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Digital Visualization of Intangible Cultural Heritage Based on Computer Intelligent Algorithm

Huixia Yu[1,a*], Zhenfu Mao[1,b] and Faxian Jia[1,c]

[1]School of Management, Henan University of Urban Construction, Pingdingshan, Henan, China
[a]279237624@qq.com, [b]maozhf453@163.com, [c]fxj163@163.com
[*]Corresponding author

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Abstract: In recent years, digital visualization technology of intangible cultural heritage has attracted extensive attention. With efficient digital visualization methods, it can reflect the colorful living history and culture of human beings from multiple angles. It is an inevitable development trend to use digital technology to protect and promote intangible cultural heritage. This paper takes cultural space as the core element, based on conceptual abstraction, object type division and information characteristic analysis, and uses the related concepts and algorithms of long short-term memory model (LSTM) to digitally model the intangible cultural heritage information space. In this paper, the computer intelligence algorithm is used to train the LSTM data set, and the node parameters in the LSTM are mapped to the corresponding weight vector and bias vector, and then the solution space with the mean absolute error as the objective function is constructed, and the computer intelligence algorithm is used to optimize in the digital space. The experimental results show that the mean square error (MSE) results of training LSTM based on the computer intelligence algorithm show that the prediction accuracy of the training set, test set 1 and test set 2 of the gray wolf optimization algorithm (GWO) is 87.82%, 45.55%, 58.22%, the training set prediction accuracy of IGWO-GA algorithm is 98.85%. Moreover, the error between the prediction results and the actual value in the training set and test set is low, indicating that the improvement effect is good. It verifies the advantages and feasibility of LSTM digital model in organizing and expressing intangible cultural heritage digital information.

1. Introduction

Intangible cultural heritage is a living ancient culture and a tangible embodiment of human spirit, ideals, morality and wisdom. As a means of cultural communication, digital mobile platforms are widely used in people's production and life, and are very attractive to young people in the use of visual images and application tools. Therefore, the digital mobile platform should be an active participant in the protection of intangible cultural heritage, and contribute to the inheritance and dissemination of intangible cultural heritage. Based on the background of the digital age, information technology represented by digital visualization technology has played an active role in the digital collection, storage, display and dissemination of intangible cultural heritage resources, opening up new ways for their inheritance and protection. However, the research on auxiliary design of intangible cultural heritage for the public is still weak, and there is a large research gap in the research on the dissemination and development of intangible cultural heritage among the public.

In recent years, computer intelligent algorithms have attracted widespread attention from scholars in the fields of humanities, history, and social sciences due to their powerful spatiotemporal information organization and management and visual expression capabilities. Using computer intelligent algorithms as a platform for collecting, analyzing and displaying humanities, history and other information has become an important research direction and hotspot in related fields. By analyzing and summarizing the rich information types and the evolution characteristics of objects in the evolution of intangible cultural heritage through relevant theories and technical means in computer intelligent algorithms, it provides a theoretical basis for further promoting the connection between intangible cultural heritage and digital visualization technology. The innovation of this paper is to use the establishment of a digital visual data model to sort out the trivial intangible cultural heritage information, which provides technical support for the visual expression and analysis of the deep laws in the evolution of intangible cultural heritage. At the same time, this paper explores the application methods of the model in the fields of digital protection of intangible cultural heritage and public information services, promotes the combination of interdisciplinary comprehensive research and computer intelligent algorithms, transforms and empowers the public's understanding of the meaning and value of intangible cultural heritage resources, carries out cultural innovation, expands the application scope of intangible cultural heritage, and promotes intangible cultural heritage and protection.

2. Related Work

In the human civilization that can be like a galaxy, intangible cultural heritage has an extremely important position. It is the crystallization of people's wisdom in life and production, and embodies the spiritual and cultural connotation of a region, a nation and even an era. Hu W studies and shows that the protection of intangible cultural heritage can achieve the modern aesthetics of traditional craftsmanship with the continuous expansion of the artisan's vision and the improvement of the production capacity of new products [1]. Broude T pointed out that intangible cultural heritage may interact with trade regulation in various situations [2]. Martyn H showed that intangible cultural heritage is recognized as having historical, social and anthropological value and is considered as a driving force for sustainable development [3]. Ming Z's research found that the Informedia digital video library contains more than one thousand hours of video, and the previous system can be used to represent the multimedia abstraction of intangible cultural heritage, and its visualization technology [4]. Bradley AJ pointed out that the two disciplines of intangible cultural heritage and digital visualization jointly promote the research goals of their respective disciplines [5]. Scholars believe that intangible cultural heritage is of great significance for inheriting human civilization and building advanced culture. However, most of the current organization of intangible cultural heritage knowledge is still limited to the connection between the internal basic knowledge elements, and the application in digital visualization and other aspects lacks the deep integration of conceptual theory and practice.

Due to the development of digital technology, scholars have begun to combine computer intelligent algorithms to store and manage the rich spatiotemporal information in intangible cultural heritage, and to show the public the advancement and evolution of intangible cultural heritage in historical time and space. According to Sun H's research, it is found that computer intelligence algorithms are helpful to understand the system properties represented by complex networks, and are of great significance to a wide range of applications [6]. Yao S pointed out that the reconstruction performance of existing matching pursuit algorithms is closely related to the signal sparsity [7]. Lu J showed that in practice computer intelligence algorithms are often affected by the complex structure of data sets, including data distribution and dimensionality [8]. Camero A showed that a highly scalable routing system based on a micro-steady-state evolutionary algorithm takes significantly less time to compute the shortest path [9]. Scholars have found that computer intelligent algorithms can provide technical support for the visual expression of intangible cultural heritage spatiotemporal information and the analysis of deep-level laws in the evolution. However, when sorting out and organizing the spatiotemporal information in the evolution of intangible cultural heritage, most of them are only from a technical point of view, lacking generality and research on data model construction and related application methods based on computer intelligent algorithm software.

3. Digital Visualization Technology Based on Computer Intelligent Algorithm

3.1 Data Model Based on Digital Visualization Technology

(1) The dissemination of digital visualization information

The advantage of digital visualization technology is that data processing includes storage, transformation, generation, etc. In recent years, the development of computer intelligence technology has also made long-term progress in digital visualization technology in the understanding, analysis, identification, induction, classification and creation of data content. These advantages have played an important role in the protection and development of intangible cultural heritage [10]. Therefore, the digitization of intangible cultural heritage is essentially a form of information. Borrowing from the theory of information dissemination, it is expressed that dissemination is a process through which other people are influenced [11]. This process is purposeful, and the encoding and decoding of information is a social process, produced by an intentional, formulaic encoding process that leads to mutual understanding. The three-level problem of dissemination is shown in Figure 1.

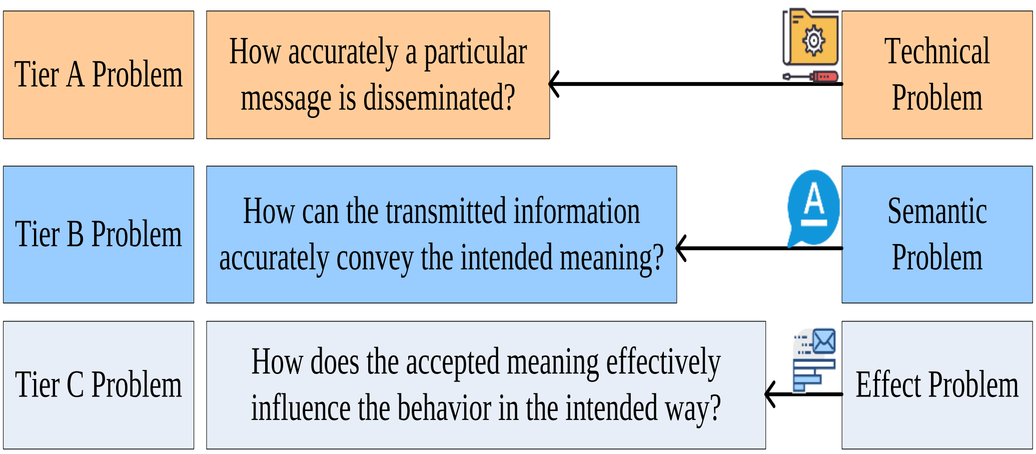


Figure 1. Three levels of information dissemination

As shown in Figure 1, the three-level issues of digital visualization and dissemination of intangible cultural heritage require in-depth research based on information theory. However, the main problem in the current digitalization of intangible cultural heritage is the comprehensive, in-depth and effective synergy between the two fields. In order to ensure the effectiveness of cooperation, it is necessary to construct a framework scheme to provide cooperation prerequisites [12-13]. Therefore, the establishment of the "information space" model provides a theoretical basis for the cooperation among cultural scholars, non-genetic inheritors, and digital information experts. This theory holds that any information product, value and its meaning can be explained from three dimensions, namely encoding, abstraction and diffusion. Coding, abstraction and diffusion together form a three-dimensional information space, as shown in Figure 2.

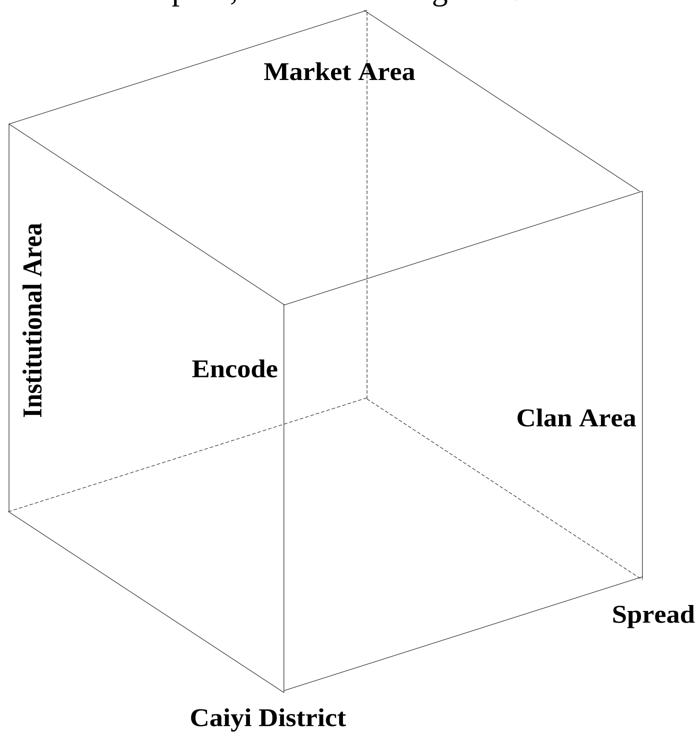


Figure 2. I-space frame model

As can be seen in Figure 2, the information space composed of three dimensions includes four areas, namely the fief area, the clan area, the institutional area, and the market area [14]. From the perspective of geographic information system (GIS), it analyzes its inheritance characteristics, proposes relevant spatiotemporal database design schemes for different types of data, and builds a digital information platform for the study of intangible cultural heritage. Using the technology based on key events, a method for structured organization and visual expression of the evolution process of intangible cultural heritage was established [15].

(2) Model-based approach to intangible cultural heritage

In the field of culture, an important person can be related to multiple cultures and play an important role in the development of multiple cultures. Therefore, the one-to-many relationship between characters and culture should also be considered in intangible cultural heritage[16-17]. Specifically, a character may be involved in multiple intangible cultural heritage events, and these events are distributed in different intangible cultural heritage projects. Some tools and activities in intangible cultural heritage may also appear in other different intangible cultural heritage projects. As a result, through the correlation of intangible cultural heritage events involving people and things, the correlation between intangible cultural heritage items can also be found, as shown in Figure 3.

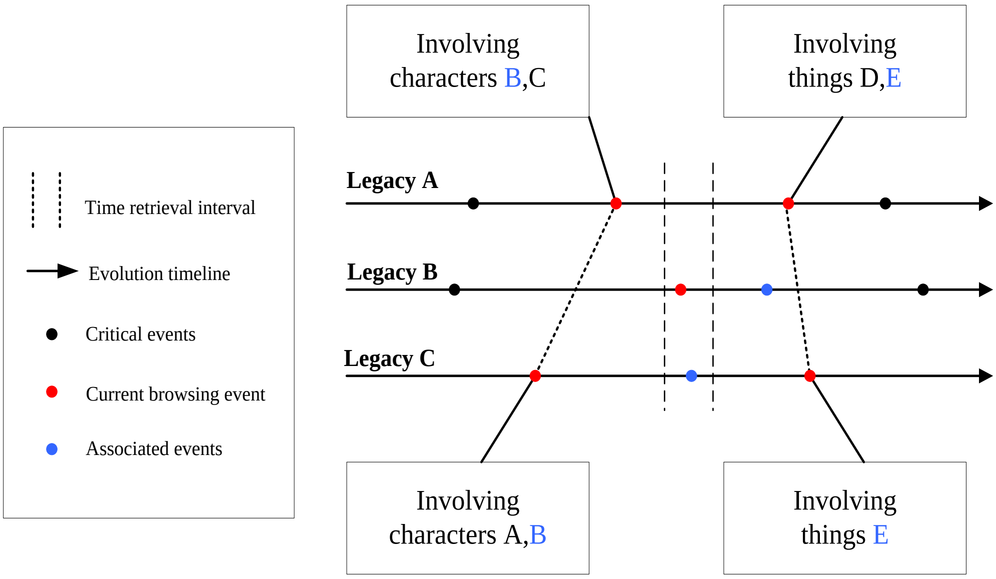


Figure 3. Intangible cultural heritage item associations based on people, things, and time

As can be seen from Figure 3, among different intangible cultural heritage items, the locations where key events occur are also spatially related, for example, multiple events may have occurred at one location, or the areas where two events occurred are adjacent. At this time, according to the situation of spatial data (type is point, line or area) and actual needs, intangible cultural heritage events can be screened through spatial relationships such as inclusion, adjacency, buffer zone, etc., and the spatial association of items can be found, as shown in Figure 4.

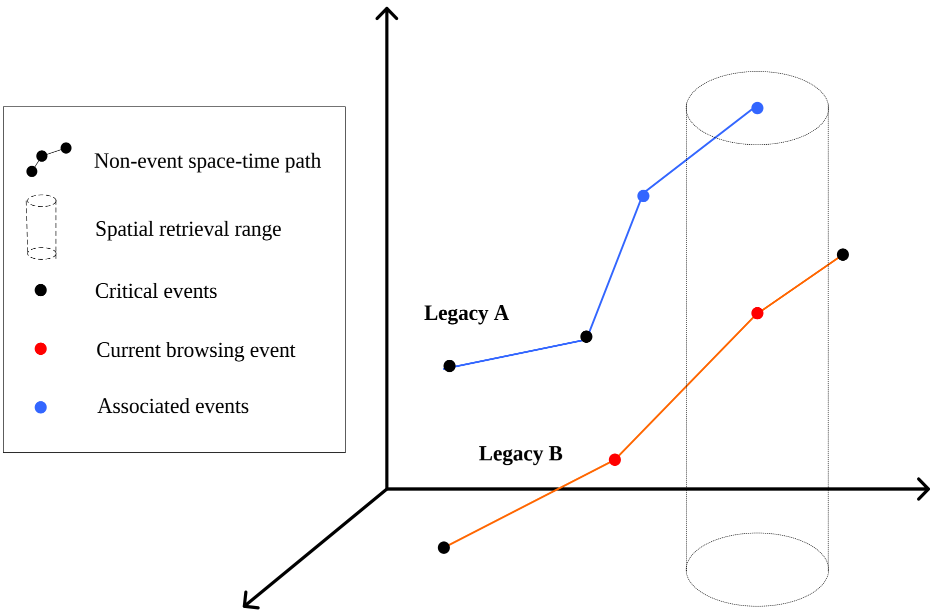
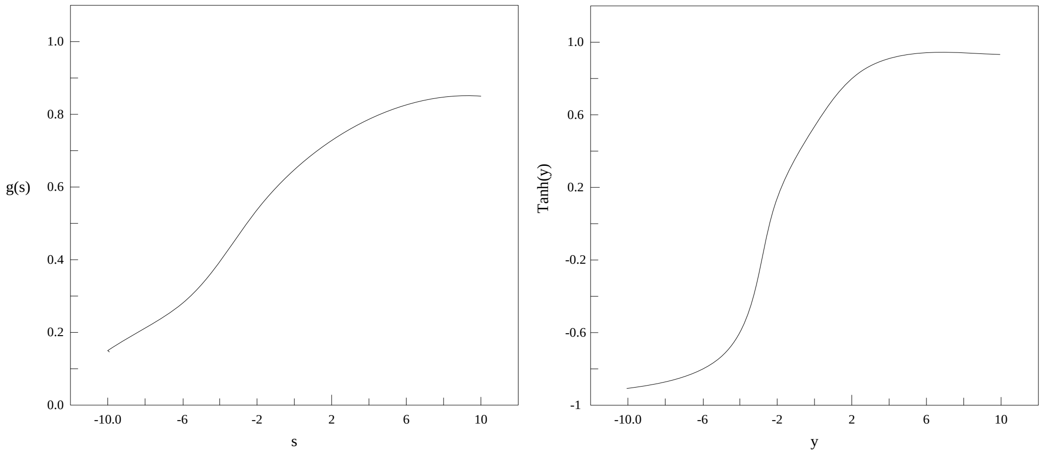


Figure 4. Schematic diagram of spatial association of intangible cultural heritage items

As shown in Figure 4, there are two ways to achieve the above functions: First, the current mainstream relational databases (Oracle, MySQL, etc.) already support spatial query through SQL statements; the second method is that the location field of the event table only stores the pointer to the corresponding vector data, and then reads the spatial data and performs spatial relationship query operations at the code level, and finally returns the screening results [18]. This method is more flexible, there is no restriction on data format, and mainstream data formats such as shp and geojson can be used directly.

3.2 Common Activation Functions Based on Computer Intelligence Algorithms

Activation functions are crucial for numerically visualizing data models to learn complex nonlinear functions [19]. In order to enhance the expressive power of numerical information, it is necessary to supplement nonlinear factors with activation functions. The sigmoid function is the most common nonlinear activation function, and the tanh function is relatively common. The function image is shown in Figure 5.



(a) Sigmoid function (b) tanh function

Figure 5. Image of Sigmoid function and tanh function

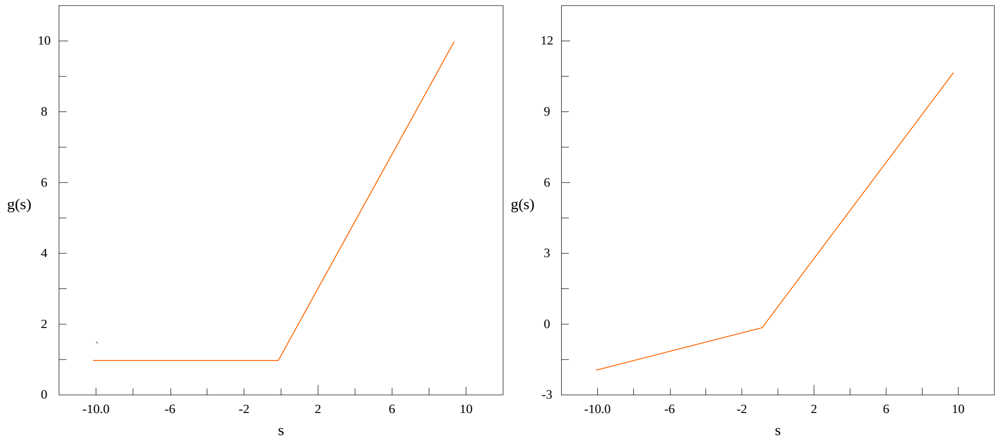
It can be seen from Figure 5(a) that the sigmoid function maps a number with a value of $(-\infty,+\infty)$ to (0, 1), and its function expression is shown in formula 1.

$$g(s)=\frac{1}{1+b^{-s}} \quad (1)$$

It can be seen from Figure 5(b) that the tanh function maps a number with a value of $(-\infty,+\infty)$ to (-1, 1), and its expression is shown in formula 2.

$$\tanh(y)=\frac{b^{y}-b^{-y}}{b^{y}+b^{-y}} \quad (2)$$

The inherent disadvantage of the sigmoid function and the tanh function is that the gradient is prone to disappear. Secondly, both functions contain power operations, which will increase the training time [20]. The ReLU function and the Leaky ReLU function solve the gradient disappearance problem for the Sigmoid function and the tanh function, and are a piecewise function, as shown in Figure 6.



(a)ReLU function (b)Leaky ReLU function

Figure 6. Image of ReLU function and Leaky ReLU function

According to the ReLU function image in Figure 6(a), it can be seen that the ReLU function does not have the problem of gradient disappearance, the calculation speed is very fast, and the convergence speed is greatly improved. Its function expression is shown in formula 3.

$$g(s)=\begin{cases} s, if & s>0 \\ 0, if & s<0 \end{cases} \quad (3)$$

According to the Leaky ReLU function image in Figure 6(b), it can be seen that the Leaky ReLU function is an improvement of the ReLU function. The function expression is shown in formula 4.

$$g(s)=\begin{cases} s, if & s>0 \\ xs, if & s<0 \end{cases} \quad (4)$$

Among them, x is usually taken as 0.01.

3.3 LSTM Data Model Based on Computer Intelligent Algorithm

(1) Training method of back propagation algorithm (BPTT)

Based on the above function method, taking the training of the recurrent neural network (RNN) model as an example, when training the RNN model, it needs to pay attention to the parameters of weights V, W, U, bias x, y, which determine the prediction effect of the RNN model.

Taking the parameter weight W as an example, the loss function calculates the partial derivative of W:

$$\frac{\partial T^{(z)}}{\partial W}=\frac{\partial T^{(z)}}{\partial r^{(z)}}\cdot\frac{\partial r^{(z)}}{\partial W} \quad (5)$$

But the loss will accumulate over time, so it can't just ask for the partial derivative at z moment.

$$T=\sum_{z=1}^{b} T^{(z)} \quad (6)$$

Its overall loss function is shown in formula 7.

$$\frac{\partial T^{(z)}}{\partial W}=\sum_{q=1}^{z}\frac{\partial T^{(z)}}{\partial r^{(z)}}\frac{\partial r^{(z)}}{\partial f^{(z)}}\left(\Pi_{j=q+1}^{z}\frac{\partial f^{(j)}}{\partial f^{(j-1)}}\right)\frac{\partial f^{(q)}}{\partial W} \quad (7)$$

Similarly, the partial derivatives of weight U and weight V can be obtained as formula 8 and formula 9 respectively:

$$\frac{\partial T^{(z)}}{\partial U}=\sum_{q=1}^{z}\frac{\partial T^{(z)}}{\partial r^{(z)}}\frac{\partial r^{(z)}}{\partial f^{(z)}}\left(\Pi_{j=q+1}^{z}\frac{\partial f^{(j)}}{\partial f^{(j-1)}}\right)\frac{\partial f^{(q)}}{\partial U} \quad (8)$$

$$\frac{\partial T^{(z)}}{\partial V}=\sum_{q=1}^{z}\frac{\partial T^{(z)}}{\partial r^{(z)}}\frac{\partial r^{(z)}}{\partial f^{(z)}}\left(\Pi_{j=q+1}^{z}\frac{\partial f^{(j)}}{\partial f^{(j-1)}}\right)\frac{\partial f^{(q)}}{\partial V} \quad (9)$$

When the activation function derivatives are all less than 1, it will lead to the problem of gradient disappearance. At this time, it is difficult to deal with the BPTT algorithm to train the hierarchical RNN model. And in the face of multi-dimensional data, the matrix for derivation of parameters may not exist, and some equivalent substitutions need to be used. These issues all affect the accuracy of the trained model.

(2) LSTM data model application

LSTM is a variant of RNN. In image description, speech recognition, and natural language processing, the LSTM model has performed well and is widely used in various fields. LSTM has a similar macro structure to RNN, but LSTM has a more subdivided hidden layer structure. Among them, P_z is the hidden layer state at time z, R_z is the calculation result at time z, t_z is the output result at time z, σ is the gate function is the Sigmoid activation function, and q is the gate function is the Tanh activation function.

The calculation process of the training method of the LSTM model is as follows:

Forgetting gate: The input vector at time z and the output vector of the output layer at time $z-1$jointly determine the output state of the forgetting gate at time z. The calculation method is shown in formula 10:

$$q_z=\sigma(V_q\cdot[p_{z-1},y_z]+f_q) \quad (10)$$

q_z is the forget gate output vector at time z, which is jointly determined by the input state $y_{(z)}$ at time z and the hidden state $P_{(z-1)}$ at time $z-1$. The forget gate determines whether to forget the previous state. When its operation result is 0, it represents the state before forgetting. The input gate calculation process can be expressed by formula 11:

$$i_z=\sigma(V_i\cdot[P_{z-1},y_z]+f_i) \quad (11)$$

The state of the memory cell at the current moment can be calculated in two steps, and it is calculated by formula 7 and formula 8. First is the co-influence matrix D'_z by y_z and P_{z-1}, D'_z is the variable matrix that affects the current memory cell, and then calculates the influence of the current input determined by i_z and D'_z. These two parts together form the memory cell state D_z at the previous moment.

$$\mathrm{D}'_z=q(V_D\cdot[p_{z-1},y_z]+f_D) \quad (12)$$

$$\mathrm{D}_z=q_z*D_{z-1}+i_z*\mathrm{D}'_z \quad (13)$$

Output gate: R_z is the weight matrix of the calculation result of the LSTM model at the current moment, P_z is the current hidden state, and$t_z$is the final output at the current moment, that is, the prediction at the z moment. They are represented by formula 14, formula 15, and formula 16, respectively:

$$\mathrm{R}_z = \sigma(V_R \cdot [p_{z-1}, y_z] + f_R) \quad (14)$$

$$\mathrm{P}_z = q(D_z) * R_z \quad (15)$$

$$\mathrm{t}_z = \sigma(V_t * P_z) \quad (16)$$

In summary, the forgetting gate, the input gate, the memory unit and the output gate jointly determine the value of the output result t_z. Due to the various gate structures in the LSTM model, the memory units existing in each layer can save long-term information, but there is still a problem of gradient disappearance.

(3) Improved GWO-GA algorithm to train LSTM model

When using the intelligent algorithm to train the LSTM model, it is already different from any intelligent algorithm test function, and the performance of the algorithm in the test function cannot be used as a reference for the final application. Operations such as population initialization, selection, crossover and mutation using chaotic sequences will affect the entire process of the algorithm. At present, there are many different chaotic mappings, and the common mappings are unimodal (Logistic) mapping, tent (Tent) mapping and so on.

The logistic mapping formula is:

$$\mathrm{Y}_{q+1} = \mu Y_q (1 - Y_q) \quad (17)$$

Among them, μ takes the value [0.6]. The Tent mapping formula is:

$$\mathrm{Y}_{q+1} = \begin{cases} Y_q / \beta & Y_q \in (0, \beta] \\ (1 - Y_q)(1 - \beta) & Y_q \in (\beta, 1] \end{cases} \quad (18)$$

Logistic mapping is less dependent on the initial value and can produce more kinds of initialization results; when β is set close to 1, the Tent map has better long-term unpredictability, as shown in Figure 7.

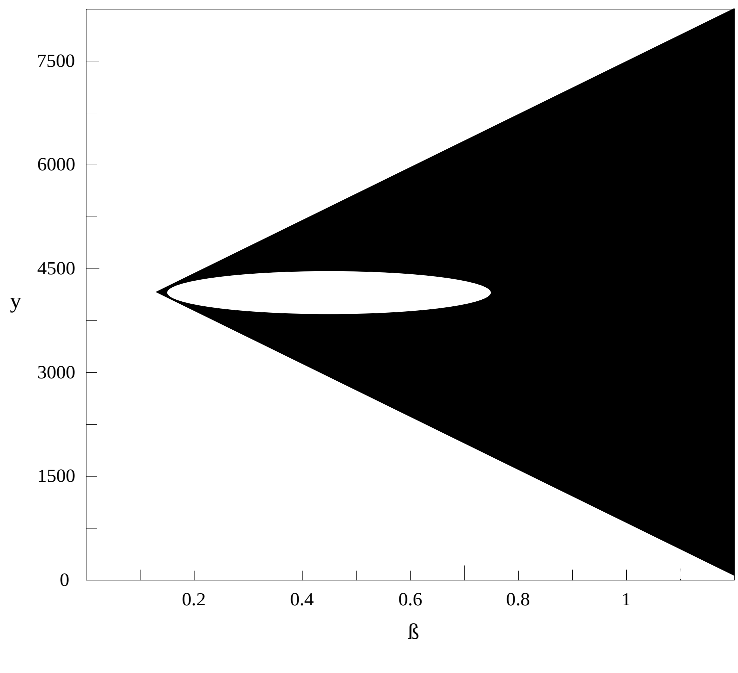


Figure 7. Tent map bifurcation diagram

The genetic algorithm simulates the gene recombination in the process of biological evolution and adds the crossover process. It generates new individuals by recombining and crossing the gene fragments of the parents, which improves the global search ability of the algorithm. Genetic algorithms for floating-point encoding often use formula 19 for the crossover operation.

$$\begin{aligned} y_M^{z+1} &= \alpha y_N^z + (1-\alpha) y_M^z \\ y_N^{z+1} &= \alpha y_M^z + (1-\alpha) y_N^z \end{aligned} \quad (19)$$

The constant α is the crossover probability, y_M^z and y_N^z are the parent generation, and the gene fragment before the α position of each parent generation is connected with the gene after the other parent generation to form a new offspring. However, the traditional single-point crossover and multi-point crossover are not suitable for training the LSTM model. There is a problem of insufficient ability in the exploration stage when training the LSTM model. In order to improve the algorithm's exploration efficiency of the solution space, this paper proposes an improved crossover operation:

$$\begin{aligned} y_M^{z+1} &= \sum_{i=1}^{b} Z_{Nij}\alpha_{ij} + (1-\alpha_{ij}) \sum_{i=1}^{b} Z_{Mij} \\ y_N^{z+1} &= \sum_{i=1}^{b} Z_{Mij}\alpha_{ij} + (1-\alpha_{ij}) \sum_{i=1}^{b} Z_{Nij} \end{aligned} \quad (20)$$

Among them, Z_{Mij} is the gene fragment in y_M^z, and similarly Z_{Nij} is the gene fragment in y_N^z. According to the mapping, the gene is divided into segments, and each segment has an independent crossover probability m_{ij} to determine whether it performs the crossover operation.

The main task of training an LSTM is to find suitable values for the model node parameters, which is a very challenging optimization problem. When using the improved GWO-GA algorithm to train LSTM, it is necessary to select the model node parameters to use floating-point vector encoding to encode, and convert the parameters of each node in the LSTM into algorithm solution space information.

4. Experimental Results and Analysis of LSTM Data Model Based on Computer Intelligent Algorithm

4.1 Experimental Parameters of BPTT Algorithm

In order to test the performance of the IGWO-GA algorithm in the training of LSTM, according to the concept classification of intangible cultural heritage, five types of intangible cultural heritage item data are selected as the research object. Its inputs have 5 different variables: oral traditions and expressions, performing arts, festivals, knowledge and practices about the natural world and the universe, and traditional crafts. So the LSTM input layer is 5 nodes and the output layer is 1 node. The number of hidden layer nodes obtained from experience is 20; the LSTM cycle is set to: 76 epochs, 380 data sets, and 140 consecutive data sets are randomly selected as training sets; two test sets are randomly generated, each with 110 consecutive data sets. The experimental problem setting and the LSTM model structure used are shown in Figure 8.

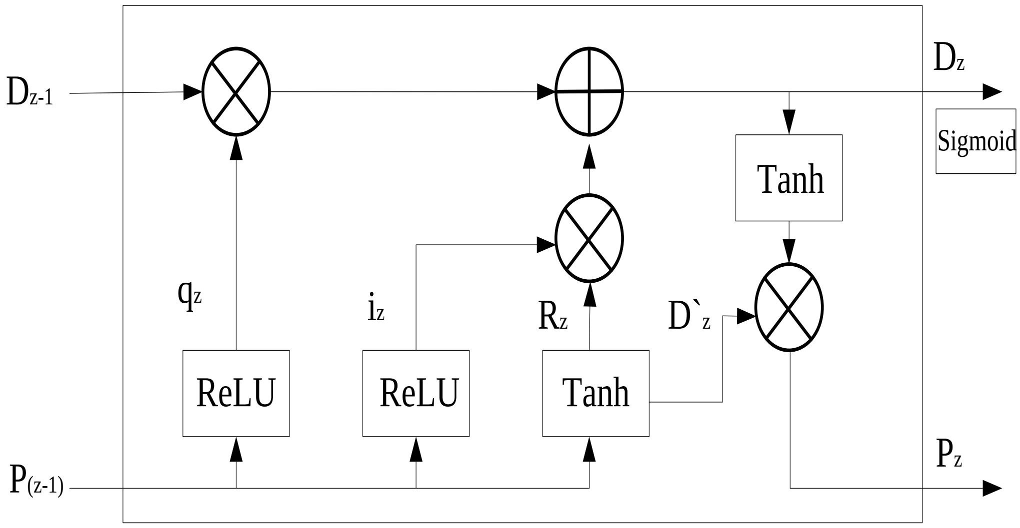


Figure 8. The LSTM model used in the experiment

In order to improve the effect comparison, GA, WOA and GWO are selected as LSTM trainers for experimental simulation, and the effect of each improvement point on the algorithm is discussed at the same time. This problem is set to test the training effect of computer intelligent algorithm training LSTM model. In the experiment, the population size of the intelligent algorithm is set to 160, and the maximum number of iterations of all algorithms is 900. The parameters of each intelligent algorithm in training are set as follows.

For the WOA algorithm, the random number h value is 0.6; for the GA algorithm, single-point crossover, the crossover probability is 0.8, and the initial mutation probability is 0.02; for the TWGO algorithm, $\beta = 0.4$ is used, the Tent map of $y_0 = 0.145$ initializes the population; for the IGA algorithm, the initial mutation probability is 0.02. For the IGWO-GA algorithm, $\beta = 0.4$ is used, the Tent map of $y_0 = 0.145$ initializes the population, the initial mutation probability is 0.02; the learning rate for the BPTT algorithm is $\alpha = 0.02$.

4.2 Time Complexity and Performance of the Improved Algorithm

It is a feasible solution to use the intelligent algorithm to train the digital model, and the intelligent algorithm with better effect is improved, and the effectiveness of the improved strategy is further verified, but the following problems will be encountered in the subsequent development. It is known from the No Free Lunch Theorem (NFL) that when training digital models with different structures, different algorithms and improvement strategies need to be used, and neither a single intelligent algorithm nor a specific improvement strategy has broad adaptability. Therefore, specific problems need to be analyzed in detail. In the face of different application scenarios and different data sets, targeted improvements need to be made on the basis of experiments. Based on the proposed improved Grey Wolf Optimizer (IGWO) algorithm, the time complexity analysis of each link is as follows:

The time complexity of GWO algorithm is $O(B \times \dim \times z_{max})$;

The IGWO algorithm uses the Tent chaotic map to initialize the population, and the time complexity is $O(B \times \dim)$. Therefore, the time complexity of the GWO algorithm with chaotic initialization is $O(B \times dim \times (z_{max} + 1)) = O(B \times dim \times z_{max})$;

The time complexity of GA is $O(B \times dim \times z_{max})$; the time complexity of IGA using the improved crossover algorithm is increased by V_z, and the time complexity is $O(B \times dim \times z_{max} + V_z) = O(B \times dim \times z_{max})$;

The IGWO-GA algorithm uses the Tent chaotic map to initialize the population with a time complexity of $O(B \times dim)$ and a time complexity of $O(B \times dim) + (B \times dim \times z_{max}) + V_z = O(B \times dim \times z_{max})$. Among them, B is the number of individuals, z_{max} is the maximum number of iterations, and dim is the dimension.

Through the experimental verification of the classical classification problem, the weight parameters and bias parameters in the nodes of the multi-layer perceptron (MLP) are mapped to the solution space that can be explored by the intelligent algorithm. And using a variety of intelligent algorithm training, in view of the problem of imbalance in the discovery and search stages in the GWO training process, a nonlinear convergence factor is used, and the adaptive update formula is improved. IGWO has good performance in training MLPs with different structures, and the specific data are shown in Table 1.

Table 1. MSE results and classification accuracy of GWO algorithm training MLP classification

Trainer Algorithm	Average Value	Standard Deviation	Optimal Value	Prediction Accuracy
GWO	4.62E-02	8.81E-03	3.71E-02	85.13%
NGWO	4.39E-02	1.39E-03	2.31E-02	87.67%
CGWO	4.29E-02	9.92E-03	9.17E-03	88.93%
EGWO	4.13E-02	2.21E-03	1.83E-02	85.91%
IGWO-GA	3.67E-02	4.15E-03	1.15E-02	91.12%

It can be seen from Table 1 that the standard value and optimal value of CGWO are better than the other algorithms, which shows that the CGWO algorithm has high convergence accuracy when dealing with MLP problems with a large number of associated nodes, and at the same time, CGWO is also higher than other algorithms in the classification accuracy of MLP test samples. The performance of the GWO algorithm on the standard deviation reflects its good robustness. Through the experimental results, the effectiveness of the improved IGWO-GA algorithm is verified.

4.3 Experimental Results of the Improved Computer Intelligence Algorithm

By using the intelligent algorithm to train the LSTM model, the parameters of each meta-gate node in the LSTM are mapped to vectors, and these vector shapes are combined to construct a solution space with the mean absolute error as the objective function, and use intelligent algorithms to optimize within this solution space. The two algorithms were fused for training. After the experiment, Table 2 shows the statistics of the MAE calculated by using the intelligent algorithm to train the LSTM model for 10 independent runs. The mean convergence curves of the MAEs calculated from independent runs are shown in Figure 9.

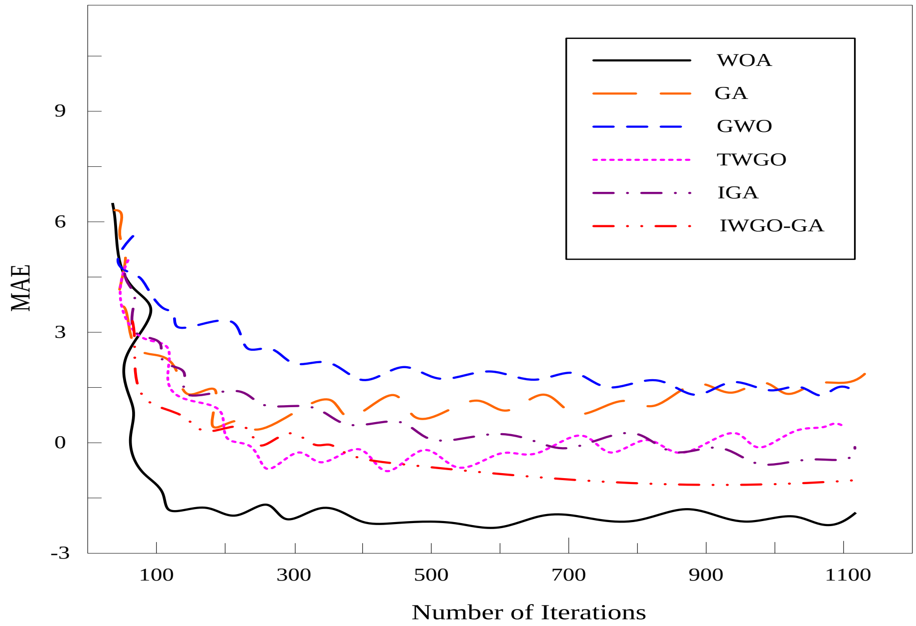


Figure 9. MAE mean convergence curve of computer intelligence algorithm training LSTM

From Figure 9, it can be found that WOA has the worst performance in the process of training LSTM. The performance of the discovery stage and the exploration stage is not as good as that of other algorithms. It quickly falls into the local optimum and fails to escape this dilemma successfully; the local development stage of GA is not as good as GWO, but in the global exploration stage, GA can maintain the solution space retrieval ability, gradually catch up and eventually surpass GA; GWO shows its excellent global retrieval ability and shrinks rapidly in the discovery stage, but the shortcomings of the algorithm's insufficient local retrieval ability are also exposed after reaching the exploration stage; TWGO uses Tent mapping, the stage is complicated, and the retrieval trial is long, but in the exploration stage, its diversity allows TGWO to catch up and eventually surpass GWO; the improved IGA algorithm improves the local retrieval ability of the algorithm by changing the cross operation of GA. Although the improvement reduces the global retrieval ability of GA, it greatly improves the local retrieval ability and improves the overall ability of the improved algorithm; the IGWO-GA that combines the above two improvements has a faster convergence rate in the discovery phase, and can take into account the exploration phase. The algorithm has fully explored the solution space, as shown in Table 2.

Table 2. MSE results and classification accuracy of LSTM trained by computer intelligence algorithms

Trainer Algorithm	Average Value	Standard Deviation	Optimal Value	Prediction Accuracy
WOA	1.73E-02	1.61E-02	5.32E-03	81.82%
GA	8.11E-03	7.32E-03	2.39E-03	97.52%
GWO	7.92E-03	7.62E-03	2.37E-03	87.82%
TWGO	7.56E-03	7.56E-03	9.11E-04	97.62%
IGA	7.65E-03	7.54E-03	5.37E-04	98.31%
IGWO-GA	6.37E-03	6.78E-03	7.98E-03	98.85%

It can be seen from Table 2 that 6 kinds of intelligent algorithms train the LSTM model, and

WOA is not as good as other algorithms in terms of the results of MAE and the classification accuracy of training, and the performance of robustness is the worst; both GA and GWO have a certain retrieval of the solution space and obtained certain good results, but the robustness of the two algorithms in training LSTM is only slightly better than WOA; the improved IGA and TWGO have significant improvements in the optimization results and Lupin performance compared with the original algorithm. IGWO-GA performs the best, inherits the improvement effect, fully searches the solution space, and finds a suitable position. Its prediction accuracy, the average and optimal values of MAE are better than the original algorithm, and it also has the strongest robustness. The prediction results of LSTM models trained by different algorithms on different datasets are shown in Table 3.

Table 3. MSE results and classification accuracy of LSTM trained by computer intelligence algorithms

Trainer Algorithm	Training MAE	Test Set 1MAE	Test Set 2MAE
WOA	1.73E-02	7.81E-03	5.31E-02
GA	8.11E-03	6.11E-02	3.91E-01
GWO	7.92E-03	6.15E-02	1.98E-01
TWGO	7.56E-03	4.23E-02	1.69E-01
IGA	7.65E-03	3.26E-02	6.89E-02
IGWO-GA	6.37E-03	6.03E-01	2.73E-02
BPTT	4.37E-02	3.86E-01	1.91E-01

It can be seen from Table 3 that under a uniform number of iterations, the prediction accuracy of LSTM trained by intelligent algorithm is higher than that of BPTT algorithm. The LSTM data model has used ReLU instead of Sigmoid as the activation function, but the cumulative Tanh activation function still brings difficulties to the training of the BPTT algorithm. The prediction accuracy of LSTM for training set, test set 1 and test set 2 is shown in Figure 10.

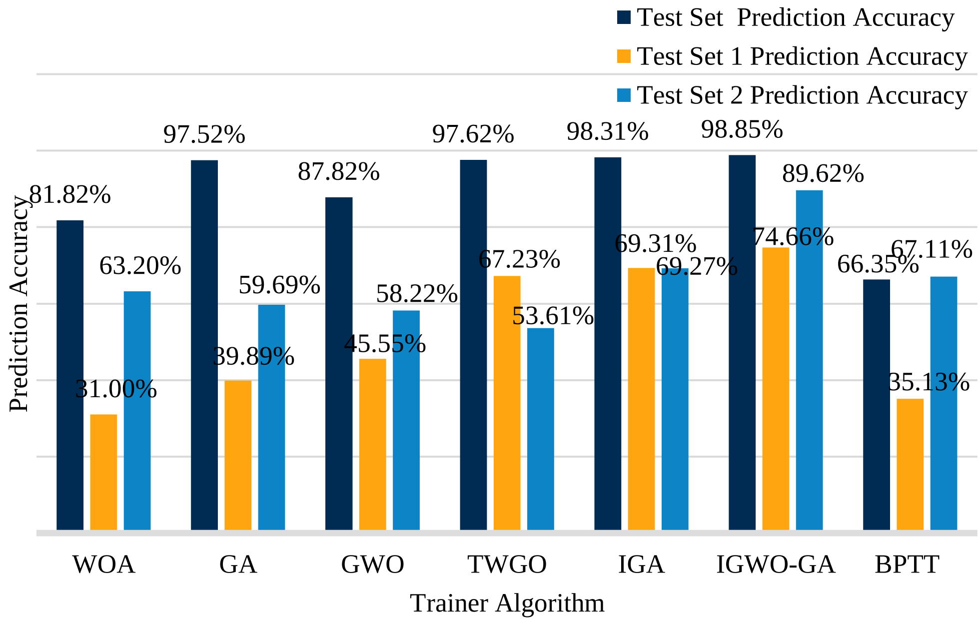


Figure 10. The prediction accuracy of the LSTM model trained by the intelligent algorithm on the training set, test set 1 and test set 2

As can be seen from Figure 10, comparing the prediction accuracy of the training set and the test set, the prediction accuracy of the training set, test set 1 and test set 2 of the GWO algorithm are 87.82%, 45.55%, and 58.22%, respectively. Moreover, the error between the prediction results and the actual value in the training set and test set is low, indicating that the improvement effect is good. At the same time, it is also found that in addition to the stronger generalization of LSTM trained by IGWO-GA, GA, GWO, TGWO, and IGA also have a certain overfitting phenomenon. The LSTM trained by IGWO-GA shows good generalization, the prediction accuracy of the training set is 98.85%, and the prediction accuracy of different test sets is higher than the training results of other algorithms. The LSTM trained by IGA has the lowest MAE in test set 1, but the prediction accuracy is lower than that of IGWO-GA, indicating that IGA is indeed affected by the decline of global retrieval ability, and the algorithm has the risk of falling into local optimum. From the MAE point of view, in the comparison of the training set, test set 1 and test set 2, the LSTMs trained by WOA, GA, GWO, and TGWO are all better than the training results of BPTT. After that, the GWO improvement with better performance was selected, and the initialization of Tent mapping was added to improve the diversity. For the training object is the LSTM model, combined with the application of the improved GWO and GA algorithms, the advantages of the algorithms in the previous and later stages were exerted. The effectiveness of each improved strategy and the advantages of the improved algorithm for training LSTM are verified through experiments.

5. Conclusions

At this stage, the rapid development of network technology has widely and deeply affected the younger generation. The digital visualization research of intangible cultural heritage should be effectively digitally displayed for better inheritance and development, and with the advent of the era of big data, the application scenarios of data models represented by computer intelligence will continue to increase. However, with the richness of data information, the dimensions of the datasets that need to be processed continue to increase. This paper proposes a plan to train the LSTM data model using a computer intelligent algorithm, and improves the training effect by improving the intelligent algorithm used in the training. At the same time, the model information data is also constantly improving, and new data models are constantly appearing. These intelligent algorithms can be used for training new data models, improving the local retrieval capabilities of the algorithms. It is verified through experiments that such improvements can improve the effectiveness of algorithm training and the accuracy of the model after training, and the improved algorithm has better robustness. Due to the over-fitting phenomenon of the current algorithm, the data research in this area needs to be further studied and verified.

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Data Availability

Data sharing is not applicable to this article as no new data were created or analysed in this study.

Conflict of Interest

The author states that this article has no conflict of interest.

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