Retraction

Retracted: Wavelet Transform-Based 3D Landscape Design and Optimization for Digital Cities

International Journal of Antennas and Propagation

This article has been retracted by Hindawi following an investigation undertaken by the publisher [1].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

(1) Discrepancies in scope

(2) Discrepancies in the description of the research reported

(3) Discrepancies between the availability of data and the research described

(4) Inappropriate citations

(5) Incoherent, meaningless and/or irrelevant content included in the article

(6) Peer-review manipulation

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

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

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

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

References

[1] Y. Chen, X. Wang, and C. Zhang, "Wavelet Transform-Based 3D Landscape Design and Optimization for Digital Cities," *International Journal of Antennas and Propagation*, vol. 2022, Article ID 1184198, 10 pages, 2022.

Research Article

Wavelet Transform-Based 3D Landscape Design and Optimization for Digital Cities

Yang Chen , **Xiaolin Wang** , **and Chang Zhang**

College of Art and Design, Hunan First Normal University, Changsha 410000, China

Correspondence should be addressed to Xiaolin Wang; wxl@hnfnu.edu.cn

As a hot concept, the digital city has developed rapidly in recent years. The digital city uses information technology to realize all the contents of the past, present, and future of the city on the network, and can build a three-dimensional visual landscape. However, the traditional information fusion model has the problems of noise susceptibility and low efficiency in landscape design. In order to solve the above problems, this article proposes a wavelet transform-based 3D landscape design and optimization method for digital cities, which removes the noise influenced by wavelet change and builds an information fusion model based on neural network to complete the design optimization of the three-dimensional landscape of the digital city. Firstly, for the wavelet change denoising problem, an effective denoising algorithm for natural noise and abnormal noise is proposed by combining convolutional neural network and wavelet transform. The algorithm extracts mixed feature information of local long path and local short path based on the information retention module, and decomposes the information by combining wavelet transform, inputs the different components obtained from the decomposition into the network for training, and removes the noise by subsequent feature screening of the network structure. Then, aiming at the optimization of 3D landscape design, an information fusion model based on long-short time memory network and radial basis backpropagation network is proposed for fusing multiple sources of information in the digital city to evaluate the landscape. The method collects digital city feature information at the information layer and preprocesses the feature information by a rate detection algorithm. Then, LSTM and RBF-BP neural networks in deep learning are used in the feature layer for adaptive learning of multiple feature signals, and finally, fuzzy logic is used to control the system decision output to improve the efficiency of 3D landscape design. Finally, the simulation experimental results show that the proposed denoising method in this article can better retain the texture details in the images and the denoised images have better visual effects; the proposed information fusion model has higher accuracy compared with the traditional methods. Combining this method to design and optimize 3D landscapes in digital cities can improve the efficiency of landscape design.

1. Introduction

Digital city is the derivative content of digital Earth, digital city is a virtual space that combines and stores the geographic information of the city on the computer network, allowing the city and the extra-urban space to be connected together. At present, in the context of the rapid construction of information technology set off worldwide, China also urgently needs to use information technology to vigorously accelerate the modernization of urban management and improve the level of comprehensive urban management in China. Digital city construction aims to link spatial location information with city-related planning, management,

people's livelihood, and economy through GIS to achieve more accurate services.

Seven technologies are needed to support the realization of digital city, which are information superhighway, aerospace remote sensing technology, Web GIS technology, virtual reality technology, distributed data management, grid computing, and cloud computing [1]. The traditional two-dimensional GIS expression form abstracts the city in the form of symbols, which shows more of the flat location information of the city elements and lacks the three-dimensional spatial information, and it is difficult for the general public who are not professionals to get the city information from the two-dimensional GIS data [2]. At

present, the development of digital city starts to focus extensively on how to replace the traditional two-dimensional GIS representation form with three-dimensional visualization, and the three-dimensional landscape modeling and visualization of digital city is an important research content in digital city. The digital city 3D landscape design process is shown in Figure 1.

Reviews of 3D landscapes for digital cities often revolve around esthetics. Some researchers argue that landscape quality evaluation is based on an objective physical paradigm and a subjective psychological paradigm. The physical paradigm treats the landscape as a characteristic element of space, which can be classified and rated according to the category, and this evaluation is based on the judgment of planners, landscape practitioners, and other experts; while the psychological paradigm regards the landscape as a quality in space that visitors can view, experience and enjoy, and this type of evaluation is more concerned with the subjective feelings of viewers [3]. In a word, visual landscape quality evaluation is carried out based on perceptual cognition, and the evaluation results can be descriptive language extended by subjective judgment, or combined with eye-tracking and other technologies using scoring and rating means to visually represent the evaluation results, which may be divergent due to changes in the population involved in the evaluation.

In terms of digital urban 3D landscape research, foreign researchers have tried to expand the research scope of landscape architecture in order to increase the close connection between their disciplines and architecture and urban planning, and demand outlets from digital methods in urban planning and architecture. Domestic scholars have made promising progress in the study of professional information technology in landscape by conducting research on theoretical models of landscape esthetic quality evaluation and theoretical framework of integrated information system in landscape, respectively [4]. But the degree of applying information digital technology in China's landscape is still relatively low. Most landscape workers are biased toward simple cartography, or the fumbling stage hovering outside the threshold of application. The most important reason for this phenomenon is that China's landscape has long been influenced by traditional classical gardens, the attention is on the aesthetics and humanities of the landscape. The study of landscape planning and the theoretical framework of systems is neglected.

Although a lot of progress has been made in the key technologies related to digital city 3D landscape modeling at home and abroad, but in general, there are still problems that restrict its rapid development, mainly in the following aspects:

(1) At present, many local digital city 3D project modeling method is still using the traditional manual modeling method, mainly through some professional modeling software such as 3DMAX to establish 3D model by manual modeling. Although the 3D model established in this way has high fineness, the modeling efficiency is low, the modeling cycle is
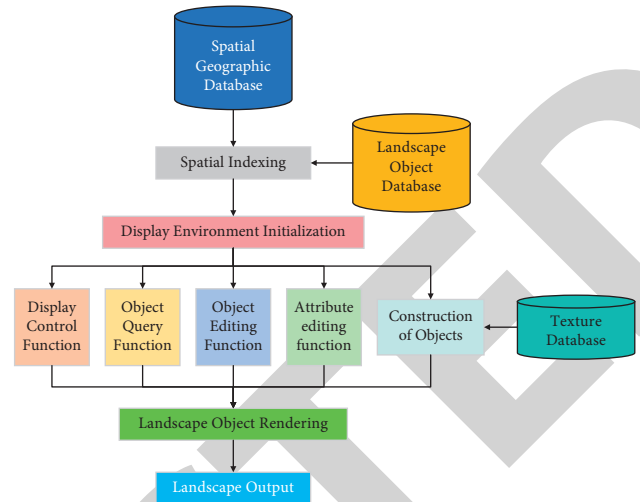

Figure 1: Digital city 3D landscape design process.

long, and it is difficult to combine the existing GIS data in the attribute information, the established model [5]. The model lacks spatial location information and needs to be programmed for batch modification, and the model format needs to be converted before it can be used for GIS spatial analysis and query, which greatly limits the development of 3D GIS.

(2) Since there are many methods of terrain construction, the factors of image terrain accuracy are not uniform, and the data structure and organization of feature model and terrain model are different, when the two are integrated, there is often a mismatch between terrain and feature, so it is necessary to study the relevant data processing methods to make the terrain and feature seamlessly integrated.

(3) With the development of traditional GIS to the direction of Internet interaction and cloud GIS, the sharing of geographic information resources in the network environment is getting more and more attention [6]. Under the existing technical conditions, how to realize the network publishing and sharing of 3D city scenes is an urgent problem to be solved.

Based on the above background, this article proposes a wavelet transform-based 3D landscape design and optimization method for digital cities, which combines wavelet transform and information fusion model to evaluate the 3D landscape in digital cities. Firstly, for the wavelet transform denoising problem, the image is firstly wavelet decomposed to obtain high-frequency and low-frequency components, which are used as the input to train the residual network to learn the residual information, and the image denoising problem is transformed to the feature domain, where the residual structure of hopping connection is used for denoising. Then, to address the defects of existing information fusion models, we propose a multisource information fusion model based on LSTM and RBF-BP neural

networks, using multiple information sources in digital cities as extracted features, and train the LSTM and hybrid RBF-BP neural networks on the extracted features. This article presents a three-dimensional landscape evaluation model. Finally, the simulation experiments show that the denoising method proposed in this article has excellent performance, takes less time, and the information fusion model can evaluate the 3D landscape rationally, and the combination of the method can assist the relevant staff to complete the construction of the digital city.

2. Related Works

2.1. The Current Situation of Digital City Development. In a narrow sense, digital city construction is to improve the level of informationization of the city, and to analyze and manage all activities of the city, including human, material, financial, resources, and information, by means of digital technology, in order to achieve the optimal allocation of all kinds of resources and provide assistance to the overall development of the city.

In the study of digital cities in various countries, some researchers point out that the UK has applied digital city technology to its national development strategy and planning for decades, and after years of development, the country has initially established a national digital city management system with its own characteristics from the national level [7]. The Netherlands is one of the countries in the European Union that started the construction of digital cities early, and has established a functional and stable digital city service system after years of development. In addition, the technology has been widely used in many aspects of government decision-making and urban governance, which has significantly improved the level of urban management [8]. On this basis, some researchers have given suggestions on the construction model of digital city in Australia, saying that the whole society should be fully mobilized to form a joint effort to promote the construction of digital city.

Compared with foreign countries, China's digital city construction progresses relatively late and develops slowly for a period of time, but nevertheless, after years of efforts, China's digital city construction has made significant progress, especially in recent years, some cities have made breakthrough development in digital technology application [9]. From a comprehensive point of view, the progress made by China's digital city construction is mainly reflected in the following aspects: firstly, the ability of urban management problems processing and solving has been improved; secondly, the integration ability of urban management network has been obviously strengthened; and thirdly, the pull effect of urban digital construction has appeared, and the digital industry and its application have been promoted to achieve great development.

Research on the basic functions of digital city management: some researchers point out that the emergence of digital city model is a kind of change to the city management system, through which not only can realize the efficient use of resources, but also can effectively reduce the loss of resources. On this basis, some researchers point out that the e-governance model developed based on information technology is a kind of improvement of the traditional government governance deficiency [10]. With the development and improvement of the e-governance model, it will have a significant impact on the interaction of society and individuals, and help to improve their social interaction ability and relationship.

Research on the content related to the framework of urban digital system: some researchers have analyzed the main contents of the system architecture from the technical point of view with the city digital system architecture as the object, and the digital city system architecture can be divided into five layers according to different functions such as user layer, application layer, business support layer, data resource layer, and basic platform layer.

Based on this system architecture, the unified management and control of digital resources of the whole city can be realized, and different users can realize the interface with the digital city-related application systems in various ways [11]. At the same time, the construction of urban digital system architecture also needs a set of perfect specification system and security system to provide the basic guarantee for it.

In the construction mode, the government leads and the market participates. In conclusion, China has made good achievements in digital city construction, and domestic scholars have carried out a lot of research around it and relevant practitioners have given specific solutions with their own practice, which has positive significance for future research and construction [12]. Digital city construction and development is a dynamic process, although China's research in digital city has achieved some results and has a basic understanding of its development, but the overall view of the existing research is still limited for the realistic guidance of digital city construction.

2.2. Current Status of Wavelet Transform Denoising Research. After hundreds of years of development, wavelet transform theory has become an effective time and frequency domain analysis tool and method. Moreover, the wavelet transform can amplify the details of the signal, especially for non-stationary time series signals, so that we can better process the signal to provide convenient analysis.

The multi-resolution analysis of wavelet transform can study the local characteristics of the signal and the time-frequency information in depth, so the problems related to the local characteristics of the signal need to use wavelet transform, such as the analysis of the image signal edge mutation location problem research; fault diagnosis problems in the study of singularity; and signal acquisition in the waveform oscillation phenomenon problems [13]. Since wavelet analysis can solve these problems, it has become a powerful tool for signal processing.

A large number of methods have been proposed by researchers to better remove the noise from the data. Among them, wavelet transform is more widely used in noise removal in various fields because of its multi-resolution characteristics and good performance in terms of time-

frequency localization. Different decomposition and reconstruction principles in wavelet variation have in turn led to the derivation of different methods in wavelet analysis, which include several kinds of discrete wavelet transform, smooth wavelet transform, and boost wavelet transform.

Its high and low pass decomposition and reconstruction filters are used in the decomposition and reconstruction. The smooth wavelet transform is a time-invariant non-orthogonal wavelet transform, which is similar to the discrete wavelet transform, but does not use down-sampling operation in the decomposition, so the decomposition coefficients keep the same length as the original signal [14]. In contrast to the conventional wavelet transform, the boosted wavelet transform does not use a filter in the decomposition and reconstruction.

Generally speaking, the hard threshold function can well retain the wavelet coefficients generated by the useful signal, but due to its discontinuity at the threshold and the signal will produce some discontinuities after reconstruction [15]. The soft threshold function is relatively smoother and continuous at the threshold, but has the defect of reducing the wavelet coefficients generated by the useful signal in amplitude, and therefore produces signal distortion after signal reconstruction.

The discrete wavelet transform has artificial noise in the denoising process and is prone to pseudo-Gibbs phenomenon in the neighborhood of singularities, which is a phenomenon of up-and-down jumping of the signal at singularities, especially at the beginning and end of the wave group in ECG signals [16]. Some researchers have documented that translational invariant wavelet threshold can effectively eliminate the pseudo-Gibbs phenomenon. The so-called translation-invariant threshold is the idea of translation-noise-reverse translation-averaging, which eventually removes the pseudo-Gibbs phenomenon while restoring the original position of each sampling point. The pseudo-Gibbs phenomenon is related to the location of the discontinuity points of the signal, however, there may be several locations in a signal with poor continuity, and the optimal translation of any two discontinuities may not be the same, so the measure of varying the translation, multiple translations, is usually used, and the maximum translation is the length of the original signal.

At present, many fields of signal research, such as communications, electronic systems, control systems, and other electronic fields are facing the same problem, that is, before processing the signal, the signal needs to be denoised, because the useful signal needed is mixed with noise, and this noise can interfere with the relevant work of the system and the accurate measurement of the signal [17]. How to get rid of the noise in the noisy signal and retain the pure signal is a key issue in signal processing, and this problem is also attracting more and more attention from researchers. To achieve the purpose of removing the noisy signal, we must use a technique to separate the signal from the noise and restore the pure signal, and the filtering technique can improve the accuracy of signal processing and make the data signal more reliable.

2.3. Current Status of Information Fusion Model Research.

Information fusion technology is defined as a technology that correlates and combines information from multiple sensors to achieve more accurate location inference and identity estimation. With in-depth research on this technology, it is gradually popularized in more fields. For a variety of application scenarios, information sources have evolved from traditional sensor data to various types of data that need to be fused, such as database data and human input data [18]. Therefore, data fusion is a technique to obtain a judgment about the target after certain analysis and processing of all kinds of information that can be obtained and have an influence on the target. Information fusion is divided into the following four steps: (1) sensing information and obtaining data, (2) information pre-processing, (3) information feature extraction, and (4) fusion processing and outputting results.

(1) Data-level fusion preserves the original state of the data and respects the details of the data, but it also brings shortcomings: (1) directly fusing unprocessed data, the data load is large, which will affect the fusion performance and consume more; (2) influenced by the original data, some interference will affect the final result, very dependent on the performance of the sensor, poor anti-interference ability; and (3) because data-level fusion is directly fusing the original data it needs, the data types are the same, that is, fusing the same type of sensor data.

(2) Since feature-level fusion first refines the data source, compared with data-level fusion, the amount of data for feature set fusion is reduced, the time complexity of the algorithm decreases, and the cost consumed becomes smaller [19].

(3) The decision-level fusion does not require the same type of data sources because it fuses the decision results of each data source, so it can fuse data from any type of sensors, which enhances the robustness of the system. In addition, each data source goes through feature extraction and decision-making first, so the data transmission bandwidth is greatly reduced.

From the above, it can be seen that: data-level fusion can retain the initial state of data source information to the maximum extent, but it requires the same type of sensors, poor interference resistance, large amount of computational data, and large transmission bandwidth; decision-level fusion does not require the type of data source, good interference resistance, small amount of computational data, and small transmission bandwidth, but because the fusion is the processed decision information, the original information loss is large; and feature-level fusion is in between the two [20]. In general, each level of fusion, with its own advantages and disadvantages, should be considered according to the needs and conditions of the system.

Some researchers have solved the problem of incomplete information and incomplete data of target objects obtained from single data source in open pit slope monitoring by

checking the interconnectivity of point data obtained from measurement robots and surface data obtained from 3D laser scanners as well as fusion analysis. On this basis, some researchers have successfully extracted the characteristic values of electricity theft behavior by conducting in-depth research on the coupling relationship between electricity information and electrical quantity information of low-voltage distribution network, which has greatly improved the efficiency of electricity inspection [21]. Other researchers have established a comprehensive assessment model for the fusion of multi-indicator evidence of cable-stayed bridges by fusing long-term monitoring data and manual inspection information of steel cable-stayed bridges.

However, there is no precedent of applying this technology to digital city 3D landscape assessment at home and abroad. In view of the complexity of urban construction, it is necessary to use information fusion technology urban environmental information for processing, correlation, and synthesis, and apply it in 3D landscape evaluation.

3. Algorithm Design

3.1. Design of Wavelet Transform-Based Denoising Method. The wavelet transform coefficients have sparsity and scale decomposition properties. And these properties are beneficial for people to represent the signal flexibly. The main energy of the signal is represented by a few large coefficients, and the rest of the energy is represented by many small coefficients. Most of the noise signal exists in the small coefficients, so these small coefficients can be modified according to certain rules to remove the noise signal from the image. In addition, some methods achieve image denoising by simulating the statistical distribution of the sub-bands of noiseless wavelet coefficients, such as generalized Gaussian distribution, Gaussian scale mixture distribution, and mixture Laplace distribution [22]. However, these methods are only applicable to specific noise types and distributions, so these methods are less flexible to deal with realistic images. There are also some methods based on wavelet hierarchical correlation, but there are also the following problems: (1) the optimal threshold function and the optimal threshold cannot be determined effectively at the same time; and (2) some a priori assumptions need to be made on the statistical distribution of noiseless sub-band wavelet coefficients assumptions.

These single image denoising methods can suppress the noise to some extent, but they also remove the edge information of the image mistakenly as noise, resulting in blurred edges of the de-noised image, which leads to the loss of edge information of the image. To improve these problems, in this section we propose an image denoising algorithm that combines wavelet transform and artificial neural network.

Neural network is a signal processing model based on bionics, which simulates the nervous system of human brain, and many simple neurons are linked according to some specific rules to form the basic network model. These advantages of artificial neural networks provide a strong guarantee for image denoising work.

The traditional denoising method generally uses the threshold method to denoise the high-frequency components in different directions, and the denoised image can be obtained by inverting the smooth wavelet transform for the denoised components [23]. The wavelet coefficients obtained from the smooth wavelet decomposition have a strong correlation both within and between scales, so it is often difficult for denoising algorithms such as the threshold method to achieve good denoising results. In this article, the algorithm performs a two-dimensional discrete smooth wavelet decomposition of the image at scale 1 to obtain a low-frequency component and three high-frequency components in different directions:

$$[L, H, V, D] = swt2(X, n, 'haar'), \tag{1}$$

where X denotes the image to be decomposed, n denotes the decomposition scale, L denotes the low-frequency component of the image obtained by two-dimensional discrete smooth wavelet decomposition, H denotes the horizontal high-frequency component, V denotes the vertical high-frequency component, and D denotes the diagonal high-frequency component. 'Haar' denotes the use of haar basis in wavelet decomposition. The expressions are:

$$\psi(x) = \begin{cases} 1, & 0 \le x \le 2, \\ -1, & \dfrac{1}{2} \le x \le 1, \\ 0, & \text{other.} \end{cases} \tag{2}$$

Wavelet decomposition enables multi-scale representation of images in terms of spatial ratio, orientation, and frequency range. A multi-convolutional neural network for image denoising is trained using the wavelet multiscale representation as a regression feature. The decomposed low-frequency and high-frequency components are input to multiple networks to obtain the corresponding prediction components, and then the above components are inverted using a smooth wavelet to obtain the final prediction image, which can be expressed as:

$$\widehat{I} = iswt2\left(\widehat{L}, \widehat{H}, \widehat{V}, \widehat{D}, 'haar'\right). \tag{3}$$

Residual learning of CNNs was originally proposed to address the performance degradation of convolutional neural networks, that is, as the network levels increase, the training accuracy of the network starts to decrease. The residual network learns the residual mapping and using this residual learning strategy, it is easy to train very deep CNNs and improve the accuracy of the network to optimize the algorithm performance. The network framework proposed in this article mainly consists of four residual networks with identical structures, except for the last convolutional layer, and each convolutional layer is followed by the linear correction unit activation function ReLU as the activation function, and the complete network structure is shown in Figure 2.

As shown in Figure 2, each residual network contains two residual blocks, each of which consists of two identical
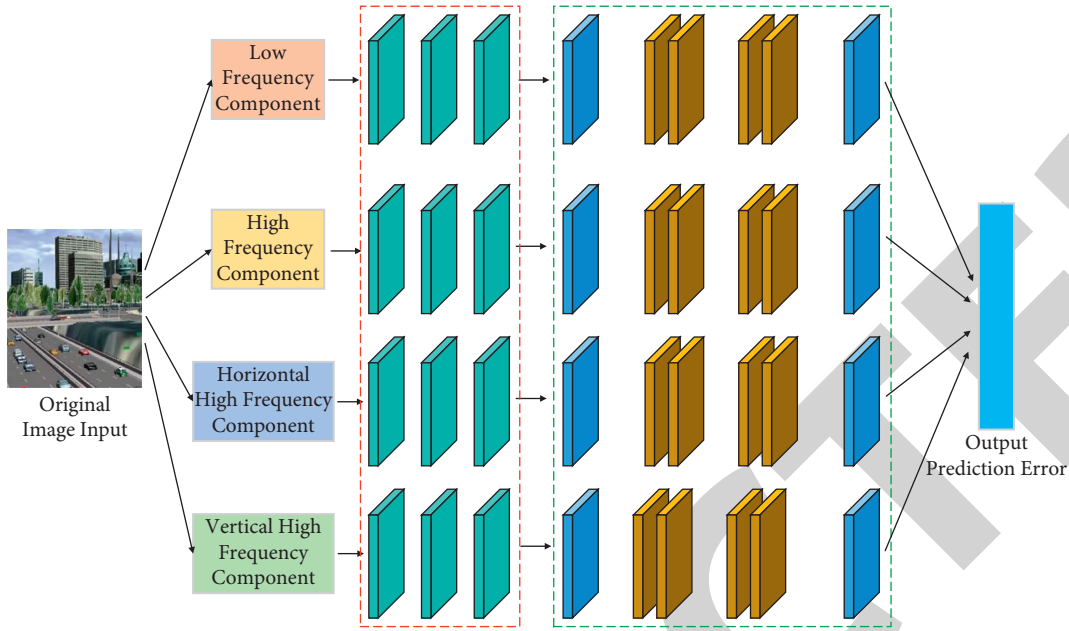
FIGURE 2: Wavelet transform denoising model combined with residual network.

convolutional layers. The three convolutional layers in the red dashed box use $9 * 9$, $1 * 1$, and $5 * 5$ convolutional kernels, and the number of convolutional kernels is 64, 32, and 1. Each convolutional layer in the green dashed box uses $3 * 3$ convolutional kernels, the last layer in the green dashed box has 1 convolutional kernel, and the other layers have 64 convolutional kernels. The network in the red dashed box has reached convergence, and the main function is to remove the noise in the high and low-frequency components in different directions. The residual network in the green dashed box is mainly used to enhance the texture detail information in high and low frequencies.

In the training process, the original image is now cropped into blocks of the same size, and then these blocks are subjected to non-down-sampling wavelet decomposition, and then the original image blocks are added with noise and then subjected to the same wavelet decomposition, and the decomposed image information is correspondingly input to the pre-designed network, which is back-referenced by the mean-square loss function:

$$L_{loss} = \frac{1}{K} \sum_{i=1}^{K} \|R(L_i) - R_i\|_2^2. \tag{4}$$

The main work we do in this part are: (1) in order to preserve the clear edge details of the image and improve the detail information of the image to obtain better visual effect, this part of the algorithm is different from other algorithms that directly input the image for training. (2) In the residual network is used in training, and only the residual information is learned, which can avoid using too deep network structure and speed up the convergence of the network; the convolution kernel with smaller size and number is used to reduce the computational complexity and the number of parameters. (3) The image denoising problem is transformed to the feature domain, the residual structure of the hopping

connection is used in the feature domain for denoising, and the noise distribution is removed from the feature distribution. Residual noise features exist in the obtained de-noised features, which are removed by subsequent feature screening of the network structure, and finally, the noise-free features are fused using a smooth wavelet inverse transform to generate the de-noised image.

3.2. Information Fusion Model Design.

In order to improve the accuracy of the evaluation of 3D landscape, two issues need to be considered: what environmental information is used as the feature quantity and how to obtain the information. The information fusion model is designed for these two problems, and the model structure is shown in Figure 3. As can be seen from Figure 3, three sets of environmental information are collected and sent to the information layer for pre-processing. In the process of local decision-making, a threshold is set, and a rate detection algorithm is used to determine whether each signal is abnormal at a certain time, and when the set threshold is exceeded, the three sets of feature signals are sent to the neural network model [24]. The decision layer gets the environment fusion information and enters the fuzzy control model, which is further analyzed according to the defined fuzzy inference rules to obtain the evaluation of the 3D landscape.

As a special form of recurrent neural network, LSTM neural network overcomes the shortcomings of ordinary recurrent neural network which cannot remember information for long time, has good ability to analyze the time series, and can analyze the hidden data relationship of time series. According to the above characteristics of LSTM neural network, the feature signal is exactly a series of time series, which fully meets the requirements of LSTM neural network. The basic structure of LSTM is expanded by time series as shown in Figure 4.
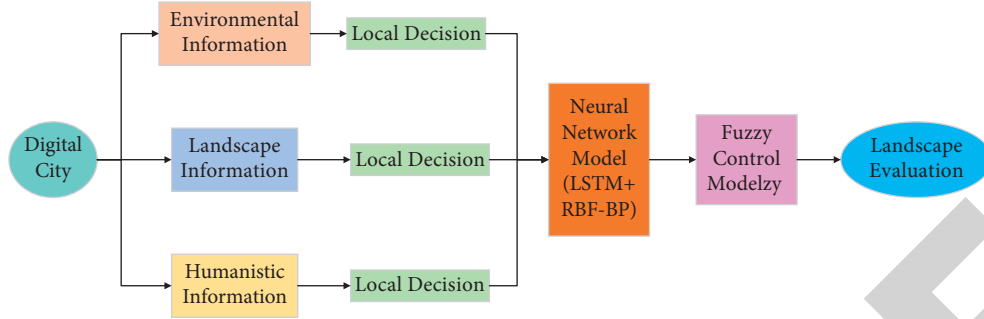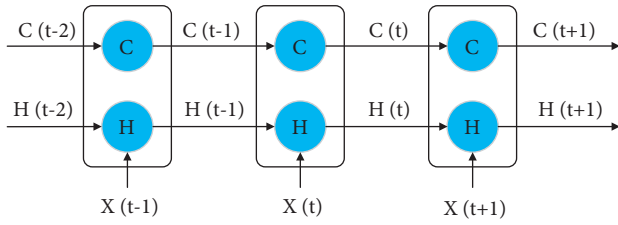
FIGURE 3: Information fusion model.

FIGURE 4: LSTM network expansion diagram by time dimension.

The forgetting gate is mainly done by a Sigmoid function, which takes as input the output data signal $H(t-1)$ of the previous cell and the signal $X(t)$ of the input at that moment, and determines the degree to which the $C(t-1)$ cell state information is forgotten by generating (0, 1) values, which are calculated as follows:

$$f_t = \sigma\left(W_f \cdot \left[H_{(t+1)}, X_t\right] + b_f\right). \tag{5}$$

The tanh function is used to determine which new signal inputs can be fed into the network. The tanh function is computed to obtain a new variable $C(t)*$, and the input gate generates a value of (0, 1) and assigns it to $C(t)*$, thus controlling how much of the new input information is fed into the network. We obtain the unit state information $C(t)$ of the new memory cell, whose equation is shown below:

$$C(t) = f_t * C(t-1) + i_t * C(t). \tag{6}$$

The output gate controls how much state information is missing from the current cell. The output gate controls the degree of filtering of the cell state by generating a value of (0, 1) and assigning it to each item of the cell state, which is given by the following equation:

$$H(t) = O_t * \tanh\left(C(t)\right). \tag{7}$$

BP neural network is a traditional feed-forward fully connected neural network, which sets the learning rate and loss function, and updates the weights and thresholds through the backward error propagation algorithm, and the activation function is usually an S-type function, which can effectively train the network, but the convergence rate is slow and there is a problem of local minima [25]. The RBF neural network only contains a three-layer network structure, and the activation function is generally Gaussian, which has the generalization ability that the BP neural network cannot, and

the training accuracy is better than that of the BP neural network, but the accuracy of the test data prediction is not sufficient [26–30].

In order to obtain a more accurate and efficient network structure for landscape assessment, the BP neural network is combined with the RBF neural network to obtain the advantages of both networks. The RBF-BP neural network model is shown in Figure 5.

The feature signal is trained by the LSTM neural network and then enters the RBF-BP neural network. The forward propagation is to multiply the input value of each neuron with the weight matrix and then add the bias term to obtain the output of the neuron after the activation function, which is shown in the following equation:

$$out_i = \sigma\left(w_i * x_i + b_i\right). \tag{8}$$

Error backpropagation is a process of constantly updating the weights and bias values by setting the loss function and selecting an optimizer to continuously reduce the value of the loss function, where the optimizer is the gradient descent method and the loss function is the root mean square error function with the following formula:

$$\mu_{mse} = \frac{1}{N}\sum_{i=1}^{N}\left(y_{tar} - y_{pre}\right)^2. \tag{9}$$

4. Experiments

4.1. Experiment of Denoising Based on Wavelet Transform

4.1.1. Experimental Parameter Settings. The experimental training dataset is a BSDS68 natural image set, and the ADAM algorithm is used to optimize the loss function with parameter beta1 of 0.9 and parameter beta2 of 0.999. The experimental results of this article are all 100000 iterations, and the learning rate is a fixed value of 0.001. The hardware configuration of the computer for the experimental simulation is Intel Corei5-7300 with NvidiaGeForceGTX1060, the operating system is Windows10, and the Caffe deep learning framework is used to train the neural network, which supports GPU computing; the software used for testing is Matlab R2017a. Subjective evaluation means human observation of the image to assess the quality of the output image. This part uses two evaluation metrics to
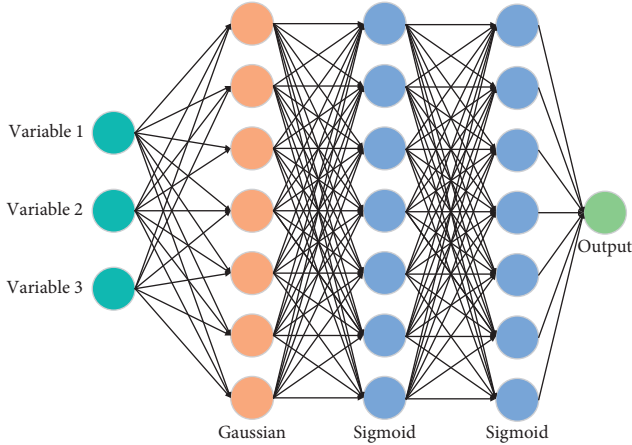
Figure 5: RBF-BP neural network model.

quantify the experimental results: peak signal-to-noise ratio (PSNR) and structural similarity index matrix (SSIM).

The comparison algorithms selected in this article are median filtering (MF), wavelet-based soft threshold denoising (ST), and EPLL, and the images used for testing are randomly selected from set5, set14, and set12.

4.1.2. Experimental Results and Analysis. The training data and the test are successively input into the residual neural network, and it can be seen from Figure 6 that the mean square error value of the network model gradually decreases and finally stabilizes as the number of iterations increases. The value of the loss function decreases rapidly in the first 150 cycles and stabilizes at about the 300th cycle.

Table 1 shows the PSNR values of five test images with relatively low Gaussian white noise added after processing by different algorithms, and the mean PSNR value of this algorithm can reach 29.28 dB. NCSR can also achieve relatively good processing results, but the average time consumed is far more than the algorithm in this article. For the SSIM values, the SSIM values of the four images processed by the method in this article are higher than those of the other algorithms.

Table 2 shows the PSNR values of five test images with more Gaussian white noise processed by different algorithms. Four of the images processed by our algorithm have higher PSNR values than other comparison algorithms can reach 0.73.

4.2. Information Fusion Model Experiments. In order to verify the effectiveness of the proposed information fusion model, the experiments were conducted using BP, RBF, and RBF-BP models for landscape prediction, and the experimental data were pre-processed by disordering and rearranging to enhance the reliability of the experiments. The training set is 400 sets and the test set is 80 sets.

The performance of the three networks is compared by using the root mean square error of the output variables as the comparison condition. The RBF-BP neural network has a lower RMS error than the other two neural networks mentioned in the article, indicating that the RBF-BP neural
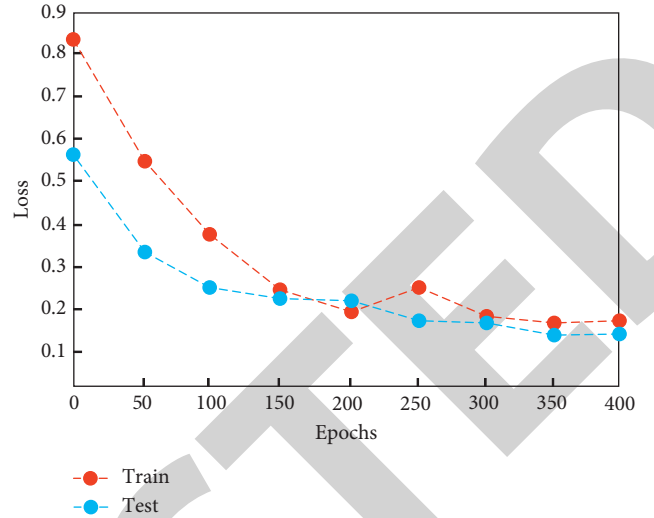

Figure 6: Experimental results of residual network loss function.

Table 1: Experimental results with less Gaussian noise (PSNR/dB).

Method	Starfish	Airplane	Monarch	Parrot	Bridge	Avg.
MF	24.38	23.91	26.14	24.56	25.42	24.93
ST	25.07	24.36	24.69	26.48	25.87	25.48
EPLL	26.52	25.73	27.35	28.39	27.26	27.53
Ours	28.87	29.60	28.26	30.53	28.64	29.28

Table 2: Experimental results with more Gaussian noise (PSNR/dB).

Method	C. man	Lena	Peppers	Baby	Woman	Avg.
MF	19.65	20.08	21.46	21.83	22.42	21.21
ST	18.74	20.62	20.83	22.26	28.67	24.86
EPLL	23.15	25.91	24.35	27.35	23.59	25.39
Ours	26.37	26.69	28.96	29.08	28.34	28.17

network is more accurate than the BP neural network and the RBF neural network for landscape prediction, which means that the network is better than the other two neural networks in terms of landscape prediction performance. The RBF-BP neural network is more accurate than the BP neural network and the RBF neural network in landscape assessment. A comparison of the prediction results of different neural network algorithms is shown in Figure 7.

The comparison between the predicted output value and the true value of the test data is given in Figure 8. From Figure 8, it can be seen that our proposed network model has good fitting performance, and the curve trends of the true and predicted values roughly overlap, indicating that the predicted values have high accuracy and can achieve the expected results. According to the experimental results, we can obtain the efficient accuracy of this information fusion model for data prediction on time series, and the landscape can be evaluated based on digital city feature information.
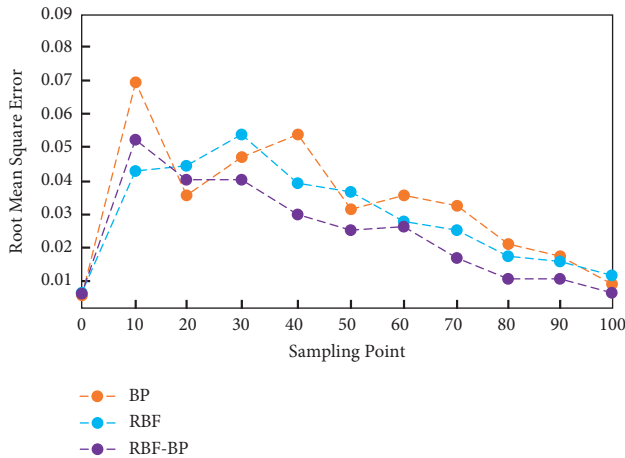
Figure 7: Comparison of prediction results of different neural network algorithms.
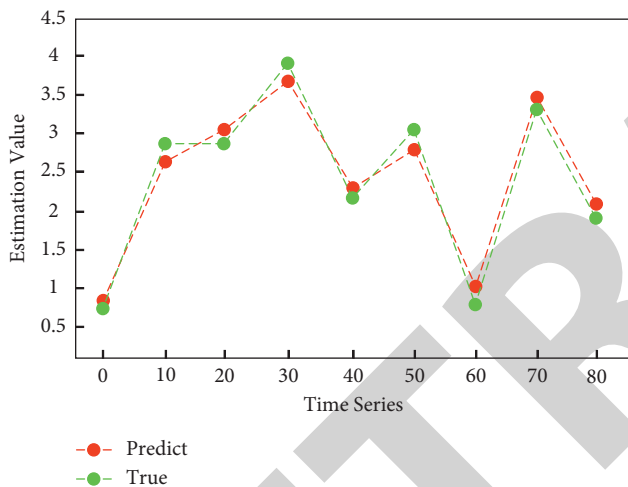

Figure 8: Comparison results of predicted value and real value of the model.

5. Conclusion

The construction and application of digital city 3D landscape cannot be realized overnight, and it requires a lot of human, material, financial, and technical resources. In the specific construction process, if it cannot be reasonably evaluated based on the urban environment data, it is likely to cause a huge waste of resources, thus bringing great impact to the development of digital city. To this end, this article proposes a wavelet transform-based 3D landscape design and optimization method, which combines wavelet transform denoising and information fusion model to evaluate the 3D landscape in digital cities. First, a denoising algorithm with strong generalization ability is proposed for the wavelet transform denoising problem. The algorithm takes advantage of the combination of smooth wavelet transform and residual learning, and uses a convolutional neural network with a relatively simple structure, low computational complexity, and a small number of parameters to eliminate the noise generated during the imaging or transmission of

images. Then, for the evaluation problem of 3D landscape, a multi-source information fusion model based on LSTM and RBF-BP deep learning model is proposed to apply the deep learning theory and multi-source information fusion method to the landscape evaluation. The method uses LSTM and RBF-BP neural networks to train the feature signals in the feature layer of multi-source information fusion, which reduces the false alarm rate of the assessment system and improves the accuracy of prediction. Finally, the simulation experiments show that our proposed denoising method is able to maintain the texture details of the image with a better denoising effect, and the proposed information fusion model has a faster convergence speed and smaller error than the traditional methods. Combined with this method, it can assist relevant personnel to improve the evaluation of 3D landscapes in digital cities and help to enhance the efficiency of digital city construction. In the future, we plan to carry out digital urban 3D landscape design and optimization based on graph convolutional neural network.

Data Availability

The datasets used during the current study can be obtained from the corresponding author upon reasonable request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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