Research Article
Research on the Design of VR Tourism Service System Based on Deep Learning and Emotional Experience

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VR tourism has become an important part of mass tourism. With the advent of the “VR +” era and changes in public consumption habits, tourism must integrate VR, AR and other new technological means of high-quality development and innovative transformation and upgrading. Firstly, the concept of VR + tourism is clarified, and then the biggest problem in the current tourism development is the lack of application of new technologies and the lack of professional talents for local needs. For tourism enterprises, service providers, tourists, service facilities and scenarios, and service processes are all key elements in the implementation of emotional experiences. Possible elements of emotional experience in tourism services include designing attractive tourism experience themes, enhancing the experience value of tourism services, displaying experiential tourism tangibles, creating an atmosphere for interactive tourism experiences, and attaching importance to sensory stimulation for tourists.

1. Introduction

With the rapid spread and application of 5G, artificial intelligence and big data, virtual reality (VR) technology is being rapidly promoted and applied in all walks of life. In recent years, virtual reality companies have introduced a variety of VR tourism materials and actively promoted them as practical teaching resources for tourism majors in major universities, which are expensive and limited to famous attractions [1].

VR + tourism is a new paradigm where the integration of virtual reality technology can bring a new and exciting experience to visitors. This allows visitors to walk around the virtual space and view the scenery in a 360 degree view, which is visually no less impressive than viewing the scenery in the field. Wearing virtual reality equipment can also enhance the experience of hearing, smelling and touching, so even if you use virtual reality equipment to watch the scenery, you will not find it boring. [2].

In the current society, more and more geeks and nerds are eating, drinking and playing without going out, and “otaku” has become synonymous with a new generation of young people. “VR + tourism has brought new travel experiences to people at home and has brought them into close contact with their favourite landscapes. At present, China’s virtual tourism is still mainly focused on panoramic displays, from the traditional single picture viewing into 360-degree real-world appreciation, lack of immersive experience [3]. And because of the inclusion of three-dimensional modelling and three-dimensional animation technology production of virtual tourism due to the very high cost of development, the development of the difficulty, VR + tourism popular application is low [4].

Tourism is essentially a service industry, or more accurately, a mixture of service industries. As Faulkner, (1998) states “tourism is a collection of complementary services for a specific destination” [5]. In the case of services, while the traditional management areas of quality and productivity are
important, these are merely what Crompton calls the ‘technical part’. The other side of the management equation is the ‘psychological environment’, the subjective personal reactions and feelings that consumers experience when consuming a service. This phenomenon is known as the service experience and in recent years has been found to be a very important part of consumers’ evaluation of service satisfaction [6]. In the tourism industry, it is important to understand the phenomenon of experience in tourism because the behavioural decisions of travellers are often based on their emotional responses.

Philip Kotler divided human consumption behaviour into three stages: quantitative satisfaction, qualitative satisfaction and emotional satisfaction. In the emotional satisfaction stage, consumers are not looking for quantity and quality, but for an emotional desire to match the product with their ideal self-concept [7]. The recognition of this consumer characteristic has led to the emergence of experiential marketing. Toffler, a pioneer of the “experience economy”, predicted 30 years ago that “the next step in the service economy is to move towards an experience economy, where businesses will win by experiencing services”.

From a psychological and economic point of view, experience is essentially a phenomenon based on a physiological response, a personalised need, a good feeling that arises in a person’s consciousness when he reaches a certain level of emotional, physical, intellectual or even spiritual well-being. Unlike products and services, which offer solutions to customers’ problems, experiences do not leave anything tangible in the customer’s mind, but they do leave an indelible memory in the customer’s mind. Emotional experiences are a new marketing approach based on this concept. Compared with product marketing and service marketing, emotional experience aims to provide valuable experiences to customers, and seeks to attract and retain customers and make profits by satisfying their experiential needs [8]. In fact, emotional experience does not treat experience as an amorphous thing, but as a real economic offer, as a value carrier different from products and services to “sell”. As with traditional marketing, the key to an emotional experience is to make the customer’s needs known in the experience.

2. Related Work

To date, there has been a lot of tourism-related research both nationally and internationally. A mobile travel recommendation system is described in [9]. Reference [10] used 34,206 travel photos shared on the Flickr platform and the tagging of the images for attraction recommendations. Reference [11] uses a context-aware system to calculate users’ preferences for attractions and then makes recommendations for them, which are obtained by matching the generated association rules using contextual information, based on collaborative filtering. Reference [12] used a Bayesian network to calculate the user’s preference for an attraction for recommendation by building a tourist attraction decision support system (ITAS), which uses a model-based collaborative filtering approach. Reference [13] proposed a multi-criteria collaborative filtering recommendation method and applied it to hotel recommendation. The method uses an adaptive neuro-fuzzy inference system, a Gaussian hybrid clustering algorithm and an analytical dimensionality reduction technique to overcome the problem of multicollinearity of data in multi-criteria collaborative filtering and improve the accuracy of the recommendation [13]. The system proposed by [14] uses demographic information for tourist attraction recommendation, and solves the cold-start problem by recommending attractions of interest to other users in the same category with some effectiveness by using Bayesian methods and support vector machines to classify users and assuming that users in the same category have similar interest preferences [15].

Reference [16] by using cases for tourism service recommendation, they organise and store the user’s historical data in the form of cases, when the user has a demand, the system will search in the cases through the method of similarity calculation to find out the cases close to the user’s demand, and then adjust the cases according to the user’s specific needs to produce the recommended solution. Reference [17] proposed a hybrid model for travel recommendation, which uses semantic similarity based on ontologies to build a combination of association rules through the user’s display and implicit information, and its recommendation for the user is made using a hybrid collaborative filtering technique, using the similarity calculated between ontologies. Reference [18], to profile users, find out information such as their ratings and points of interest, and make recommendations by forming groups of similar users through similarity calculations. The geolocation information is then integrated and the users are recommended by the proposed letter step algorithm and recommendation mechanism. Reference [19] designed an intelligent system for travel recommendations, which makes full use of situational awareness information on the mobile side to provide visitors with real-time information on weather, opening hours of attractions and other information, and also to recommend travel options for visitors through artificial intelligence methods.

3. An Emotional Experience Model for Tourism Services

Based on the experiential nature of tourism services and the components of emotional experience, we have constructed an emotional experience model of tourism services (Figure 1), which not only contains the four components of emotional experience: product, service, facility and experience process, but also describes how these factors interact with each other during the interaction between tourists and tourism service providers, and ultimately achieve the emotional experience goal of the enterprise. It also describes how these factors interact with each other during the interaction between the tourist and the tourism service provider to achieve the emotional experience of the business. The emotional experience of tourism services cannot be achieved without the four components of service providers, tourists, scenarios and the tourism service process. The service providers include those who are in direct contact
Experience benefits are the benefits that tourists derive from the tourism experience, which depend on the service process and are related to the service outputs of tourism. In different segments of the tourism service, tourists want to obtain different experiential benefits. The experiential benefits of tourism services depend on two dimensions of tourism service quality: functional quality and output quality.

### 4. Construction of CNN-DNN

#### Network Architecture

After preprocessing the data, a vector of users and a vector of tourism services is obtained. The most straightforward idea is to use these vectors to calculate the similarity through some similarity calculation methods and make recommendations directly based on the similarity. However, this approach has major problems, as it does not analyse and explore the inherent connections between these vectors, and the computational effort is so large that the results are seriously biased if calculated directly. Therefore, here we build a deep learning based neural network model, called the deep prediction model, which consists of three parallel neural networks coupled at the last layer, to mine and learn the hidden potential relationship between users and tourism services, so that the learned network can be used to make rating predictions and thus complete the recommendation task.

#### 4.1. Model Framework

As shown in Figure 2, the network framework of the proposed in-depth prediction model is shown in this paper. The network model as a whole consists of three parts, including the user review information network, the tourism service item review information network and the other information network. The various vectors obtained after data preprocessing are used as the input to the network, which can be seen as various information representations of users and tourism services. After this information has been computed through the network, each part outputs a set of low-dimensional dense spatial vectors that can be seen as further abstracted descriptions after feature extraction. In order to enable the features extracted from the three parts to interact with each other, a common action layer is added at the top of the three part network to integrate the features extracted from the three parts together for the final rating prediction.

In the coaction layer, this paper uses the factor decomposer technique to construct a model function to predict the rating of items. As we want to mine the interactions between the learning vectors and use these interactions to predict scores for the target items, this task can be well accomplished by a factorisation machine.

#### 4.2. Construction of an Information Network of User-Reviewed Texts

The structure of the user review information network is shown in Figure 3, which is a convolutional neural network based network architecture. It contains an input layer, a convolutional layer, a pooling layer and a fully connected layer.
Convolutional Neural Networks (CNN), also known as Convolutional Networks, are neural networks that specialise in processing data with a grid-like structure. CNN are very effective in extracting hidden features from textual information.

4.3. Construction of an Information Network for the Text of Tourism Services Reviews. The basic structure of the travel service review information network is the same as that of the user review information network, in that a convolutional neural network is constructed to process it. The network structure is shown in Figure 4.

For the tourism service reviews, we obtain a vector matrix of tourism service reviews $V_{1:n}$ by preprocessing the data as described in the previous section, which is fed into the network as input. Each layer of the network, i.e. the input layer, the volume layer, the pooling layer and the fully connected layer, is consistent with the user review information presented above, i.e. it corresponds to the parallel structure of the user review information network, through which we finally obtain the tourism service item review information features, which will be noted as $x_i$.

5. VR Setup

The construction of the 3D model in this paper is divided into the following steps: ① Select a suitable project site. Prepare the filming equipment and, once at the project site, carefully observe the surroundings to see if it is suitable for the drone to fly and make sure the project site is not a no-fly zone. ② Check whether the drone equipment is normal and set the drone flight and filming parameters on a tablet computer using DJI GS Pro software. ③ It is particularly important to set the image heading overlap rate to 80% and the side overlap rate to 60% to ensure that the aerial images have a large image overlap rate.

After confirming that the basic parameters of the drone were set correctly, 10 aerial flights were taken from 5 angles according to the principle of tilt photography. ④ The UAV is recovered and the image data is checked to see if it is available, otherwise the data is rechecked and problems are identified, corrected and recollected until the data is available. ⑤ Data processing. Import the aerial imagery into Pix4D mapper 3D modelling software for model generation, then select a solid 3D model in OBJ format for output and...
import into 3D Max for refined editing and optimisation (Figure 5).

The edited and optimised model is imported into the Unity 3D engine using the OBJ format, and then dynamic interactions are written in C++ to make the scene interactive in real time, giving the user the immersion of a first-person tour [20].

6. Comparative Analysis of Experimental Results

In this subsection, for MF and PMF, we use grid search to find the best value for the number of hidden factors in \( \{25, 50, 100, 150, 200\} \) and the best value for the regularisation parameter in \( \{0.001, 0.01, 0.1, 1.0\} \). For LDA, the number of topics is chosen from \( \{5, 10, 20, 50, 100\} \) using the validation set, and it is found that the best results are obtained when the number of topics is chosen from \( \{5, 10, 20, 50, 100\} \), so here we choose the topics. For the proposed method DPMR, in the previous subsection we analysed the influence of the number of hidden factors, the number of convolutional kernels and other factors on the model, and here we set some other hyperparameters accordingly, the convolutional kernel window size \( t \) is set to \( t = 3 \), the dimension of the transformed word embedding vector is set to 300, the parameters of the optimisation algorithm Adam are set by default, i.e. the step size \( \varepsilon = 0.001 \), the momentum \( \rho_1 = 0.99 \), \( \rho_2 = 0.999 \), the small constant \( \sigma = 10^{-8} \) for numerical stabilisation, and the batch size set to 100 were all chosen by using grid search on the validation set. The results of the MSE values for these four methods are given in Table 1.

As Table 1 shows, the DPMR method proposed in this paper has the best performance. Since MSE and MAE reflect the error in predicting ratings and lower values indicate higher accuracy of recommendations, Table 1 shows that the MSE and MAE values of the method proposed in this paper are the lowest among the four methods. Although PMF is more effective than MF, both methods do not perform as well as the DPMR method proposed in this paper. This is mainly because both methods cannot use information other than rating information, such as review text information, and cannot extract more information from the review text. This also suggests that considering review text information can improve the accuracy of rating prediction. Although LDA can learn some features from comments to improve the accuracy of prediction by using the comment text information, Table 1 shows that there is still a gap with the DPMR proposed in this paper, because the modelling process of LDA for comment text is independent of the scoring, so it is difficult to guarantee that the learned features will be beneficial to the prediction of scoring.

As can be seen from Table 2, the proposed DPMR method still maintains good performance in generating personalised recommendation lists for users, with the sensitivity and accuracy of its recommendation lists remaining first among the four algorithms. Compared to the other algorithms, DPMR makes good use of some basic information and comment text information, and also exploits the hidden interactions between these information, which the other algorithms do not have. They are therefore less accurate and less sensitive than the DPMR algorithm in terms of the list of recommendations they generate [21].

The emotional experience seeks to attract and retain customers by satisfying their experiential needs and gaining profit. The interactive experience model of tourism services describes the various factors that influence the benefits of the tourism experience and their interactions during the interaction between the tourist and the tourism service provider. According to the nature of the experience of tourism...
3D modeling process

- UAV photography
- Tilt photography
- Duplicate image
- Control point data
- Pix 4dmapper modeling
- Model generation
- Suspended solids removal
- Texture modification
- 3DMAX model optimization
- Model planting shear
- Add interactive functions
- Unity3d engine virtual scene construction

**Figure 5:** Flow chart of solid 3D modelling.

**Table 1:** Comparison of MSE and MAE for different algorithms.

|     | MSE   | MAE   |
|-----|-------|-------|
| MF  | 2.081 | 2.035 |
| PMF | 0.064 | 2.021 |
| LDA | 1.982 | 1.946 |
| DPMR| 1.673 | 1.562 |

**Table 2:** Comparison of accuracy and MAP of different algorithms.

|     | P5   | P10  | P20  | MAP  |
|-----|------|------|------|------|
| MF  | 0.458| 0.431| 0.307| 0.315|
| PMF | 0.461| 0.443| 0.311| 0.320|
| LDA | 0.573| 0.547| 0.469| 0.471|
| DPMR| 0.647| 0.615| 0.493| 0.572|

**Figure 6:** Confusion matrix of different tourism experiences.
services and emotional experience model, develop the emotional experience content of tourism services, as shown in Figure 6, different tourism quality sports effect.

As shown in Figure 7, there is considerable subtlety in the interplay between the experience of tourism services and satisfaction, with satisfaction being the result of the experience of attention seeking, power, pastime/forgetfulness, self-confidence/self-worth, and self-importance in tourism service activities. The twin themes of seeking and escaping are prevalent in the psychology of tourism consumption, and maintaining a balance between the two is the ideal state of satisfaction. Within the field of service marketing, the most common marketing measurement tools focus on the functional and technical aspects of service quality evaluation and service delivery. In fact, traditional measurements of service quality have been used in the tourism industry to evaluate service quality.

7. Conclusions

Tourism services are essentially one or more experiences and experiences for tourists. This experiential nature of tourism services determines that tourism service providers should not only focus on the service quality of tourism itself, but also on the quality of tourists’ experience. As a tourism service provider, you should be aware of the importance of emotional experience for your company. Therefore, tourism enterprises should develop emotional experiences in a comprehensive manner to enhance the competitiveness of tourism services, from tourism theme design, experience value enhancement, tourism display, tourism atmosphere creation and tourists’ sensory stimulation.

Data Availability

The dataset used in this paper are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest regarding this work.

Authors’ Contributions

Li Sui and Zhenzhen Dong contributed equally to this work.

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