants is stable and long-term, which ensures the maximization of ecological benefits and the diversity of the ecosystem [13].

2.1.3 Meet the Demand for Sightseeing and Experience Activities

Finally, the design of a garden landscape is intended to serve people, and humanization has become the basic principle of design consideration. With the continuous development of landscapes, people's demands are becoming clearer. Appropriate landscape space can promote the communication and interaction between people and the environment, especially in public spaces such as landscape parks [14]. Nowadays, the landscape park has become the carrier space of the ecotourism boom. The design should meet people's desire for natural countryside and a better tourism experience. In particular, the plant landscape design should consider people's desire and sense of belonging in the landscape environment. Before design, we should first understand the requirements and needs of people's physiology, psychology, behavior and spirit, so as to make the design better realize humanistic care, analyze and design plant landscape with people as the first priority, and create positive feelings.

2.2 Plant Feature Extraction of Landscape Configuration

After the above principles of landscape plant configuration are determined, the characteristics of landscape plants need to be extracted to lay the foundation for subsequent plant configuration. In this paper, plant landscape features are obtained using the SIFT algorithm to ensure the effectiveness of plant feature extraction [15]. The features of green plants in landscape gardens can be obtained by Formula (1):

$$A(x, y) = \sum_{P} \sum_{n} [S_1(x, y)]/[S_2(x, y)]^2 \tag{1}$$

In the formula, $S_1(x, y)$ represents the plant feature extraction operator and P represents a fixed threshold.

For plant feature extraction, extract the characteristics of green plants and flowers in landscape gardens, namely:

$$\begin{aligned} E(x) &= e(v(t-1)) + e(t) \\ E(t) &= \varpi V_1(t) + \varpi V_2(t) + \varpi V_3(t) \end{aligned} \tag{2}$$

In formula, E represents the plant length, V_1 represents distance between plant planting, V_2 represents plant growth area, V_3 represents the actual plant planting area, and ϖ represents the characteristic parameters.

The digraph extracted from all green plant features is the key value reflecting the features, and its digraph reflects the proportion of key features of each feature [16]. The directional diagram of green plant characteristics is shown in Figure 1.

In general, the flower configuration in landscape architecture needs to be compact to reflect the suitability of flowers. Among them, the irregular planting area in landscape architecture is the to affect the garden plant configuration. When planting and designing flower landscapes, attention should be paid to the coordination between various elements to ensure that their configuration conforms to the aesthetic point of view. Generally, flowers are planted in clusters, he cluster shape index is set as H. The formula for calculating the cluster shape index is:

$$H_i = \frac{k_i}{\sqrt{B_i}} \tag{3}$$

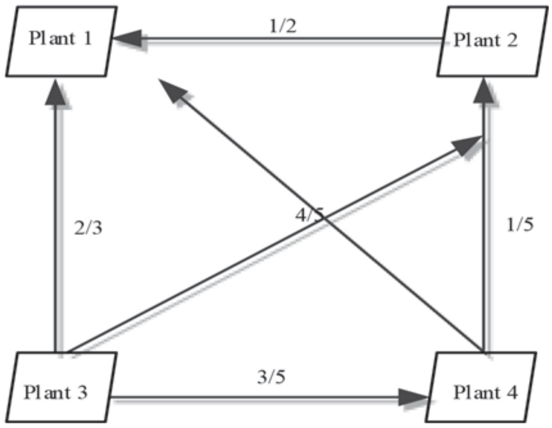

Figure 1 Directional diagram of green plant characteristics of landscape garden.

In formula, H_i represents the compactness of the cluster of flower type, k, B represents the circumference and area of flower planting, respectively.

The features of flowers can also be reflected through the surrounding environment [17]. The domain identity index is used to reflect it, namely:

$$U_k = \sum_{i=1}^{n} \sum_{j=1} \psi_i \cdot \gamma_i \tag{4}$$

In formula, ψ_i represents the unit γ_i of the flower planting land type.

The green plant feature in landscape garden plant configuration is extracted with the help of the SIFT algorithm, and the flower feature is determined using the cluster shape index. The plant feature extraction of landscape garden configuration is realized by combining the green plant and flower features, which provides data support for the following landscape garden plant configuration.

2.3 Color Quantification of Landscape Plants

Based on the feature extraction of landscape plants, the color of plants in plant configuration is also the key to successful landscape planning. Therefore, this section discusses the method of color quantification of landscape plants. For color quantization, the beauty evaluation method (SBE) is applied. SBE is a visual sensory evaluation method that is both simple and highly reliable. The evaluation result obtained by this method is determined by the two dimensions of the evaluator's aesthetic scale and the characteristics of the landscape itself. The SBE value is a comprehensive score generated by the interaction between the evaluator's landscape perception and the evaluation standard [18]. It is suitable for the visual evaluation of plant color, so the SBE beauty evaluation method is suitable. In order to intuitively express the relationship between the beauty value and various factors of plant landscape color, the beauty value is divided into five grades by the equal difference method. The five grades represent the best, good, average, poor and worst landscape qualities respectively. The scope of each equal diameter plant landscape is:

$$T_i = (d_{MAX} - d_{MIN})(q_i - 20\%) + d_{MIN}(d_{MAX} - d_{MIN})q_i + d_{MIN} \tag{5}$$

Among them, T_i represents grade, i is taken from one to five, q_i represents equality, d_{MAX} represents the maximum of plant landscape beauty, and d_{MM} represents the minimum of plant landscape beauty.

Based on the evaluation of plant landscape beauty, the HSB color model is used in this paper to express the color characteristics of the plant landscape. The color is divided into different combination forms, and the three color components are combined into one-dimensional feature vectors, namely:

$$Q = G \times p_s \times p_b + S(p_b + B) \tag{6}$$

In formula, p_s/p_b represents the quantization level of S and B, both levels are 6; therefore, the final expression is:

$$Q = 49G + 7S + B \tag{7}$$

In terms of weight, hue H is the main factor used to distinguish color features. Therefore, when choosing the quantitative index of color composition, we start from the hue property. The main indexes selected for this study are hue index, saturation index and lightness index.

The formula for calculating the plant hue index in landscape architecture is:

$$R_a = \sum_{a=1}^{n} (O_i + g_{ra}) \tag{8}$$

Specifically, O_i represents the i the color value, and g_{ra} represents the plant color comparison.

The calculation formula is:

$$R_b = \sum_{b=1}^{n} (h_i + g_{ri}) \tag{9}$$

where h_i represents the saturation value, and g_{ri} represents the saturation value ratio.

The calculation formula of plant color lightness index is:

$$R_c = \sum_{c=1}^{n} (v_i + r_{ci}) \tag{10}$$

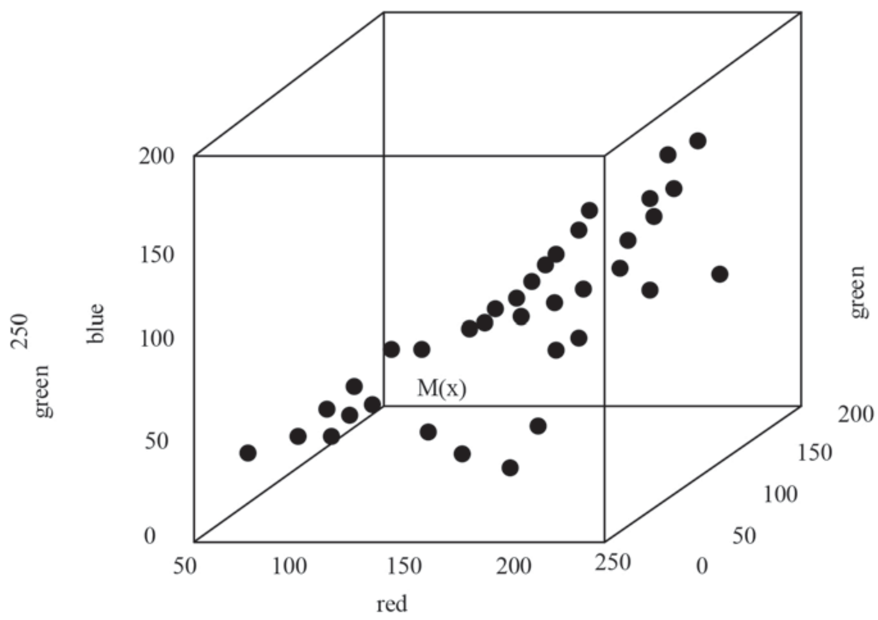

Figure 2 Spatial diagram of color distribution in landscape configuration.

Among them, v_i represents the plant color lightness index, and r_{ci} represents the plant color lightness value ratio.

The calculation formula of plant color uniformity is:

$$R_e = \frac{H_l}{\ln(S_l)} \tag{11}$$

Among them, H_l represents the color diversity index and S_l represents the total number of plant colors.

According to the above quantified color results for landscape plants, the analysis of color space is helpful to the plant configuration of landscape gardens [19]. The spatial diagram of color distribution in the landscape configuration is shown in Figure 2.

When quantifying the plant color in landscape architecture, the plant landscape color is divided using the SBE method, and the quantitative indexes of plant color are determined. These include: plant landscape hue index, color saturation, color lightness index and plant color uniformity.

3. THE IMPLEMENTATION OF LANDSCAPE PLANT CONFIGURATION BASED ON NEURAL NETWORK

The neural network is an important element of artificial intelligence, which uses digital technology to simulate the connection and function of human brain neurons. A neural network is a highly nonlinear processing system formed by the extensive interconnection of a large number of artificial processing units (neurons), which is suitable for simulating complex systems. In most cases, a neural network is an adaptive system that can change its internal structure on the basis of external information. A modern neural network is a nonlinear statistical data modeling tool. A typical neural network consists of three parts: 1) Structure: the structure specifies the variables in the network and their topological relationships. For example, the variables in the neural network can be the weights of neuron connections and the excitation values of neurons. 2) Excitation function: most neural network models have dynamic rules with a short time scale. To define how neurons change their excitation values according to the activities of other neurons. The general excitation function depends on the weight in the network (i.e., the parameters of the network) [20]. 3) Learning rules: learning rules specify how the weights in the network will be adjusted over time. This is generally regarded as a long-time scale dynamic rule. In general, the learning rules depend on the excitation value of neurons. The basic structure of a neural network is shown in Figure 3.

In this paper, a landscape configuration model is designed with the help of a neural network. In the model configuration, the pre-training data are determined first. The pre-training data are the extracted landscape plant characteristics and plant color quantitative data.

The first step of a neural network requires the pre-training of the data model on large datasets. Pre-training is divided into two processes: forward propagation and backward propagation. Assuming that the training set has class c and m training samples, a single training sample is represented as $(x^{(i)}, y^{(i)})$, where $x^{(i)}$ is the n-dimensional input sample and $y^{(i)}$ is the category where that sample is located.

z is a certain network layer, z layer has input $x^{(z-1)}$, output $x^{(z)}$, convolution kernel weight w^Z, and bias b^Z. Then the forward propagation process of the Z-layer has the following operations:

$$x^Z = f(u^Z)w^Z x^Z + b^Z \tag{12}$$

where $f()$ represents the activation function.

For a data set containing M samples, the final pre-training data set is:

$$Y(x, y) = \frac{1}{m}\left(\frac{1}{2}\left\|h_i(x^{(i)} - y^{(i)})\right\|^2\right) + \frac{\gamma}{2}\sum_{z=1}^{n}(w^Z s^Z) \tag{13}$$

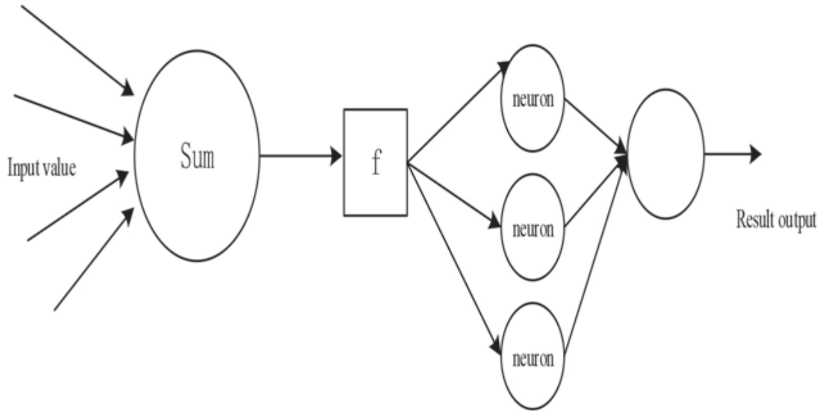

Figure 3 Schematic diagram of artificial neural network.

where γ represents the decay coefficient of the configured plant sample data, h_i represents the number of layers of the total neural network, and s^Z represents the number of neurons.

According to the sample data of the initial pre-trained plant configuration, the plant data in each layer of neurons are updated. The results of the pre-training data of the updated landscape plant configuration are:

$$w_{ij}^{(z)} = w_{ij}^{(z)} - \alpha \frac{\partial}{\partial w^z} u(a, b) \tag{14}$$

where α represents the learning rate of the neurons, and u represents the partial derivatives of the neural network.

Based on the pre-training data of the landscape plant configuration, with the help of a neural network, it is necessary to determine the loss function, which is related to the accuracy and rationality of landscape plant configuration. In the construction of loss function, using the MMD measurement, the overall mean of two different fields is calculated, and the mean difference is used to represent the distribution difference between the two fields. It is assumed that the active domain data and the target domain data are respectively:

$$A_s = [a_1^s, a_2^s, \ldots a_{ns}^s] \in R^{s \times ns} \tag{15}$$

$$A_t = [a_1^f, a_2^f, \ldots a_{nt}^f] \in R^{f \times nt} \tag{16}$$

The MMD is then defined as:

$$MMD^2 = \left\| \frac{1}{n_s} \sum_{i=1}^{n_s} \phi(a_i^s) - \frac{1}{n_t} \sum_{i=1}^{n_t} \phi(a_i^t) \right\|^2 \tag{17}$$

where ϕ represents the MMD matrix.

Then, with the help of AlexNet as the model architecture, five convolution layers and three fully connected layers are created. Set MMD is set to degrees.

The amount is embedded into the learning of deep convolution neural network to obtain the following loss function:

$$LOSS(x) = KL_i(a^s, y) + \gamma MMD^2(a^s, a^t) \tag{18}$$

where $L_i(a^s, y)$ represents the empirical error value of the neural network classifier in the source domain, and K represents the cross-entropy loss value.

Thirdly, the weight of plant configuration data in landscape plant configuration is calculated. In order to avoid negative migration, the source domain samples need to be screened first. Samples are selected by calculating the relative weight of source domain samples. According to the eigenvectors of training data and test data, the density of each sample can be estimated, and then the weight can be obtained:

$$W(x) = e_s(x)/e_t(x) \tag{19}$$

However, it is usually difficult to estimate the sample density, and the density ratio obtained by estimation is not accurate enough. Therefore, this paper proposes an algorithm to calculate the relative weight based on PE divergence. PE divergence is the square loss variable of KL divergence. Since KL divergence introduces a nonlinear log term, the emergence of PE divergence solves this problem. Its definition is:

$$PE = [P(X) \| Q(x)] \frac{1}{2} E_q(x) \left[\frac{p(x)}{q(x)} - 1 \right]^2 \tag{20}$$

where $E_q(x)$ represents the divergence introducing a nonlinear log term, and $\frac{p(x)}{q(x)}$ represents the squared loss variable.

After calculating the pretraining data weight of landscape plant configuration, the landscape plant configuration model is constructed with the help of a neural network. In neural networks, the fully-connected layers are tailored to their original tasks, so they cannot be directly migrated to the target domain through simple fine-tuning. The feature representation of fully-connected layers is constructed based on the feature representation of the convolution layer. Assuming that all discrimination information is captured in the convolution layer, but this assumption is not always correct. Occasionally, the convolution layer captures the differentiated information in the source domain, but in the target domain, the differentiated information is lost. The incomplete information in the convolution layer will be transferred to the fully-connected layer, and the latter has no mechanism with which to recover the information. In this case, the domain adaptation of the joint convolution layer will ensure better learning, fully-connected layer feature representation and more adequate minimization of the inter-domain difference. Therefore, it is very important to add the first convolution layer to the MMD measurement and jointly use the information from the

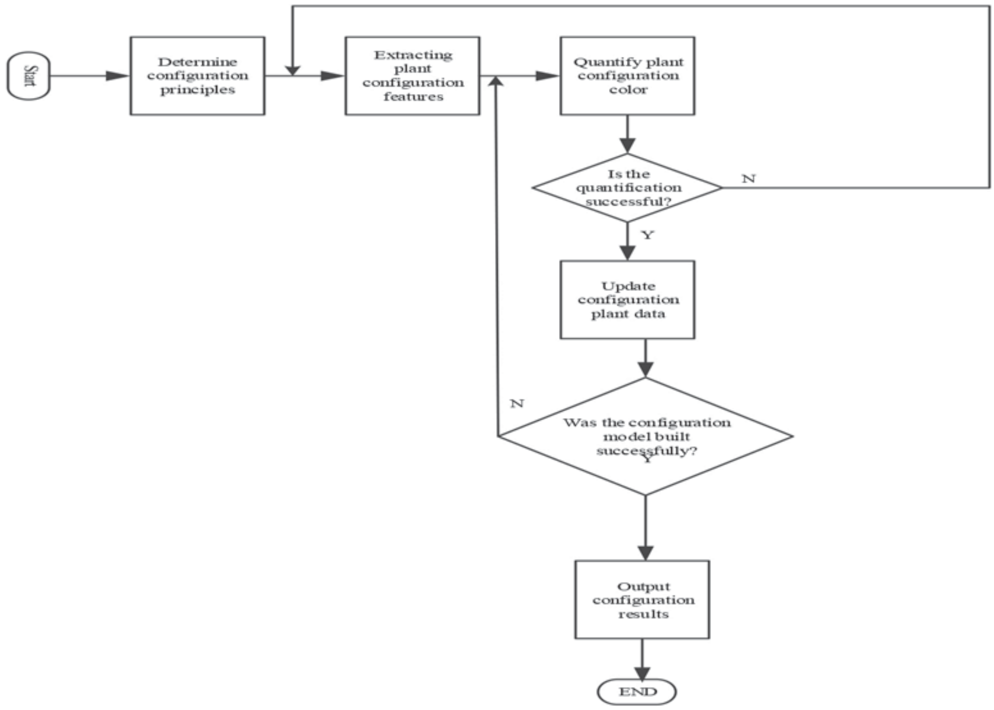

Figure 4 Configuration process of landscape plants.

first layer of the network. Therefore, the modification of the original MMD loss should be considered. This method involves adding the output characteristics of the first layer convolution layer and the last layer full connection layer to the MMD measurement to complete the joint adaptation of the full connection layer and the landing layer. The weight of the joint adaptation layer will be jointly trained by the source domain and the target domain to build a landscape plant configuration model, namely:

$$\vartheta = \min -\frac{1}{n_s}\sum_{i=1}^{n_t} D(a_i^s, y_i) + \gamma (MMD_{fc}^2(a^s, a^t) \qquad (21)$$

where D represents the penalty function, ϑ represents the configuration result output, and fc represents the projection matrix.

Due to the influence of various external factors in the landscape plant configuration, there is a certain deviation in the configuration results output by the landscape plant configuration model. Therefore, it is necessary to further correct the source domain and target domain and examine the distribution of their characteristics. After the last layer has been completely connected, the correction results are as follows:

$$\vartheta' = \frac{1}{n_s}\sum_{i=1}^{n_t} D(a_i^s, y_i) + \left\| s(MMD_{fc}^2(a^s, a^t)\right\|^2 \tau\xi \qquad (22)$$

where τ represents the deviation coefficient, ξ represents the feature matrix, and s represents the error threshold.

In the design of landscape plant configuration model, the plant data in each layer of neurons are updated by pre-training the landscape plant configuration data, and the loss function is determined by calculating the overall mean value of two different fields with the help of MMD measurement. On this basis, the landscape plant configuration model is constructed using a neural network, and the source domain and target domain are further corrected to achieve the configuration of landscape plants. This configuration is shown in Figure 4.

4. EXPERIMENTAL ANALYSIS

4.1 Experimental Scheme

In order to verify that the design configuration method in this paper can improve the rationality and effectiveness of landscape architecture configuration, experimental analysis was carried out. In the experiment, an area without plant configuration in a landscape garden in a certain location is taken as the research object. The area is a rectangular shape, about 100m long and 50m wide. At present, there is no detailed configuration. The current state of the area is shown in Figure 5.

The experimental parameters of the plant configuration in the specific experiment are shown in Table 1.

The landscape plant configuration is designed based on the landscape experiment parameters and experimental environment shown above. The selected plants and flowers are effectively configured according to appropriate color, terrain and other elements. The configuration process is shown in Figure 6.

The experimental results and data are analyzed according to the configured landscape plants. In the experiment, the data are analyzed by comparing the configuration method proposed in this paper, the configuration method in Reference [9] and the configuration method in Reference [10]. In the experiment, the rationality of plant configuration, the beauty of color

Figure 5 Sample diagram of the areas to be configured.

Table 1 Content table of the configuration parameters of landscape garden plants.

Parameter	Content
The area where the landscape garden is located	north
Garden terrain	Level the land
Specific elevation of the highest peak	15m
Maximum elevation difference	35m
Total area	500m^2
The overall direction of garden	From north to south
Land range shape	Rectangle
Aspect change	More obvious
Climate conditions	Summer is longer and winter is shorter, and the climate is humid and mild
Average annual temperature	16.2°C
Rainfall situation	Autumn and late summer are relatively dry; late summer and early spring rainfall is relatively abundant
Frost-free season	About 240 days
Red maple	Neutral, cold resistant
Green maple	Weak positive, half-shade resistant,
Acer trifidum	Weak positive tree
Magnolia grandiflora	Like light, strong negative resistance,
Osmanthus fragrans	Like warm wet, Strong high temperature resistance
Judas tree	Like light, like warm
Camellia; camellia japonica	Like half Yin, like wet

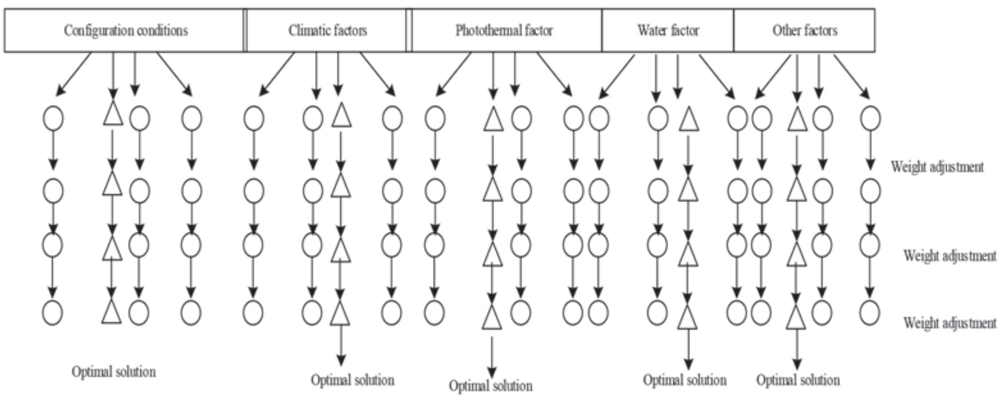

Figure 6 Sample landscape garden plant configuration process.

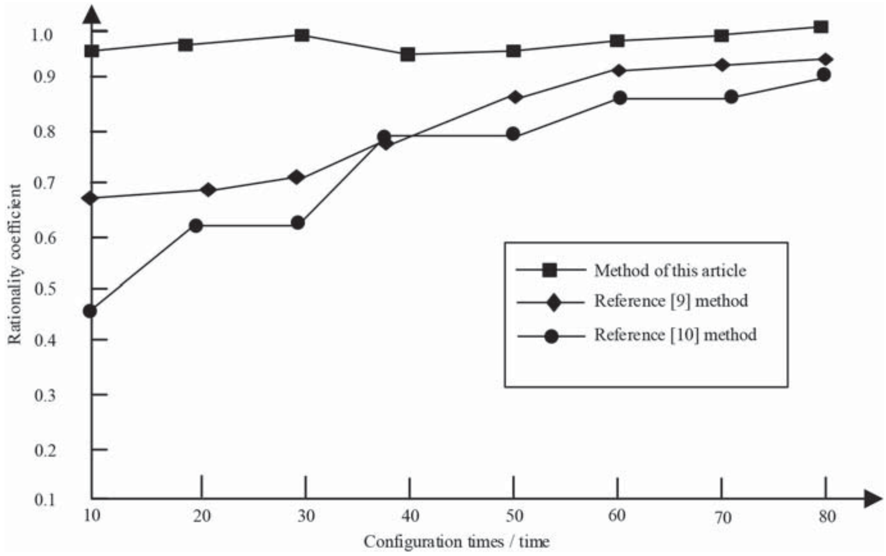

Figure 7 Rationality of different plants in landscape gardens.

matching and the survival rate after plant configuration are the experimental indicators, and the experimental results are analyzed.

4.2 Experimental Results

In the experiment, the rationality of the allocation of landscape plants in the sample area is reflected by the rationality coefficient by comparing the allocation method in this paper, the allocation method in Reference [9] and the allocation method in Reference [10]. Among them, the closer the rationality coefficient is to 1, the better the result of the allocation. The rationality of the experimental configuration is shown in Figure 7.

The experimental results shown in Figure 7 indicate that with the continuous change of configuration times, there is a certain gap in the rationality coefficient of landscape plant configuration in the sample area when using the configuration method proposed in this paper, the configuration method in Reference [9] and the configuration method in Reference [10]. For all three methods, the rationality coefficient of this method for landscape garden plant configuration in the sample area remains above 0.9. Although the configuration rationality of the other two methods shows an upward trend, it is always lower than that of the proposed method. This is also because this method considers the characteristics of configured plants in plant configuration and constructs a reasonable configuration model according to certain characteristics, demonstrating the effectiveness of the proposed method.

In the experiment, the color matching beauty of landscape plants in the sample area is analyzed by comparing the configuration method proposed in this paper, with those of Reference [9] and Reference [10]. The results are shown in Figure 8.

As shown in Figure 8, the color matching and beauty of landscape plants in the sample area are different by using the proposed configuration method, the configuration method suggested by Reference [9] and the configuration method used in Reference [10]. Among them, after the configuration obtained by the proposed method, the color of plants and flowers and other plants is reasonably matched, so that the beauty degree is always higher than 80%, while the color matching beauty degree of landscape plants in the sample area configured by the other two methods is lower, thereby indicating the superior performance of the proposed method.

In the landscape configuration, the survival rate of plants is another indication of the success of plant configuration. The infectious diseases are different according to the pathogenic organisms. The invasion of plant diseases and insect larvae can lead to fungal diseases, and such diseases and pests occur frequently. In the right climatic conditions, fungal spores sprout and invade the plant, causing the plant to have symptoms such as lodging, dead seedlings, spots, black fruits and so on. Therefore, this paper compares the survival rate of plants after the configuration of landscape plants in the sample area configured with the proposed method, the configuration method in Reference [9] and the configuration method in Reference [10]. The results are shown in Table 2.

The data in Table 2 indicates that the survival rate of plants configured by the three methods is different under different conditions. Among them, the survival rate of plants configured by the proposed method under different conditions is over 90% higher, while the survival rate of plants configured by the other two methods is far lower by comparison. This is because the proposed method considers the planting conditions and adapts measures to local conditions, which improves the survival rate of plants.

5. CONCLUSION

In this paper, a landscape plant configuration method based on neural network is designed to address the problem of poor rationality in landscape plant configuration designs. The SIFT algorithm is used to extract the characteristics of green plants in landscape plant configuration, and the characteristics

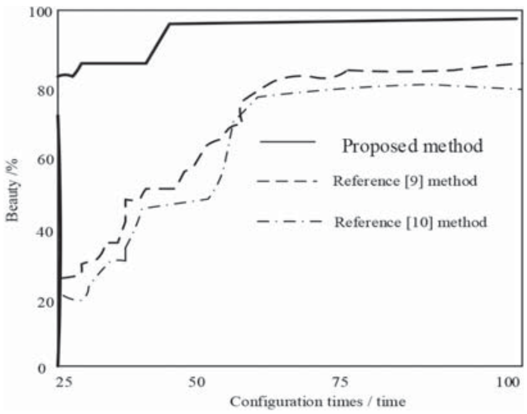

Figure 8 Aesthetic results produced by different methods.

Table 2 Survival rate of offline plants exposed to different diseases and pests (%).

Diseases and insect pests	Reference [9] Methods	Reference by [10] Methods	Proposed method
Aphid	85	67	95
Root knot nematode	84	82	97
Wire worm	90	86	98

of green plants and flowers are combined to extract the characteristics of plants in landscape plant configuration. The plant landscape color is divided by the SBE method, and the quantitative index of plant color is determined to complete the quantitative research on landscape plant color. With the help of MMD measurement, the loss function is determined by calculating the overall mean value of two different fields, the landscape plant configuration model is constructed with the help of neural network, and the source domain and target domain are further corrected to achieve the landscape plant configuration. The experimental results show that the proposed method can effectively improve the rationality of plant configuration and enhance the beauty of the landscape.

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