Research Article

Algorithm of Scenic Spot Tourism Route Planning Based on Convolution Neural Network

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Based on convolution neural network, a tourism route planning method for scenic spots is proposed. The method of performing primitive trajectory adaptive learning is used to plan and design the tourism route nodes and path space. On this basis, the shortest distribution grid structure model of tourism routes is constructed. Using the visual servo mobile route optimization control method, the constraint parameters of tourism route planning are optimized. In order to avoid the crowded area of tourists and the shortest path as the planning standard, the path planning problem is regarded as a constraint problem. The convolution neural network is used to activate the constraint function with the shortest path, and the output planning results are calculated iteratively. The simulation results show that this method has good learning control ability and convergence performance and improves the reliability of scenic spot tourism route planning.

1. Introduction

Driven by economic globalization, with the steady and sustained growth of the national economy and the all-round and healthy development of society, tourism has become a new form of entertainment consumption and an important activity to improve people’s quality of life [1, 2]. Tourism forms are rich and colorful, from pleasant scenery tourism to challenging adventure tourism. From a series of themed tourism such as honeymoon tours and island tours to red tourism full of revolutionary feelings and education, tourism products and services have become the leisure fashion that people are eager to pursue [3, 4]. At the same time, tourism has effectively stimulated the development of urban economy, driven the employment of society and promoted the effective integration of culture and environment. People can not only choose the more and more group tour products provided by travel agencies, but also try personalized self-service tourism. A reasonable tourist route is not only conducive to tourists’ destination choice and arrangement of their own tourism activities to avoid “roaming,” but also conducive to giving full play to the functions of various tourist attractions, tourists’ rational use of time, and planned disposal of tourism expenses [5, 6]. Therefore, it is necessary to design reasonable tourist routes so that tourists can take the shortest distance at less cost and in a short time and visit the most scenic spots on the premise of abundant physical strength and comfort.

Scenic spot route planning is a specific example of path planning problem, that is, when the node and path information are known, plan the most suitable route to optimize a certain measurement index, which can be time cost, path length, cost, road capacity, etc. Scholars at home and abroad have done a deep research on this problem. The main solutions are Dijkstra search, heuristic A* search, genetic algorithm, neural network, ant colony algorithm, and so on. On the basis of determining the use of the historical landscape of Siak Sri Indrapura, reference [7] identifies the historical tourism objects and formulates the landscape planning for the historical tourism route of Siam Sudan. In Reference [8], based on the background experience of civil engineering and territorial planning, the role of tourism in urban
regeneration is discussed. Tourism plays an important role in creating a high-quality, global environment in which cities operate. Reference [9] used the improved tourism impact attitude scale to investigate the views of residents on bicycle tourism on the bicycle route of the Danube River in Serbia. In addition, multiple regression model is used to test the impact of independent variables on residents’ perception of bicycle tourism development. Reference [10] improved adaptive large neighborhood search method that is used to solve the problem of family travel route planning.

Convolutional neural network has the ability of representation learning and can classify the input information according to its hierarchical structure. Applying it to scenic spot tourism route planning can effectively improve the planning effect and convergence speed. Therefore, when planning scenic routes, based on the convolution neural network model, this paper obtains the shortest route distribution grid map under different tourist intense scenes and the corresponding reference route, which is used as the model input to realize scenic route planning, in order to further improve the planning effect and provide convenience for tourists.

2. Technical Route

The main technical route of this paper is as follows:

Step 1: Design and plan tourism route nodes and path space, build the shortest distribution grid structure model of tourism routes, and obtain the optimal constraint parameters of tourism route planning

Step 2: Take the path planning as the constraint condition, use the convolution neural network to activate the avoidance and the constraint function with the shortest path, and continuously iteratively calculate the output planning result

Step 3: Experimental analysis

Step 4: Conclusion

3. Grid Model of Scenic Spot Tourism Route Distribution

In order to realize the scenic spot route planning based on convolution neural network, the method of self-adapting learning of primitive path is adopted [11, 12] to design the node and route space of scenic spot. Firstly, the distribution grid model of scenic spots is constructed, and the distribution of scenic spots is shown in Figure 1.

According to the distribution of scenic spot tourism shown in Figure 1 and the geometric description of scenic spot tourism environment [13, 14], the target node of scenic spot tourism route planning is optimized. According to the intelligent planning of scenic spot tourism route, the node transmission load is obtained as follows:

\[ \nabla F(x) = \text{Rot}[v_i(x) + F(x)], \quad (1) \]

where \( F(x) \) represents the objective function of scenic spot tourism route planning and \( v_i(x) \) is the locally optimal parameter set of tourist route distribution in scenic spots.

Using Newton gradient descent algorithm [15, 16] to estimate the parameters of intelligent planning of scenic spots, the distribution of random parameters in the configuration space of scenic spots is obtained as follows:

\[ \nabla^2 F(x) = \frac{1}{\partial F(x)} - v_i(x). \quad (2) \]

Based on the distribution of stochastic parameters, the shortest path from the initial node to the target node is analyzed, and the linear programming model of path parameters is obtained:

\[ l(v_c) = \text{Tran}(P_c - P_0) + \nabla^2 F(x), \quad (3) \]

where \( \text{Tran}(P_c - P_0) \) represents the translation of the destination node path location. On the differential manifold [17], according to the analysis of the stochastic parameters in the shape space, the path optimization of the tourist route intelligent planning is carried out, and the path optimization equation is obtained as follows:

\[ T(t) = \int_0^\infty l(v_c)dv + \text{Tran}(P_c - P_0). \quad (4) \]

Using the shortest path optimization method, the self-adaptive spatial parameter design of scenic route planning is carried out, and the distribution nodes \( v_a, v_b, \) and \( v_c \) of scenic routes are obtained. The optimal solution is as follows:

\[ Q = [v_a + v_b + v_c] - \sum_{t=1}^\infty T(t). \quad (5) \]

Using the method of subsection route optimization control, the distribution grid model of scenic spots is designed, as shown in Figure 2.

Based on the shortest line distribution grid structure model in Figure 2, the shortest path is taken as the optimization objective function. The method of performing primitive
4.1. Convolution Neural Network Principle. One-dimensional CNN can be used for speech recognition, electrical signal, and ECG recognition and two-dimensional convolutional neural network can be used to recognize images, lines, etc. [26, 27]. Convolution neural network has obvious advantages over traditional machine learning algorithm. This paper selects the two-dimensional convolutional neural network model to study the scenic spot tourism route planning method.

CNN model includes three parts: input layer, middle layer, and full connection layer. The structure is shown in Figure 3.

In Figure 3, the input layer is mainly responsible for the preprocessing and other related operations of tourism route planning in the scenic spot; in case of high difficulty or lines that cannot be planned directly in the middle layer during the planning process, increase the iteration times of convolution layer and pool layer [28] until the lines are successfully planned. The output target of the whole connection layer is the score value of scenic spot tourism route planning, and the high score is selected as the final result.

4.2. Analysis of Constrained Parameters in Tourist Route Planning. Visual servo mobile route optimization control method [18, 19] is used to locate the node and deploy the shortest route of scenic spots. Set the optimal distribution of constraint parameters of scenic route planning in node coordinate system as \[ X_i(t), \] and in the initial configuration space of tourists, obtain the estimation model of route parameters of scenic route tourism, which is expressed as follows:

\[
\Delta S(t) = Q + \left( T_0 - U_0 \right) X_i(t),
\]

where \( T_0 \) and \( U_0 \) separately indicate the shortest distribution distance and the tourist distance of the tourist route of the scenic spot obtained by depth camera.

Under visual navigation [20, 21], the fuzzy directivity optimization control of scenic tourism routes is carried out, and the distribution fusion control model of scenic tourism routes is established, which is expressed as

\[
V_0 = \left\| p^1 \right\| + \sqrt{T_0^1 + \Delta S(t)},
\]

where \( T_0^1 \) represents the convolution neural network fusion feature distribution set for the optimization of scenic tourism routes and \( p^1 = (p_1^1, p_2^1, p_3^1)^T \) represents the shortest route fusion parameters of scenic tourism routes.

The gradient function of the convolution neural network for the shortest scenic spot route planning based on the spatial 3D information sampling method [22, 23] is as follows:

\[
R_r = \sqrt{\Delta T + \Delta U} + \min V_0.
\]

In the formula, \( \Delta T \) and \( \Delta U \) represent the shortest distribution distance and the average tourist distance of tourist routes in the scenic spot, respectively. The model of tourist route map is designed by using the method of stereoscopic model measurement and modeling [24, 25], and the characteristic distribution function of tourist route is \( x_i, y_i, z_i \). According to each depth projection corresponding to a programmable tourist route, the fuzzy control equation of route space planning is obtained:

\[
T_i = \frac{R_r - \sum_{i}^1 x_i + y_i + z_i}{s + c},
\]

where \( s \) indicates the location error of the tourist route and \( c \) represents the optimization parameters of tourist route planning in the scenic spot.

In the process of implementing scenic routes, the starting point of the scenic routes is \( P_0, P_1, P_2, \ldots, P_n \), and the normal vectors of each point are \( T_i \). Using adaptive transmission control method, the constraint parameter analysis
model of scenic spot tourism route planning is obtained as follows:

$$P_a = \sum_{n=1}^{t} P_a + T_0.$$  \hspace{1cm} (10)

Based on the above analysis, the optimal parameters of scenic route planning are obtained, and the node positioning and the shortest route deployment of scenic routes are carried out.

4.3. Convolution Neural Network for Tourist Route Planning. According to the analysis results of constraint parameters of scenic spot tourism route planning, combined with convolution neural network method, scenic spot tourism routes are planned. Using the spatial planning matrix and according to the three-dimensional point cloud information of the scene, the error measurement parameters of scenic spot tourism route planning are obtained as follows:

$$l = x(t) - \frac{1}{h(t, u)} + P_d,$$  \hspace{1cm} (11)

where \(x(t)\) represents the 3-D point cloud information points of scenic spots and \(h(t, u)\) represents the evaluation parameters of the response of route planning.

The quadratic convolution neural network model of scenic route planning composed of \(n\) decision variables is obtained by the convolution neural network control of scenic route planning for any \(m \times n\) dimension matrix \(A\) and the iterative optimal moving parameter analysis [29, 30], which is expressed as follows:

$$F(x) = l(\sqrt{A} + h(t, u)).$$  \hspace{1cm} (12)

A model for self-adaptive optimization of tourist routes in scenic spots is established by using the method of linear quadratic programming [31, 32], which is expressed as

$$\eta = E(MA) + E(MB)_{t=0}^{\infty} F(x) dx.$$  \hspace{1cm} (13)

The membership vector of the scenic spot in the tourism route planning is \(E(MA)\), and the inner product of the tourism route planning parameter is \(E(MB)\).

According to the stability parameters of scenic spot tourism, the optimization function of equilibrium point position is obtained, which is expressed as

$$K = f^2 + |\eta|^2 \tau,$$  \hspace{1cm} (14)

where \(\tau\) is the position information in the process of scenic route planning, \(f\) is the fuzzy state feature of scenic route distribution, and \(t\) is the time interval of scenic route optimization.

The optimal programming function of convolution neural network based on the optimal result of equilibrium point is as follows:

$$E[VA] = \sqrt{1 + K} + \int_{0}^{\infty} f(t) dt.$$  \hspace{1cm} (15)

According to the result of Formula (15), the convolution neural network optimization design of scenic spot tourism route planning is realized. On this basis, the optimization control design is carried out.

4.4. Optimization Control Design Algorithm of Tourism Route Planning. Two problems need to be solved in the optimization control design of tourism route planning which are as follows: avoiding collisions in the tourist gathering area and the shortest path. Based on these two principles, the path planning problem is transformed into a function calculation problem, and the collision energy function [33, 34] and the planning distance function are obtained. In the process of path planning under the convolution neural network, it is necessary to expand the tourist gathering area first, that is, extract and model the data of the tourist gathering area. Then, the collision energy function is calculated according to the measured environment and the constraint of convolution neural network. The shortest distance set of path points is determined by the collision constraint function.

The collision constraint function based on the convolution neural network structure is shown in Figure 4.

In Figure 4, node \(D_n\) in the top layer represents the initial data, nodes \(D_m\) and \(D_m\) in the input layer represents the coordinates of the path points, node \(\omega_{x_0} \sim \omega_{x_0}\) in the middle layer represents the constraints of the tourist gathering area, and
nodes \( x_1 \) and \( y_1 \) in the data output layer represents the final output collision constraint function and the shortest distance constraint function.

In order to clearly express the restriction ability of the constraint function on the path planning, let the output results of \( x_1 \) and \( y_1 \) be 1, which means that the planning scheme meets the function conditions. If the output result is 0, it means that the function conditions are not met and need to be recalculated. Based on this, the above relationship is expressed by the activation function \([35, 36]\), and the formula is

\[
F(x) = \frac{1}{1 + c^{-1/g}},
\]

where the higher the value of \( c^{-1/g} \) indicates the collision degree, the closer the value of \( c^{-1/g} \) is to the center of the tourist area; otherwise, the lower the value is, the farther the value is from the center of the tourist area.

The collision constraint function \( E(x) \) given by convolution neural network is

\[
E(x) = \sum_{i=1}^{n} \sum_{k=1}^{k} c^{-1/g},
\]

where \( g \) represents the influence parameter of the constraint function, and the greater the value of \( g \), the more realistic the representative constraint function is; otherwise, the smaller \( g \) means that the constraint function is more divorced from the actual situation.

After the collision constraint function is obtained, on this basis, the path length that tourists need to travel is expressed by energy, the sum of squares of all path lengths is calculated, and then the average value is obtained.

Set all path points as \( P_j(a_i, b_i, c_i), i = 1, 2, \cdots, n \) and define as

\[
E_i = \sum_{i=1}^{N-1} [(x_{i+1} - x_i)^2 + (y_{i+1} - y_i)^2].
\]

Each parameter in energy \( E_i \) is weighted. At this time, the obtained energy value \( E_j \) is small, which means that the path value is short, and the obtained energy value \( E_i \) is large, which means that the path value is long. Combined with the constraint functions \( x_1 \) and \( y_1 \), the final shortest path planning function formula is

\[
E' = \sum_{i} (\nabla E_i)^T P_i,
\]

where \( \rho \) represents the distribution density of tourist gathering area; \( P_i \) represents the traveling power of tourists; and \( x'_i = 0 \) and \( y'_i = 0 \) represents the weighted value of each point in the path. When \( x'_i = 0, y'_i = 0 \), the energy consumed at this time is the minimum value \( E' = 0 \). The planned path meets not only the shortest distance, but also the optimal area to avoid tourist congestion. So far, the scenic spot tourism route planning and design based on convolutional neural network has been completed.

5. Simulation Experiment

5.1. Algorithm Performance Analysis. The parameters of the simulation test are set as follows: the spatial parameters are \( 200 \times 300 \), the number of entities in the scenic spot is \( N = 300 \), the maximum number of iterations of the convolutional neural network is 250, and the coefficient of adaptive learning is 0.37. Under the above parameter setting, the original route of scenic spot tourism is obtained as shown in Figure 5.
Taking the original path in Figure 5 as the experimental data, the path planning results optimized by this method are shown in Figure 6.

In the analysis of Figure 6, the use of this method can effectively achieve scenic route planning and self-adaptive optimization, and optimization effect is obvious.

The method of reference [8] and the method of reference [10] are used as comparison methods to test the convergence ability of scenic spot tourism route planning under different methods. The results are shown in Figure 7.

By analyzing the results in Figure 7, we can see that the convergence performance of this method is better than other methods. At 150 times, the method in this paper can reach convergence. It shows that this method has strong adaptive planning ability and can effectively improve the reliability of scenic spot tourism path planning.

In order to further verify the validity of the convolution neural network model, the convergence rates of three methods are compared when planning the same route. The faster the convergence speed is, the better the performance of the algorithm is. The result is shown in Figure 8.

According to the convergence stage of the optimal value generated by each algorithm, Figure 8 shows that compared with the literature methods, because this method completes the scenic spot tourism route planning based on the real situation and personalized needs of the path, uses the convolution neural network model, and avoids the local optimization through the shortest distance goal and the goal of avoiding the crowded area of tourists. After continuous iteration, the optimal solution is continuously updated, and the final optimal solution is obtained at the end of the planning. The convergence speed is significantly accelerated. The methods of Reference [8] and Reference [10] no longer update the optimal solution at 100 and 220 times and fall into the local optimal state.

5.2. Analysis of Simulation Test Results. According to the current scenic environment of tourists, this paper selects two test environments:

(1) Simulation environment 1: There are a large number of densely distributed tourist gathering areas in the environment, with a density of about $\rho = 0.1$. The tourist gathering areas are equal in size and randomly distributed, with a number of 30. Compare the path planning effects of the three methods in two environments as shown in Figure 9.

As can be seen from Figure 9, in the environment of scattered and dense tourist gathering areas in environment
1, the planning curve in this paper has the lowest false touch rate, the least times, and the farthest distance to the tourist gathering areas, while the other two methods have more times of touch. It shows that the algorithm is difficult to achieve high-quality path planning in the environment with dense tourist gathering areas. This is because the two algorithms did not analyze the collected information of tourist gathering areas before planning, resulting in the lack of contrast coefficient in the planning scheme, and the thoughtless consideration of factors, resulting in the deviation between the performance and expectation in practical application.

(2) Simulation environment 2: The edges of many small tourist gathering areas are connected with each other to form different circles, rectangles, and triangles of tourist gathering areas. The number is 5 and the density is $\rho = 0.1$. Compare the path planning effects of the three methods in two environments, as shown in Figures 10.

As can be seen from Figure 10, there is no obstacle collision in the planning curve under environment 2 compared with environment 1. This paper shows that the method of planning the shortest path and avoiding the shortest distance of the curve is the most effective method to avoid the dangerous area. This is because the convolution neural network programming method used in this paper has certain constraint ability. Through the combination of collision constraint function and shortest path constraint function, it can avoid the tourist gathering area and ensure the shortest distance at the same time.

Based on the above experimental results, this paper adopts the neural network method to realize the shortest path planning of scenic tourism routes, and the planning effect is good and the convergence is strong.

6. Conclusion

This paper constructs the convolution neural network model of tourist route planning after optimization and realizes the tourist route planning and design with the optimization control method. Using the method of adaptive learning of primitive trajectory, the node and path space planning of scenic spots are designed, and the shortest path optimization parameter analysis model is established. The distribution grid model of scenic spots is designed by route optimization control method, and the intelligent planning of scenic spots is designed by convolution neural network method. The analysis shows that the adaptive optimization and control ability of the proposed method is good and the convergence is strong.

The future work of this paper is to transplant the route planning algorithm to the increasingly popular portable devices such as smart phones and tablet computers in the form of web pages and app applications and combine it with the mobile electronic tour guide system to achieve real-time tracking and positioning, dynamically plan routes, and provide current scenic spot information in the form of multimedia, so as to facilitate the information development of scenic spots and facilitate passengers’ travel. In addition, the algorithm can also be applied to many related fields, such as vehicle navigation, express delivery, bus route optimization, and supermarket goods distribution. It provides a new way of thinking and a new method to solve various path planning problems. At the same time, the proposed method needs to be further optimized to save travelers’ time and further route model.
Data Availability

The authors can provide all the original data involved in the research.

Conflicts of Interest

The authors indicate that there was no conflict of interest in the study.

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