Retraction

Retracted: Sustainable Development Garden Landscape Design Based on Data Mining and Virtual Reality

Journal of Electrical and Computer Engineering

This article has been retracted by Hindawi following an investigation undertaken by the publisher [1].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) Manipulated or compromised peer review

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] Y. Bai, "Sustainable Development Garden Landscape Design Based on Data Mining and Virtual Reality," *Journal of Electrical and Computer Engineering*, vol. 2022, Article ID 3726801, 10 pages, 2022.

Hindawi

Research Article

Sustainable Development Garden Landscape Design Based on Data Mining and Virtual Reality

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At present, there is no obvious development of virtual reality technology in the garden industry. In order to improve the application of virtual reality technology in the sustainable development garden landscape design, this paper combines data mining technology and virtual reality technology to construct the sustainable development garden landscape design system. Moreover, this paper proposes a method of using the maximum likelihood method to solve the optimal hyperparameters of the covariance function and analyzes the elite-preserving genetic algorithm and the rough steps of its optimization. In addition, this paper analyzes the digital design process of garden landscape and improves the algorithm. Finally, on the basis of virtual reality technology and data mining technology, an intelligent and sustainable development garden landscape design system is constructed. The experimental analysis results show that the sustainable development garden landscape design system based on data mining and virtual reality proposed in this paper has a good effect.

1. Introduction

Users can truly understand the three-dimensional world around them by simply clicking the mouse at will. Through the application of virtual reality technology, people can see high-rise buildings, noisy cities, and beautiful night scenes online. In addition, through the three-dimensional network technology, we can also freely appreciate and manipulate commodities. For example, in the building display in the process of real estate development, we can arbitrarily shuttle in each room to achieve an immersive effect.

The emergence of virtual reality technology provides designers with a more intuitive and accurate means of expression, which can be modified in time. Virtual reality technology is immersive, interactive, and multiperceptive. Garden is a comprehensive discipline that studies spatial landscape design. It uses plants, water, stone, stainless steel, lighting, and other materials to absorb cultural, historical, and other humanistic content. Moreover, it combines a specific environment to create a colorful and different activity space, which requires a high degree of imagination and time and space, so virtual reality technology plays an important role in modern garden design.

Designers can enter a virtual room, examine the working conditions of each part and the interconnection between each part and understand the functional use process of the entire room, which is incomparable with TV video media and physical media. In addition, virtual technology can also break through the time limit. For example, some changes that take decades or even centuries to observe can be presented in a very short period of time through virtual reality technology. The pursuit of perfect space effect is the dream of architects and planners, and the simulated three-dimensional landscape just provides the real space experience that is difficult to provide by means of expressing drawings, models, and drawings. This provides a powerful technical inspection method for organizing regional space more subtly and enriching space effects.

2. Related Work

Reference [1] carried out preliminary research work on the simulation of group photosynthesis in garden landscapes, which laid a research foundation for the development of this field in the future. Reference [2] proposed a formal modeling language called L-System (L-System). Later, he continued to

develop and perfect the modeling language based on the L-system. Literature [3] described the physiological dynamic characteristics driven by the structure and function of plants in an intuitive and regular form. After entering the 1980s, the level of computer software and hardware technology has been further improved and developed, and the theory of graphics and image technology has been further improved and matured. The application of computer as an advanced modeling tool for three-dimensional visualization of plant growth process has attracted more and more attention of researchers and has developed into a classic discipline in the field of computer graphics. It has been paid more and more attention by researchers and developed into a classic subject in the field of computer graphics. During this process, some researchers in developed countries have done a lot of research work in the field of computer simulation of crop growth, and the results have been widely used. Reference [4] developed the AMAP system based on the reference axis technology. The AMAP system comprehensively adopts the qualitative knowledge of plant construction, and the system has carried out a quantitative mathematical description of the function of plant buds. The software for simulating plant growth mainly consists of two core technologies: the first part is how to express the topological structure of plants, which mainly includes the geometric information of the positioning of plant organs in space, the growth principles and characteristics of plants, and the influence of external environment on plant growth, influence, competition, and mutual benefit mechanism between plants and plants, and the impact on the growth of plant communities; the second part is the modeling of various plant organ morphology (such as roots, stems, leaves, flowers and fruits, etc.); they are the smallest building blocks for virtual plant growth modeling and are also the premise and basis for the first part [5]. It is worth mentioning that the AMAPhydro system [6] introduces a plant hydrodynamic model, which can determine the proportion of dry matter distributed in organs according to the water content obtained by plant organs. Literature [7] established the GOSSYM software about garden landscape, and developed the CottonPlus management system about garden landscape on this basis. Reference [8] developed VirtualPlants software, the main research direction is the growth process of garden landscape and the impact of pests and diseases on crop growth. Up to now, the commonly used tools in the world are mainly based on the modeling platform L-Studio in the form of L-System and use the L + C modeling language to build 3D models of plants [9]. Another extensive platform based on the XL language is the GroIMP (Growth Grammar-related Interactive Modelling Platform). Reference [10] models fractal trees from the perspective of spatial reproduction, thereby realizing the reconstruction of the 3D model of the tree canopy. Reference [11] proposes a new algorithm for extracting plant skeletons from point cloud data, thereby realizing the rapid reconstruction of plant skeletons; Reference [12] realizes automatic 3D reconstruction of plant individuals and groups based on point cloud data. The reconstruction speed is fast, and there is no manual interaction. This method does not need to go through conventional single tree segmentation. In the realization of perennial trees in terms of 3D reconstruction work, literature [13] developed a semiautomatic tree skeleton adjustment tool PypeTree. In recent years, the use of physical models to simulate the deformation and motion of plant 3D models has also attracted the attention and interest of some researchers. However, in these studies, researchers often simulate and create plants from a larger perspective, and there is no relevant report on the research and achievements of plants in some subtle movements [14].

In the virtual experiment environment, designers can safely do various experiments that are dangerous or endanger the human body. For example, the virtual house construction experiment can avoid the dangers caused by the house construction process; the virtual interior and exterior decoration can avoid the loss of materials caused by the designers' poor consideration in the design process [15].

3. 3D Digital Technology Based on Data Mining and Virtual Simulation

The process of optimizing landscape garden design parameters using GPR response surface method can be roughly divided into three parts: experimental design, modeling, and optimization. To realize the digital design of sustainable gardens in this paper, the basic theories used for model building and optimization are briefly introduced, including Gaussian process regression, hyperparameter optimization, the principle of response surface method, and the related theory of elite retention genetic algorithm.

Gaussian process regression is a machine learning regression algorithm developed on the basis of statistical theory. Machine learning takes artificial intelligence as the core and includes multidomain knowledge such as probability and statistics, complex algorithms, and approximate theory and uses computers to simulate the science of human learning behavior. Supervised learning refers to learning the functional relationship between input and output in a given training set, so that when a new input value is given, a new output value can be obtained according to the learning result. The data set of unsupervised learning has no labels and no training process. Clustering is performed according to the similarity between samples, the hidden information in the data is extracted, and the characteristics of the data set are analyzed. Reinforcement learning also uses unlabeled data sets, but it can receive feedback on behavior from the environment, continuously obtain learning information, and then continuously update model parameters. Among the three machine learning methods, supervised learning is the most commonly used learning method. According to the type of output value in the supervised learning data set, it can be divided into classification and regression. The output value of regression is continuous data.

Usually, the essence of a regression problem is to choose an appropriate mathematical model based on the training set $D = \{(x_i, y_l)|i = 1, 2, \ldots, n\} = (X, y)$. Through a suitable optimization algorithm, it learns the functional relationship f from the input x to the continuous output Y, so as to predict any new input point and the corresponding output. The general model for a regression problem is as follows [16]:

$$y = f(x) + \varepsilon. \tag{1}$$

Among them, X is the input vector, Y is the observed value, $f(x)$ is the value of the function sought with respect to x, and ε is the regression residual.

Gaussian process is the basis of Gaussian process regression, so it is necessary to explain the principle of Gaussian process, as follows:

$$\begin{cases} m(x) = E[f(x)], \\ k(x, x') = E[(f(x) - m(x))(f(x') - m(x'))]. \end{cases} \tag{2}$$

Among them, x, x' represents an arbitrary variable, and the Gaussian process can be expressed as

$$f(x) \sim gp(m(x), k(x, x')). \tag{3}$$

Usually, in order to facilitate the calculation and make the expression more concise, the data is preprocessed, and the mean function $m(x)$ of the Gaussian process is set to zero. In practice, real experimental data will be affected by noise $y = f(x) + \varepsilon$. We assume that the variance of the noise ε is σ^2, which is $\varepsilon \sim N(0, \sigma_n^2)$. Then, the covariance function of the observations is

$$y \sim N\big(0, k(X, x') + \sigma_n^2 I\big). \tag{4}$$

By definition, the joint distribution of any finite random variable in a Gaussian process obeys a Gaussian distribution, so the joint prior distribution of the training output value Y and the predicted output f' is as follows [17]:

$$\begin{bmatrix} y \\ f' \end{bmatrix} \sim N\left(0, \begin{bmatrix} K(X, X) + \sigma_n^2 I & K(X, X^*) \\ K(X^*, X) & K(X^*, X^*) \end{bmatrix} \right). \tag{5}$$

Among them,

$$K(X, X) = \begin{bmatrix} k(X_1, X_1) & k(X_1, X_2) & \cdots & k(X_1, X_n) \\ k(X_2, X_1) & k(X_2, X_2) & \cdots & k(X_2, X_n) \\ \vdots & \vdots & \ddots & \vdots \\ k(X_n, X_1) & k(X_n, X_2) & \cdots & k(X_n, X_n) \end{bmatrix}, \tag{6}$$

$$K(X^*, X) = [k(X^*, X_1) k(X^*, X_2) \cdots k(X^*, X_n)],$$

where $K(X, X)$ is the input covariance matrix, and it is a symmetric positive definite matrix. The element $k(X_i, X_j)$ in the matrix is the correlation between X_i and X_j, and $k(X^*, X) = k(X, X^*)^T$. In order to make the form more concise, the symbol of formula (5) is abbreviated as follows:

$$\begin{bmatrix} y \\ f^* \end{bmatrix} = \begin{bmatrix} K + \sigma_n^2 I & K^* \\ K^* & K^{**} \end{bmatrix}. \tag{7}$$

According to the conditional probability formula, the posterior distribution of the predicted value f_* is further deduced as

$$f^* | y, X, X^* \sim N\big(\overline{f}^*, \mathrm{cov}(f^*)\big). \tag{8}$$

Among them, the mean is

$$\overline{f}^* = K^* \big(K + \sigma_n^2 I\big)^{-1} y. \tag{9}$$

The covariance is

$$\mathrm{cov}(f^*) = K^{**} - K^* \big(K = \sigma_n^2 I\big)^{-1} K^*, \tag{10}$$

where $\overline{f}^*$ and $\mathrm{cov}(f^*)$ are the mean and variance of the observed values predicted from the input test data X^*.

Compared with other regression methods, Gaussian process regression can not only give the predicted value but also estimate the confidence interval of the predicted value according to the variance, so its output is more probabilistic. For a new input value X^*, the confidence interval for $1 - \alpha$ of its predicted mean $\overline{f}^*$ is

$$\lceil \overline{f}^* - Z_{1-\alpha/2} \sqrt{\mathrm{cov}(f^*)}, \overline{f}^* + Z_{1-\alpha/2} \sqrt{\mathrm{cov}(f^*)} \rceil. \tag{11}$$

Among them, $Z_{1-\alpha/2}$ is the $1 - \alpha/2$-quantile of the standard normal distribution.

In the interval close to the data set, the correlation is stronger, and in the interval far from the data set, the correlation is weakened. These functions can be combined to form more complex functions to deal with corresponding problems, so there is great flexibility in the choice of covariance functions. This paper chooses the squared exponential covariance function, and the form is as follows:

$$k(x, x') = \sigma_f^2 \exp\left[-\frac{1}{2}(x, x')^T M^{-1}(X - X')\right]. \tag{12}$$

Among them, σ_f^2 is the signal variance, M is a diagonal matrix consisting of the quadratic power of the feature length scale parameter l, and $M = \mathrm{diag}(l^2)$. The set $\theta = \{\sigma_n^2, \sigma_f^2, l\}$ of unknown parameters in the covariance function is called the hyperparameters of the model.

In the learning and optimization process of the Gaussian process regression model, after the covariance function is determined, it is necessary to determine the hyperparameters according to the specific training data. Hyperparameters have an important impact on how well a model predicts. In the modeling process, the process of training data with the Gaussian process regression algorithm is the process of determining the hyperparameters. Hyperparameter optimization for Gaussian process regression can use maximum likelihood estimation (MLE). The specific derivation method is as follows:

If it is assumed that the training sample input is X, the output value is Y, and the vector composed of hyperparameters is θ, the full probability formula in Bayesian theory can be obtained:

$$p(\theta | y, X) = \frac{P(y | X, \theta) P(\theta)}{P(y | X)}. \tag{13}$$

Among them, $P(y | X) = \sum p(y | X, \theta_i) p(\theta_i), i = 1, 2, 3 \ldots, n$, $p(y | X, \theta)$ is the edge likelihood function. To obtain the above hyperparameters, it is necessary to establish the negative log-likelihood function of the conditional probability of the training samples, and take the negative logarithm of $P(y | X, \theta)$, namely,

$$L(\theta) = -\log\left(p\left(y|X, \theta_i\right)\right)\frac{1}{2}y^T\left(K = \sigma_n^2 I\right)^{-1}y$$

$$+ \frac{1}{2}\log\left|K + \sigma_n^2 I\right| + \frac{n}{2}\log 2\,\pi. \tag{14}$$

The partial derivative of the hyperparameter θ is calculated for the negative log-likelihood function $L(\theta)$, and then the partial derivative is minimized by the conjugate gradient method, and then the optimal solution of the hyperparameter is obtained.

The response surface method usually includes a factor screening stage, a region finding stage and an optimization stage. The optimization stage can also be divided into experimental design, model fitting, and parameter optimization.

The selection of factors that affect the response variable and the determination of the level are all part of the response surface method. The selection of factors often needs to be combined with specific circumstances. In practical problems, there are often multiple factors that affect the response variable. Considering the cost and efficiency of the experiment, factor screening experiments can be used to screen factors. After the factor is determined, the level of the factor needs to be determined according to the value range of the factor. The common ones are 2-level, 3-level, and 4-level, and the determination of the level needs to be combined with the specific experimental design method.

When the selected experimental area is far from the optimal area, there is an approximate linear relationship between the response variables and the influencing factors. A first-order linear model is fitted by designing a Plackett–Burman experiment:

$$y = \beta_0 + \sum_{i=1}^{k}\beta_i x_i + \varepsilon. \tag{15}$$

Starting from the center point of the experiment, we choose a certain step size and arrange the experiment in the direction of the fastest ascending (or descending), until a certain test point, and the response value no longer produces significant improvement. Then, the center point needs to be used as the new experimental center point, and the above experiment is repeated. In the process of designing the experiment, it is also necessary to add the center point experiment to check the curvature of the function. If the test results show that the function curvature is significant, a second-order regression model needs to be fitted. At this time, it can be considered that the experimental area is close to the optimal area, and the next stage can be entered.

The experimental design selects the appropriate design method according to the selected influencing factors, designs the experiments in the optimal experimental area, determines the order of the experiments and the combination of the influencing factors, and obtains the experimental results. Commonly used response surface method experimental design methods include central composite designs (CCDs) and Box–Behnken design (BBD), which can be selected
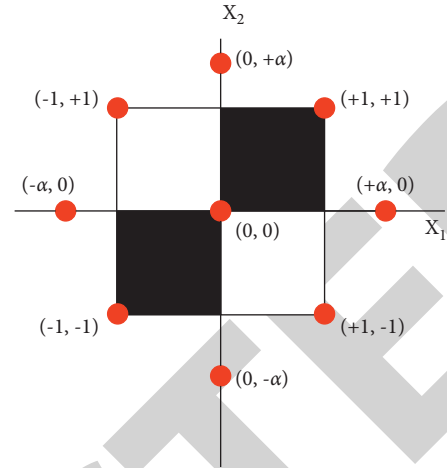

Figure 1: Center composite design with $k = 2$.

according to specific needs. Central composite design is a more commonly used second-order experimental design method in the response surface method. A central composite design consists of 2^k full factorial designs or 2^{k-p} fractional factorial designs, and $2k$ axis points added, consisting of $(\pm\alpha, 0, 0\ldots, 0), (0, \pm\alpha, 0\ldots, 0), \ldots, (0, 0, 0, \ldots, \pm\alpha)$ and n_c center points $(0, 0, 0, \ldots, 0)$. Figure 1 shows the center composite design with $k = 2$.

According to the designed experiment, after arranging the experiment near the optimal area and obtaining the experimental data, it is necessary to fit the second-order model of the response variables and influencing factors:

$$y = \beta_0 + \sum_{i=1}^{k}\beta_i x_i + \sum_{i=1}^{k}\beta_{ii}x_i^2 \sum_{i<j}^{k}\beta_{ij}x_i x_j + \varepsilon. \tag{16}$$

According to the results of model fitting, analysis of variance (ANOVA) was used to evaluate the accuracy of model fitting and the importance of regression coefficients. Through optimization methods such as graphical method or analytical method, the optimal combination of process parameters and the corresponding optimal response variable value are found.

The most basic principle of genetic algorithm is to simulate the process of biological evolution in the natural environment, and the resulting optimization algorithm. The genetic algorithm that uses only three genetic operators of crossover, mutation, and selection is called standard genetic algorithm (SGA). Research has proved that SGA is not globally convergent. The reason is that there is a selection error in SGA, which causes the elite individuals of the current population to be lost in the next generation population. This phenomenon occurs over and over again as the number of iterations increases. Aiming at the problem of slow convergence caused by the loss of elite individuals, an elite retention strategy is proposed. This strategy saves the best individual (H0 with the highest fitness value of 1) that appears during the evolution of the population and is copied to the next generation with a probability of 1. The above algorithm with elite retention strategy is called elite retention genetic algorithm (EGA). Compared with the standard
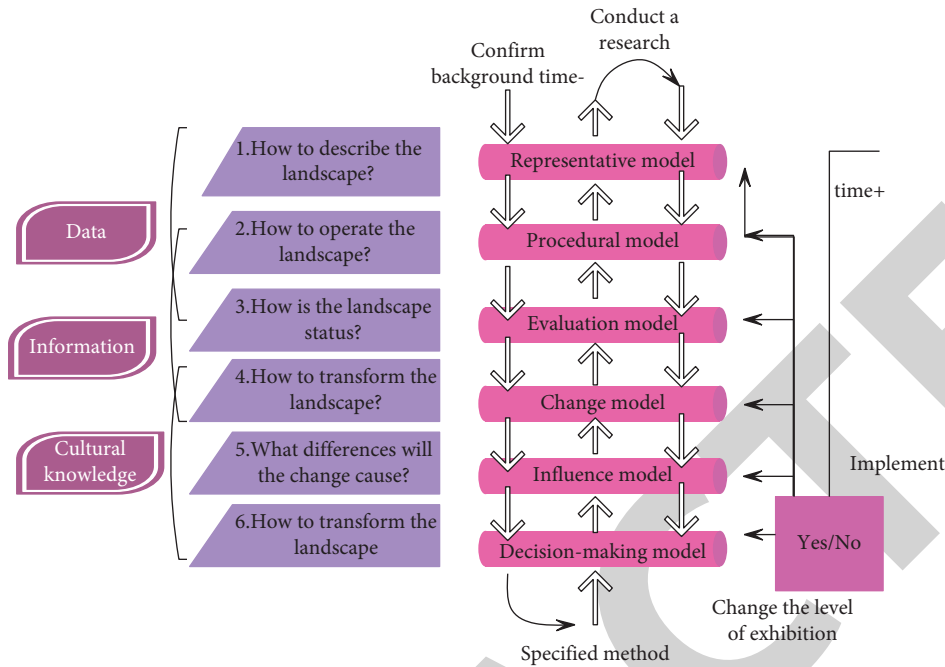
Figure 2: Landscape design model.

genetic algorithm, EGA avoids the loss of elite individuals of the population in the next generation due to the randomness of genetic operations, and ensures the global convergence of the algorithm. The general steps of using the elite-reserving genetic algorithm for optimization are as follows:

(1) The algorithm sets parameters. The algorithm creates region descriptors, define decision variable information, discreteness, etc. The algorithm sets the chromosome code, the chromosome length, and the genetic algorithm parameters: the number of individuals in the population m, the maximum genetic generation, etc.

(2) The algorithm forms the initial population. The algorithm generates random initial population spells within the defined domain of decision variables.

(3) The algorithm calculates the objective function value. The algorithm calculates the objective function value corresponding to a certain population according to the problem to be solved.

(4) The algorithm retains elite individuals. The algorithm assigns the fitness value according to the size of the objective function and retains the elite individuals with good fitness.

(5) The algorithm performs genetic operations. The algorithm performs genetic operations (selection, crossover, recombination, and mutation) on the parent individual Z to generate the offspring population E and calculate its fitness value.

(6) The algorithm merges the parent elite and the child population, removes the worst individuals in the new population, restores the original population size, and obtains a new generation of population.

(7) The algorithm reaches the maximum genetic algebra, terminates the iteration, and outputs elite individuals; otherwise, the algorithm returns to step 4.

4. Sustainable Garden Landscape Design Based on Data Mining and Virtual Reality

The sustainable development garden landscape design model based on data mining and virtual reality technology is shown in Figure 2.

According to the time axis, the process of sustainable development landscape design can be divided into the preliminary survey and investigation stage of the plan, the initial stage of method design, the plan reporting stage to the plan deepening stage, the plan construction stage, and the project completion and use to the maintenance stage. Among them, each stage can be subdivided into different steps, as shown in Figure 3.

It is presented in the form of interactive visualization and can carry out parameterized input and output, as shown in Figure 4.

The construction object is responsible for the input of each polygon area and related parameters and applying the construction rules to form a 3D geometric description synthetic model, as shown in Figure 5. Construction objects may be responsible for one or more land use types, especially those that resemble 3D forms. For example, constructed architectural styles include buildings and wall areas to be registered for processing.

This research will use ESRI's 3D visualization software ArcScence9.3 as the support to visualize various landscape elements in the ecotourism area in 3D. Moreover, this paper analyzes the distribution and coupling degree of landscape
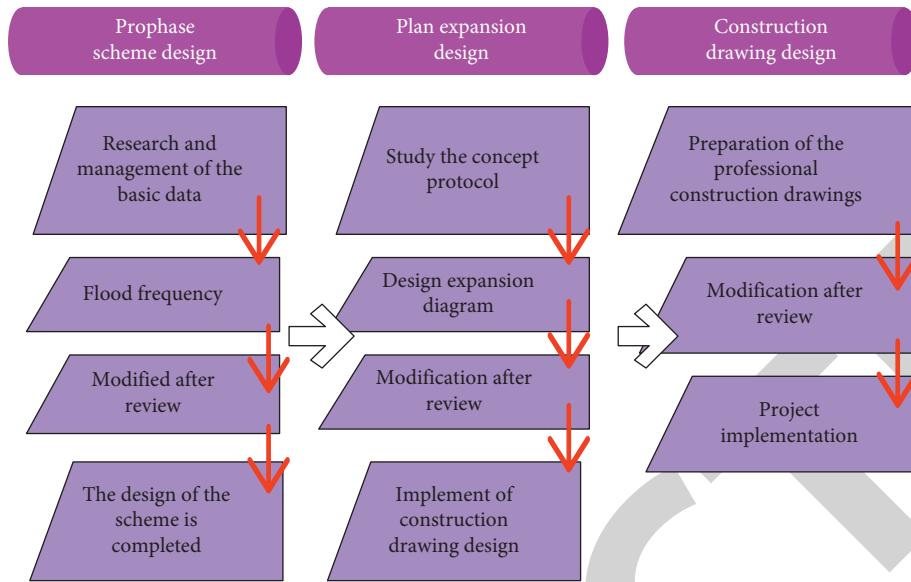
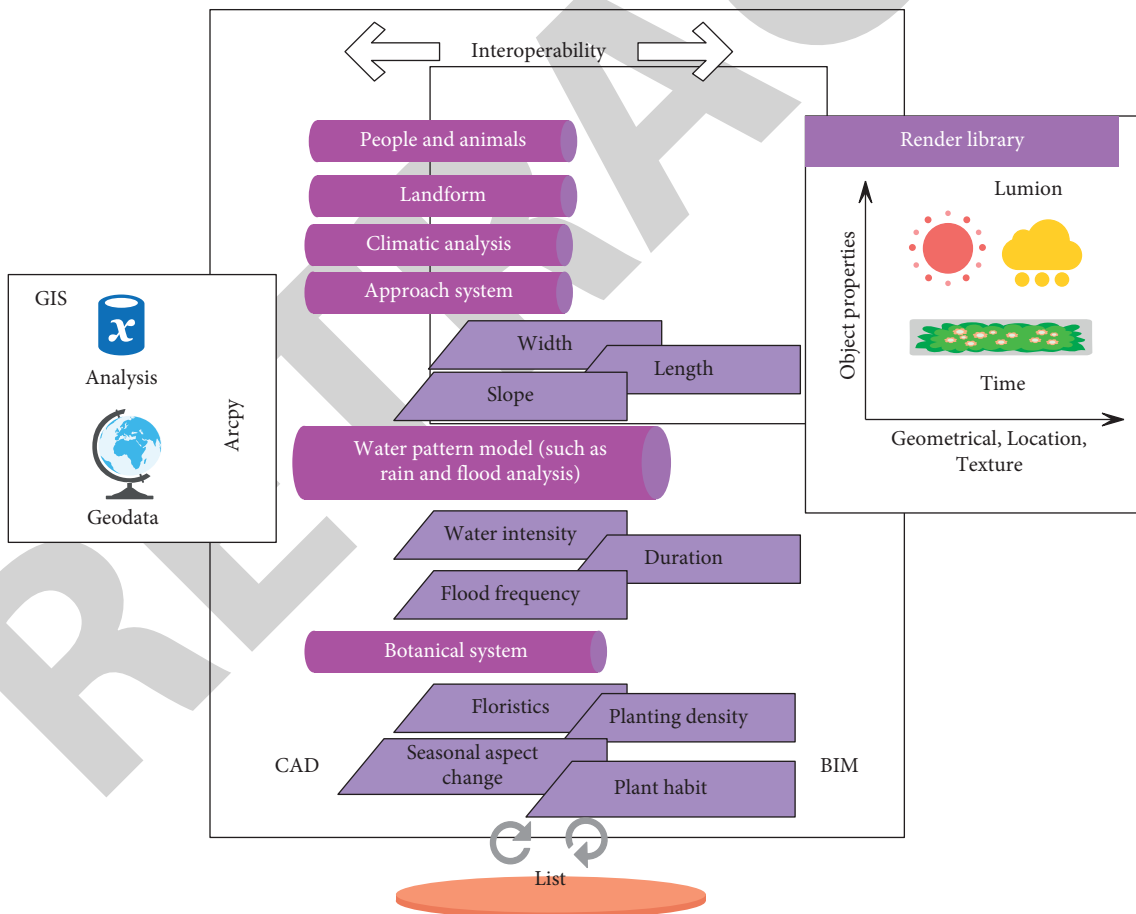FIGURE 3: Design process of sustainable development garden landscape scheme.

FIGURE 4: Landscape information model architecture.

pattern, which is used as the basis for the division of landscape patches in ecotourism areas and the functional orientation and zoning of ecotourism areas. The landscape visualization is shown in Figure 6.

The production process of the digital virtual garden system proposed in this paper is characterized by multi-process, and the start of subsequent work is directly affected by the completion of the previous process. The basis of
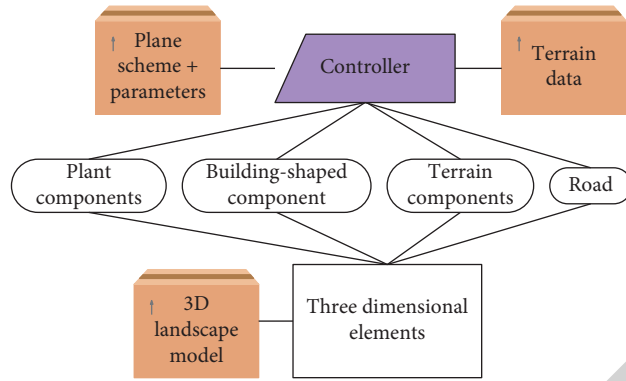
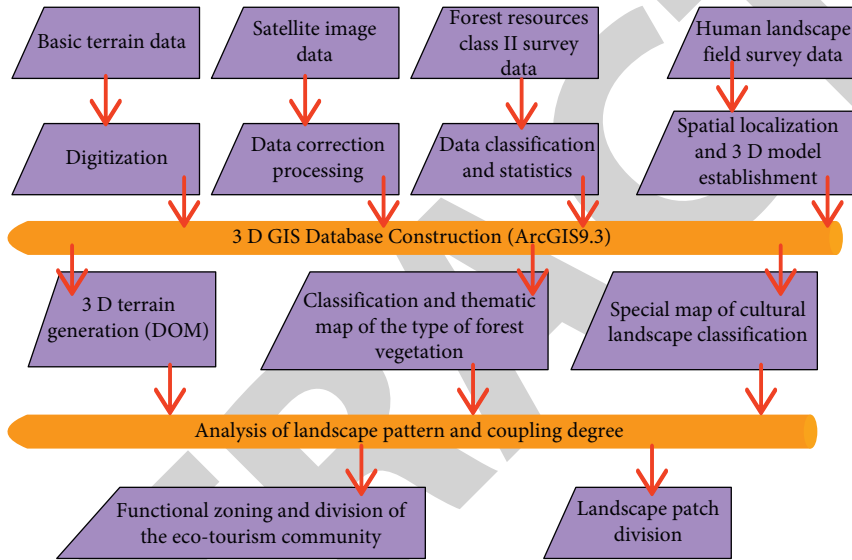Figure 5: Overview of the parameter structure system.

Figure 6: Visualization of sustainable development garden landscape.
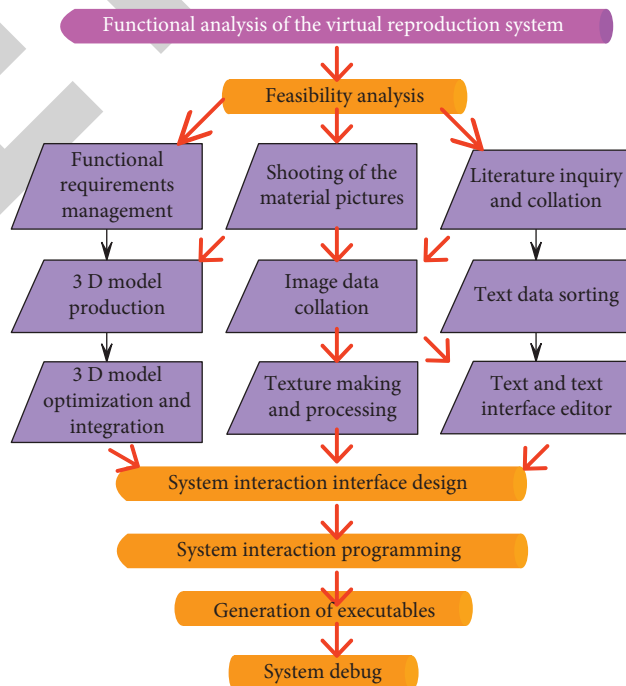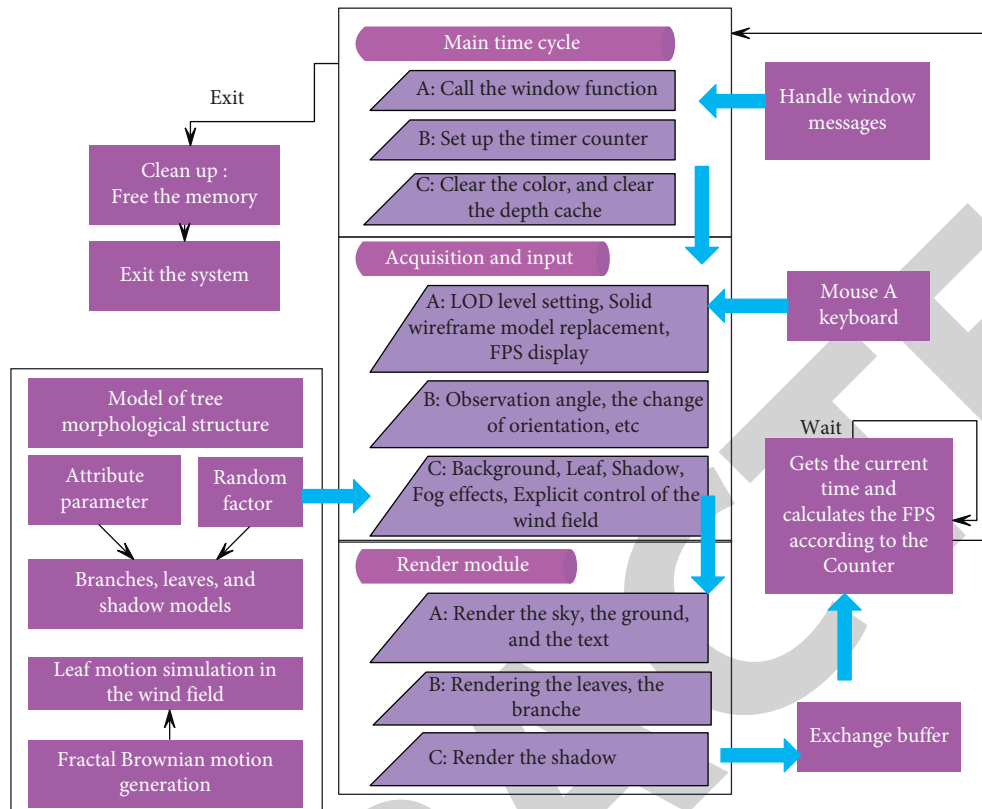

Figure 7: Development flow chart.

FIGURE 8: Implementation process of virtual tree demonstration system.

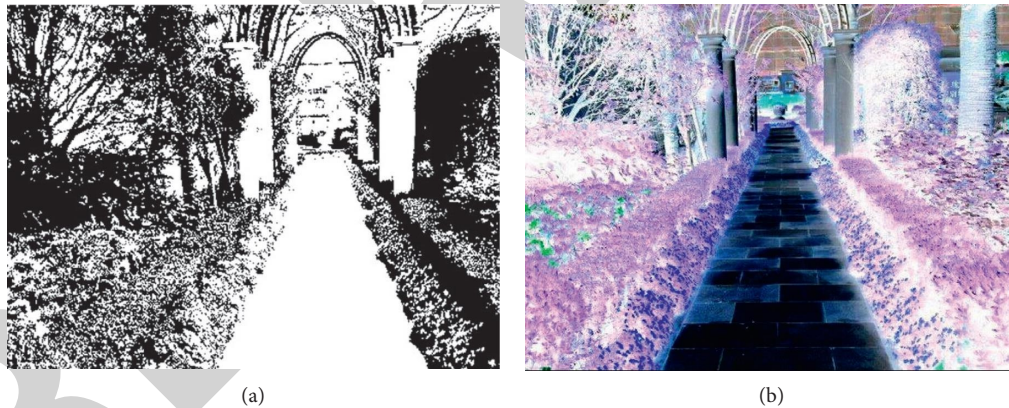(a)   (b)

FIGURE 9: Examples of sustainable development garden landscape design. (a) Sketches of sustainable landscape gardens. (b) Color rendering of sustainable development garden landscape.

subsequent system development in this project is literature query and arrangement, material picture shooting, and 3D model building. The shooting and sorting of material pictures and documents should precede the establishment of 3D models, but some 3D models can be built in parallel with subsequent work such as texture production and processing. For this reason, we use a combination of parallel and serial methods in the production process. The development process (Figure 7) is as follows.

The tree morphological structure module and the rendering module are important components of this system. The former completes the simulation of the basic

morphological structure of 3D trees based on the hierarchical branch model, and the latter completes the visualization of the 3D scene. The system implementation process is shown in Figure 8.

This paper combines data mining technology and virtual reality technology to innovate the elements of sustainable development garden landscape and perform virtual display. On the basis of constructing the above system, this paper conducts simulation research on the sustainable development garden landscape design system based on data mining and virtual reality and obtains the results shown in Figure 9 below.

Table 1: Simulation effect of sustainable development garden landscape design system based on data mining and virtual reality.

Number	Simulation effect	Number	Simulation effect
1	95.77	21	95.24
2	94.07	22	96.02
3	94.14	23	93.42
4	96.89	24	95.23
5	96.48	25	97.87
6	97.11	26	94.33
7	94.86	27	96.00
8	95.73	28	94.32
9	95.76	29	94.94
10	93.87	30	95.77
11	97.72	31	97.23
12	94.17	32	93.30
13	95.89	33	96.32
14	96.19	34	93.10
15	95.99	35	95.18
16	94.51	36	95.88
17	97.45	37	97.77
18	96.08	38	93.77
19	97.10	39	97.44
20	95.71	40	94.27

Table 2: Design innovation evaluation of sustainable development garden landscape design system based on data mining and virtual reality.

Number	Design innovation evaluation	Number	Design innovation evaluation
1	88.05	21	90.83
2	90.18	22	89.64
3	88.87	23	88.08
4	89.96	24	88.42
5	87.73	25	90.60
6	92.93	26	91.42
7	89.56	27	92.40
8	90.10	28	92.84
9	91.15	29	88.91
10	92.71	30	92.80
11	89.83	31	91.40
12	88.72	32	90.16
13	88.99	33	88.26
14	89.93	34	87.58
15	90.48	35	90.93
16	91.92	36	92.20
17	92.79	37	88.96
18	91.71	38	90.93
19	91.32	39	90.40
20	87.22	40	89.50

The effect evaluation of the sustainable development garden landscape design system based on data mining and virtual reality is carried out, the simulation effect of the sustainable development garden and the evaluation of the innovation effect of the garden landscape design are analyzed, and the results shown in the following Tables 1 and 2 are obtained.

Based on the above analysis, it can be seen that the sustainable development garden landscape design system based on data mining and virtual reality proposed in this paper has good results.

5. Conclusion

In the sustainable development of garden art design, some designs that should be made cannot be carried out due to reasons such as equipment, venues, and funds. The use of virtual reality systems can make up for these deficiencies. The VR system is a large-scale integrated environment composed of subsystems of considerable scale with different functions and levels, including computer graphics, image processing and pattern recognition, intelligent interface technology, artificial intelligence technology, multisensor technology, voice processing and audio-visual technology, network technology, parallel processing technology, and high-performance computer system, and is a highly comprehensive high-tech information technology. This paper constructs a sustainable development garden landscape design system based on data mining and virtual reality. It can be seen from the results that the sustainable development garden landscape design system based on data mining and virtual reality proposed in this paper has a good effect.

Data Availability

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

Conflicts of Interest

The author declares no conflicts of interest.

Acknowledgments

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