International Journal of Computer Information Systems and Industrial Management Applications
ISSN 2150-7988 Volume 17 (2025) pp. 1-18

https://doi.org/10.70917/ijcisim-2025-0241
Article

Research on Virtual Reality Dissemination Technology of Traditional Sports Culture of Ethnic Minorities in the Internet Era

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Abstract: As the development of science and technology has changed the original production and life style of human beings, the inheritance and dissemination of traditional sports culture of ethnic minorities have encountered an unprecedented crisis. In this paper, on the basis of virtual reality dissemination technology, the acquisition and pre-processing of images are clarified, and BP-SIFT algorithm and overlapping region linear transition method are used respectively to realize image matching and fusion, and finally complete the construction of virtual scene. In order to enhance the interactivity of the virtual scene, a natural gesture interaction model based on FOB location information data is designed, and then the GCHS recommendation algorithm is used to construct a traditional sports culture communication model for ethnic minorities, and the model is empirically analyzed. When the number of neighbors is 45, the GCHS recommendation algorithm performs optimally, with precision rate between 0.85 and 0.96, recall rate between 0.86 and 0.95, and F1 value between 0.87 and 0.96, which proves the effectiveness of the GCHS recommendation algorithm in the dissemination of traditional sports culture of ethnic minorities. In addition, the GCHS recommendation algorithm is able to locate specific users and target the traditional sports culture dissemination of ethnic minorities.

Keywords: BP-SIFT algorithm; linear transition method; interaction model; GCHS recommendation algorithm; traditional sports culture

1. Introduction

China is a multi-ethnic country, ethnic minorities are distributed all over China, each ethnic group has its own ethnic characteristics, especially ethnic minorities, their villages as well as the development mode is unique. At present, the outstanding problems of minority sports are the gradual fading of the cultural foundation of its existence, the gradual disappearance of its successors, etc. [1]. Because, most of the ethnic minority areas in the economic conditions are relatively weak, which restricts the development of unique sports and cultural villages.

Virtual reality technology is an advanced computer simulation technology, which successfully constructs a new three-dimensional virtual environment by simulating human sensory experience [2]. Through head-mounted displays and surround sound technology, users can see and hear things in the virtual environment [3]. At the same time, virtual reality can also capture and simulate the user's hand movements and body movements through devices such as grips and gloves, enabling users to interact realistically in the virtual environment [4-5]. The simulated environment of virtual reality technology achieves a high degree of accuracy in terms of realism to the extent that its boundaries with the real world become blurred. The technology integrates a comprehensive perceptual simulation that encompasses a wide range of human sensory experiences including, but not limited to, hearing, sight, touch, taste, and smell [6]. This multi-sensory integration provides users with an all-encompassing immersive experience, which greatly enhances the credibility and attractiveness of the virtual environment.

The application of virtual reality technology provides innovative solutions to bottlenecks in the development of ethnic minority sports and culture industries, and has become a new focus of technological development and a new driving force for growth [7]. By breaking the limitations of the traditional visiting experience, VR technology enables the dissemination of sports culture to reach a wider audience. From the perspective of experience, virtual reality technology plays a key role in enhancing the experience level of sports culture, which transcends the limitations of traditional senses and broadens the spatial scope of experience [8-9]. The application of virtual reality technology injects new vitality and competitiveness into the development of sports culture, and through the interaction of the depth of content between people and scenes, it becomes a key indicator for improving the quality of cultural content and value recognition [10-11]. The application of this technology makes users change from passive information receivers to active explorers, participating in sports culture communication with a posture of discovery and exploration [12].

In the contemporary sports culture industry, the demand for personalization and differentiation is growing, and how to create more immersive and experiential cultural content has become an important topic that the industry needs to address [13]. Virtual reality technology provides an innovative solution that helps to promote the development of sports culture in the direction of more personalization and differentiation [14-15]. Specifically, through virtual reality technology, integrating performance, competition and entertainment in a comprehensive sports program, ethnic traditional sports are combined with different art forms. For individuals, it has entertainment, fitness, communication as well as educational functions. The development of national sports helps to realize mutual communication and cooperation among national sports cultures, promote national unity as well as national cultural development, and enhance national cohesion. Developing sports digital resources, innovating the development path of traditional sports, and protecting the diversity of sports culture. Protection and development is the basis of innovation, through the inheritance and innovation of traditional sports culture to dig deep into its cultural resources, make it compatible with modern society, so as to promote its sustainable development.

Minority sports culture is essentially also an intangible cultural heritage, literature [16] provides users with an interactive, immersive cultural heritage experience based on the old bridge of Bosnian Mostar through virtual reality technology, which allows users to participate in a virtual diving experience under the bridge, and to gain a deeper understanding of the history of Bosnian Mostar's old bridge and its cultural connections. Literature [17] designed a virtual reality themed game in order to promote the interactive communication of Terracotta Warriors culture, the researcher designed this game through 360 degree panoramic shooting of real scenes, 3D modeling, virtual reality, and intelligent question and answer technology to provide users with immersive and realistic feelings. Literature [18] designed a virtual reality experience platform for cultural heritage wooden churches and put it into the tourism industry, the platform integrates the 3D model of wooden churches, internal global images, audio support and other data, the relevant information can be easily previewed by the user, and the platform improves the dissemination of the wooden churches as well as the economic role in the tourism industry. Literature [19] visualizes the non-heritage culture through modern technological means, so that people can participate in non-heritage manufacturing practices, understand more about the connotation and value of non-heritage production techniques, and make complex historical and cultural concepts easier to understand and remember.

The application of virtual reality technology in ethnic sports culture is rare, and only one relevant reported literature was found. Literature [20] introduced the deep meaning of red culture and its impact on the development of the new era, and used virtual reality technology to deeply excavate the connotation of red sports culture, so as to strengthen the digital construction of red sports culture and promote the dissemination of red sports culture in the new era. It may be that the current virtual reality technology still has some technical problems in the protection of national sports culture [21-23]. First, data collection and processing are difficult. Ethnic sports cultural heritage has rich forms of expression and diverse movement skills, and there are certain difficulties in comprehensive and accurate data collection for it, and the collection effect is not ideal in complex environments. Secondly, it is difficult to ensure the authenticity and accuracy of virtual scene construction. The virtual scene needs to highly restore the actual scene of ethnic sports cultural heritage, including the venue, props, costumes and so on. However, due to the lack of sufficient historical information and professional research, the construction of virtual scenes may have deviations and cannot truly show the original appearance of cultural heritage. Third, the technical standard is not unified. At present, virtual reality technology is still in the development stage and lacks unified technical standards and specifications, which leads to possible incompatibility between different digital conservation projects and data cannot be shared and operated.

Virtual reality technology has achieved more research results in the field of physical exercise. Literature [24] developed a willingness analysis model to describe the effect of interactivity of virtual reality technology on users' virtual sports participation, and based on the hypothesis validation of survey data in the Korean Cycling Information Network, it proved that interactivity has an enhancing effect on users' virtual sports participation. Literature [25] used SEM-AMOS statistical software to analyze the correlation between athletes' mental health and anxiety and athletes' performance in virtual reality sports experiences, and the researchers found that athletes' mental health had a greater impact on their sports performance. Literature [26] designed and implemented a sports virtual reality system based on virtual reality technology, and the system collected sports-related data from the Internet of Things and interacted with the virtual scene in real time, which improved students' interest in physical exercise and promoted the development of sports in colleges and universities. Literature [27] created a competitive sports simulation system, which can reproduce the environment of badminton events and track and analyze the technical behavior of players and related data, the learning atmosphere constructed by virtual reality tools is enough to stimulate the interest of learners, which further proves the practicality of virtual reality technology.

According to the definition of virtual reality communication technology, this paper proposes to use BP-SIFT algorithm and overlapping region linear transition method to match and fuse the images of traditional sports and cultural items of ethnic minorities, and complete the design of image space with the help of WEB3D software and Flash software. Then the interactivity of the virtual scene is enhanced by constructing a natural gesture interaction model based on FOB location information data, and the GCHS recommendation algorithm is added on the original basis in order to realize the accurate dissemination of traditional sports culture of ethnic minorities and thus help the inheritance and development of NRL culture.

2. Research on Virtual Reality Dissemination Technology for Non-Heritage Culture

2.1. The technological basis for the formation of virtual reality communication

2.1.1. Display technology to construct image space

Immersion is one of the core concepts of virtual reality technology; immersion refers to a subjective perception, i.e., a person's feeling and awareness of a virtual environment created and displayed by a computer system [28]. When a participant is immersed in a virtual environment, his or her sensory system processes visual and other perceptual data from the virtual world in a way that is the same as it does in the real environment, just as it processes general perceptual data. Creating virtual environments with a strong sense of immersion relies on the combined use of various technologies, including graphics and image technologies, human-computer interaction technologies, artificial intelligence and pattern recognition technologies, network transmission technologies, parallel and collaborative computing technologies, large-scale display technologies, etc., among which the display technology is the step that ultimately results in the formation of virtual environments, and its role is crucial.

2.1.2. Computer and sensing technologies provide interactivity

The interactivity of virtual reality is the basis of assisting human creative thinking, therefore, efficient computer information processing technology is the key to directly affect the performance of virtual reality system [29]. In order to enable virtual reality system to process a large amount of multidimensional information in real time, on the one hand, the processing speed of computer should be improved as much as possible, and on the other hand, more efficient algorithms and techniques of information compression and data fusion should be researched. In the virtual reality system, there are digital and analog information output by various sensors, some of which are expressed in the form of sound, picture and text, and also in the form of vision, hearing, force, touch, taste and smell. As in the real world, objects in virtual minority sports activities also have physical properties such as shape and texture, then, when the user participates in the virtual objects with his/her hands or body, he/she should also be able to feel the physical properties of the objects, as well as the action and reaction forces generated between the body and the virtual objects, e.g., the user can use his/her hands to directly grasp the objects in the environment, at which time, the hands should have the feeling of holding something For example, the user can use his/her hand to directly grasp the object in the environment, in which case the hand should have the feeling of holding something, and the weight of the object should be felt.

2.2. Traditional sports culture image space for ethnic minorities

2.2.1. Image Acquisition

Hand-held camera shooting this method is relatively easy to do by rotating the camera in place or shooting parallel to the object in a certain route. However, stitching photos taken by a handheld camera is difficult because the movement of the camera is very complicated during the shooting process. All of the above methods limit the movement of the camera to different degrees, so that the acquired images of traditional sports and culture of ethnic minorities can meet certain requirements. However, in practice, there are inevitably small parallaxes, different ratios of scaling and large angles of rotation during shooting. These make the instability of stitching increase, and it is necessary to choose a matching algorithm with better robustness performance to cope with the transformation of translation, rotation, scale and light intensity.

2.2.2. Image Preprocessing

Image preprocessing in this article mainly refers to the conversion of color maps to grayscale maps. All colors in nature can be combined by the three primary colors of red (R) green (G) blue (B), the RGB color system is the most commonly used color system by adding the three colors R, G and B to produce other colors, the RGB model is suitable for use in displays and is widely used in video monitor displays and color cameras. Generally, each pixel of a color image is represented by 3 bytes, each byte corresponds to the luminance of the R, G, and B components (red, green, and blue), and a pixel of a converted black-and-white image is represented by a byte to indicate the grayscale value of the point, which has a value between 0 and 255, and the larger the value, the whiter, i.e., brighter, the point, and the smaller the value, the blacker it is. Color images expressed through RGB colors can be grayscaled by using the formula so that we get a grayscale image before manipulation.

Let the RGB component values of any pixel point $f(x,y)$ of a color image be $f_R(x,y)$, $f_G(x,y)$, $f_B(x,y)$, respectively, then the grayscale value $G(x,y)$ of the corresponding pixel point can be expressed as:

$$G(x,y)=0.3f_R(x,y)+0.59f_G(x,y)+0.11f_B(x,y) \tag{1}$$

2.2.3. Image Matching

The gray scale difference threshold T represents the minimum contrast of the extreme points that can be detected, and also the maximum tolerance that can ignore the noise, which mainly determines the number of feature points that can be extracted. The smaller T is, the fewer extreme points are detected, and some extreme points may be missed; on the contrary, the larger T is, the more extreme points are detected, and there is a possibility of false detection. Therefore, for images with richer gray level details, using a fixed gray level threshold difference T for the whole image, the effect of the detected extreme points will be very poor, which affects the matching results.

Aiming at the above problems, this paper improves the fixed threshold T to make it adaptive for detail-rich images. The main algorithm: for the Gaussian window of each pixel, the gray difference histogram of the Gaussian window is obtained by calculating the gray difference between the extreme points and the neighboring pixel points, and then it is determined by the iterative method according to the gray difference histogram.

First, the gray level difference between the neighboring pixels and the extreme point in the Gaussian window is calculated, and the mean value of this difference is used as the iterative initial value T_0. For:

$$T_0=\frac{1}{26}\sum\left[I\left(x',y'\right)-I\left(x,y\right)\right] \tag{2}$$

Then, the gray difference histogram is divided into two parts according to the iteration initial value, and the next iteration value T_i is calculated from (2). For:

$$T_{i+1}=\frac{1}{2}\left[\frac{\sum_{m=0}^{T_i} m*h(m)}{\sum_{m=0}^{T_i} h(m)}+\frac{\sum_{m=T_i+1}^{c_{\max}} m\times h(m)}{\sum_{m=T_i+1}^{c_{\max}} h(m)}\right] \tag{3}$$

In the above equation, m is the gray level difference between the neighborhood pixel point and the extreme point pixel point in the Gaussian template, $h(m)$ is the number of points in the Gaussian template with this gray level difference, and $c_{\max}$ is the maximum value of the gray level difference.

After each iteration a judgment is made, if $T_{i+1} - T_i = 0$, then the iteration is stopped and T_i is taken as the gray level difference threshold T of the final Gaussian template. If the geometric information between different descriptors is to be taken into account when matching, a compensation function $\Phi(m)$ for the keypoints must be added to compensate for the lost geometric information and act as a global optimization. The $\Phi(m)$ is defined as:

$$\Phi(m) = \sum_{i \in I_{D_1}} \sum_{j \in I_{D_1}} \phi(i, j; m(i), m(j)) \tag{4}$$

$$\phi(i, j; i', j') = \left\| \sqrt{\left\| X_{D_1}(i) - X_{D_1}(j) \right\|_2} - \sqrt{\left\| X_{D_2}(i') - X_{D_2}(j') \right\|_2} \right\|_2 \tag{5}$$

Where: $i' = m(i), j' = m(j)$, I_{D_1} is the descriptor (feature vector) in the original image 1, and X_{D_1}, X_{D_2} are the localized information of the keypoints in images 1, 2 respectively. The solution of the global optimization problem can be obtained from the following equation:

$$\hat{m} = \arg\min_{m} \Psi(m) + \lambda \Phi(m) \tag{6}$$

$$\Psi(m) = \sum_{i \in I_{D_1}} \psi(i, m(i)) \tag{7}$$

$$\psi(i, i') = \left\| D_1(i) - D_2(i') \right\| \tag{8}$$

Where: $D_1(i), D_2(i')$ are the descriptors (feature vectors) of the key points i, i' within images 1, 2 respectively.

The BP algorithm is introduced into the matching algorithm based on SIFT features to compensate for the mis-matching problem caused by SIFT features. From Eq. (5), it can be seen that even though the objective function is proposed, it still cannot well solve the global optimization problem of the image, so Eq. (5) is rewritten in combination with the confidence propagation algorithm as:

$$\hat{m} = \arg\max_{m} \exp(-\Psi(m)) \exp(-\lambda \Phi(m)) \tag{9}$$

Equivalent to:

$$\hat{m} = \arg\max_{m} \prod_{i \in I_{D_1}} b_{Des_i}(m_i) \prod_{i \in I_{D_1}, j \in I_{D_1}} b_{Dist_{i,j}}(m_i, m_j) \tag{10}$$

Among them:

$$b_{Des_i}(m_i) = \exp\left(-\psi(i, m_i) / C_{Des}\right) \tag{11}$$

$$b_{Dist_{i,j}}(m_i, m_j) = \exp\left(-\phi\left(i, j; m_i, m_j\right) / C_{Dist}\right) \tag{12}$$

$\lambda = C_{Des} / C_{Dist}$, $b_{Des_i}(m_i)$ is the confidence level of matching the key point i in image 1 with that in image 2, and $b_{Dist_{i,j}}(m_i, m_j)$ is the confidence level of matching the key point i, j in image 1 with that in image 2.

2.2.4. Image Fusion

Image fusion is the process of adjusting the pixel values of the aligned image in image splicing, which makes the splicing traces of the image cannot be seen after splicing. There are several commonly used methods as follows: averaging method, weighted average fusion method, multi-resolution spline method and overlapping region linear transition method, etc., while in this paper, overlapping region linear transition method is used to realize the image fusion work.

In order to eliminate the splicing problem in the overlapping region, the method of gradual smooth transition is more commonly used, assuming that the width of the overlapping region is L and the transition factor $\sigma\left(0 \le \sigma \le 1\right)$. The maximum and minimum values of the two images in the overlap region in the x -axis direction are $x_{\max}$ and $x_{\min}$, respectively, then the transition factor: $\sigma = \frac{x_{\max} - x}{x_{\max} - x_{\min}}$.

Let $g_1(x,y)$, $g_2(x,y)$ and $g(x,y)$ be the gray values of the two images f_1, f_2 and the fused image at the point (x,y), respectively, the overlapping region value is:

$$g(x,y) = \sigma g_1(x,y) + (1-\sigma) g_2(x,y) \tag{13}$$

When σ changes from 1 to 0, the overlapping region image slowly transitions from the first image to the second image, so that a smooth transition between images can be realized, thus eliminating the obvious splicing traces.

We set the compensation parameter to be designed as α , then $\alpha = \frac{\bar{g}_{1overlap}(x,y)}{\bar{g}_{2overlap}(x,y)}$.

$\bar{g}_1(x,y)$ and $\bar{g}_2(x,y)$ represent the average of image 1 and image 2 in the overlap region respectively, we can't use α alone to mediate the intensity of the light in image 2 in the overlap region, it will create a new break inside image 2 will be created, so we mediate the intensity of the whole image:

$$g_2' = \alpha g_2(x,y) = \frac{\bar{g}_{1overlap}(x,y)}{\bar{g}_{2overlap}(x,y)} g_2(x,y) \tag{14}$$

Define the transition factor w to be a bilinear function, viz:

$$w = w(x)w(y) = \left(x_{\max} - x\right)\left(y_{\max} - y\right) \Big/ \left(x_{\max} - x_{\min}\right)\left(y_{\max} - y_{\min}\right) \tag{15}$$

We follow the math trick because w is between $[0,1]$:

$$\begin{aligned} \beta &= \cos\left(\frac{\pi}{2} w\right) \\ &= \cos\left(\pi\left(x_{\max} - x\right)\left(y_{\max} - y\right) \Big/ 2\left(x_{\max} - x_{\min}\right)\left(y_{\max} - y_{\min}\right)\right) \end{aligned} \tag{16}$$

It is also between $[0,1]$ and can better serve to smooth the image. Therefore the gray value of the overlapping region is:

$$g(x,y) = \beta g_1(x,y) + (1-\beta) g_{2'}(x,y) \tag{17}$$

2.2.5. Drawing virtual scenes

The Canon 500D digital camera is used to shoot multiple groups of minority sports and culture image data in 360° around the fixed point, each group of images is about 50 images, the size of each image is 4000×2000 pixels, JPEG type, and the panorama of a single scene is obtained by stitching using the above algorithm. WEB3D is a branch of the virtual realization, which is the use of the network (web page) to display the virtual minority sports and cultural scenes, and realizes the playback of each viewpoint through Flash, so that the virtual experiencer has a feeling of being completely immersed in minority sports activities.

2.3. Virtual Interaction Design for Minority Sports Culture

2.3.1. Sensors in Virtual Reality Communication Technologies

In virtual reality, there are mainly head-mounted stereoscopic displays, holographic glasses, data gloves, data suits and other user-experience sensing devices for human-computer interaction, as well as visual, force-tactile, auditory and other sensing devices that can make the user perceive correctly in the real environment.

In virtual reality, there are mainly user experience sensing devices such as head-mounted stereoscopic displays, holographic glasses, data gloves, and data suits, as well as sensing devices such as vision, force, touch, and hearing, which can enable users to perceive correctly. In virtual reality, all kinds of information that users can feel need sensors to collect relevant information. Therefore, sensors play an important and indispensable role. The virtual environment allows users to enjoy different interactive effects of visual, auditory and tactile perception both in time and space. From the previous can only unilaterally obtain visual information to the mutual interaction of the perceptual effect.

(1) Human-computer interaction sensing equipment

The interactive environment presented by virtual reality comes from sensor devices. In the environmental information system acquired by VR, sensors are essential and there are many kinds of sensors, and at present, the head motion tracking equipment mainly presents the following aspects of development:

(a) External head-mounted display, which is connected to a computer for computing and rendering and then transmits the image to the screen inside the helmet.

(b) Head-mounted cell phone box, in fact, is a set of optical systems embedded in a plastic or paper box, inserted into a smartphone to watch.

(c) Holographic glasses; capable of fully rendering the user's voice, movement, and surroundings, with built-in information collection and data processing equipment and storage, just like a real PC.

(2) Reality-aware sensors

Virtual reality can be either a purely computer-generated virtual environment or a reproduction of the real-life environment, in which the reproduction of the real environment depends on sensor technology.

(a) Visual sensors, like human visual characteristics, are the basis for obtaining the reproduction of the real environment.

(b) Tactile sensors, mainly the user in contact with the target object produced by a variety of stimulus response, the current stage of the use of more acoustic-electric tactile sensors, piezoelectric tactile sensors and so on.

(c) The capture sensors for smell and taste are still in the laboratory stage.

2.3.2. Virtual interaction model

To realize the natural interaction with the virtual scene, the virtual hand model and the 3D mouse model must be positioned in the vector field scene first, and then the virtual hand model or the 3D mouse model is made to move in the virtual scene with the movement of the data glove or the Neo Wand, etc. For different vector field data with different global coordinates in the visualized scene, the envelope box of the vector field data is first obtained, see Eq. (17). Where the middle coordinates x, y, z of the enveloping box, $x_{\max}$, $y_{\max}$, $z_{\max}$ are the maximum coordinates of the enveloping box, and $x_{\min}$, $y_{\min}$, $z_{\min}$ are the minimum coordinates of the enveloping box. Take x, y, z as the initial positions of the virtual hand or 3D mouse model in the vector field data. For:

$$\begin{aligned} x &= \frac{1}{2}\left(x_{\max} + x_{\min}\right) \\ y &= \frac{1}{2}\left(y_{\max} + y_{\min}\right) \\ z &= \frac{1}{2}\left(z_{\max} + z_{\min}\right) \end{aligned} \tag{18}$$

The position information of the tracking device bound to the data glove or Neo Wand often produces jitter of the model due to the influence of interfering signals, etc., and the movement is not smooth and continuous, etc. In this paper, we use the incremental FOB position information data to drive the virtual hand or 3D mouse model to move in the virtual scene.

The current frame data acquired first is subtracted from the previous frame data to obtain the difference, and when the data glove or Neo Wand sends out a signal to obtain the difference, the visualization system uses this difference to drive the virtual hand model as in Equation (19). For:

$$\left(x^* \; y^* \; z^* \; 1\right) = \left(x \; y \; z \; 1\right) \cdot \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ T_x & T_y & T_z & 1 \end{bmatrix} \tag{19}$$

Among them:

$$T_x = a\left(x_1 - x_0\right)$$
$$T_y = a\left(y_1 - y_0\right) \tag{20}$$
$$T_z = a\left(z_1 - z_0\right)$$

x^*, y^*, z^* are the new coordinates of the virtual hand or 3D mouse model after it is localized in the vector field scene, x_0, y_0, z_0 and x_1, y_1, z_1 are the previous and current frame position information of the FOB bound to the Data Glove or the Neo Wand respectively, T_x, T_y, T_z are the position information increments, a is the scale factor, and x, y, and z are the current positions of the virtual hand model.

In the virtual scene with the vector field data for picking up seed points and other natural interactive operations and the traditional mouse pickup interaction is different, the traditional three-dimensional display is three-dimensional projection to a plane, looks like three-dimensional, picking up objects in the scene is the use of ray intersection method. Principle from the point of view through the virtual hand model coordinates for a ray and vector field intersection, the intersection point can be used as a pickup point. The disadvantage of this pickup point method is that the points picked up are only the points on the surface of the vector field, and the internal points cannot be picked up. The display in virtual reality is the real 3D, and the interaction is the six-degree-of-freedom interaction method in the real 3D space. The coordinates of the FOB are bound to the global coordinates of the virtual hand model in the scene, and the global coordinates x^*, y^*, and z^* of the position of the virtual hand are taken as the points picked up when the virtual hand roams into the vector field area, as judged by the enclosing box method.

When the coordinates x^*, y^*, z^* of the virtual hand or NEOWAND model are in the enclosing box (i.e., between the maximum coordinates $x_{\max}$, $y_{\max}$, $z_{\max}$ and the minimum coordinates $x_{\min}$, $y_{\min}$, $z_{\min}$ of the enclosing box of the vector field data), it can be regarded as the virtual hand is already in the vector field, at this time, the color of the hand can be changed to indicate whether the virtual hand is inside the vector field or not.

2.4. Model for the dissemination of minority sports culture

In the current era of big data, the traditional sports culture dissemination of ethnic minorities has been a very common problem, and at the same time, people have also put forward a number of effective solutions to this problem, among which the recommendation algorithm is one of the most commonly used and effective dissemination methods. For this reason, this paper introduces the recommendation algorithm on the basis of the existing, and finally designs the traditional sports culture dissemination model of ethnic minorities.

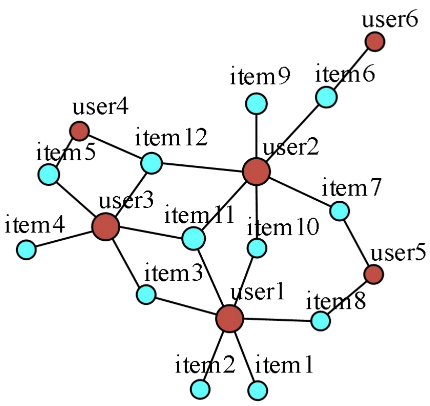
2.4.1. User-Content-Heritage Characterization Acquisition

(1) User interest preference features

Based on the user-content interaction as shown in Figure 1, the weighted features of social users are aggregated to obtain the final target user's interest preference feature vector. Define its expression as:

$$e_u^{l+1} = W_1 e_u^l + W_2 \sum_{v \in N_u} a_{uv}\left(e_v^l + e_v^l \odot e_u^l\right) \tag{21}$$

where W_1 and W_2 are trainable weight vectors, e_u^l denotes the feature vector of user u after the l th iteration, and e_u^{l+1} is the same as e_u^l. N_u denotes the set of first-order neighbors of user u in the social relationship graph; e_v^l denotes the feature vector of user v after the l th iteration. $\odot$ denotes the operation of multiplying the two vectors by their corresponding elements, and a_{uv} denotes the attentional weight of user u 's first-order neighbor, user v, at the time of aggregating his feature vector.



$$\begin{bmatrix} 1 & 1 & 1 & 0 & 0 & 0 & 0 & 1 & 0 & 1 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 1 & 0 & 1 & 1 & 1 & 1 \\ 0 & 0 & 1 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 1 & 1 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

Figure 1. Transformation of interaction graphs into interaction matrices.

(2) Non-legacy content audience features

Before feature updating through the aggregation model, the initial feature vector of the non-heritage content is obtained. Here, the averaging method is used to get the initial features of the content through the interactive user features of the content, defined by Eq:

$$e_i^0 = \frac{1}{|N_i|} \sum_{u \in N_i} e_u \tag{22}$$

Where N_i denotes the set of user nodes that have interaction with content i, e_u denotes the feature vector of the interacting user of the content, and e_i^0 is the initial feature vector of content i.

(3) Characteristics of Inheritors

Inheritors, as the main personnel in the non-genetic inheritance, influence the direction of non-heritage dissemination in the crowd. Different kinds of non-heritage will attract different user groups in the creation and promotion of the inheritor, and the average aggregation method is used to get the inheritor characteristics. Its expression is:

$$e_h = \frac{1}{|N_h|} \sum_{i \in N_h} e_i \tag{23}$$

Where e_h is the inheritor feature vector, N_h denotes the set of content posted by inheritor h, and e_i is the non-heritage content posted by the inheritor.

2.4.2. Modeling

(1) Model framework

The recommendation model framework is shown in Fig. 2, which is constructed through the acquisition methods of user interest and preference features, non-heritage content audience features, and inheritor features in Chapter 2.4.1, based on which user-content similarity computation is carried out, as well as Top-N recommendation list generation based on the results of the similarity computation, to get the final framework of the recommendation method. For the convenience of description, the recommendation method is named GCHS, which needs to use the features of user interest, non-legacy content and inheritor for the final similarity calculation.

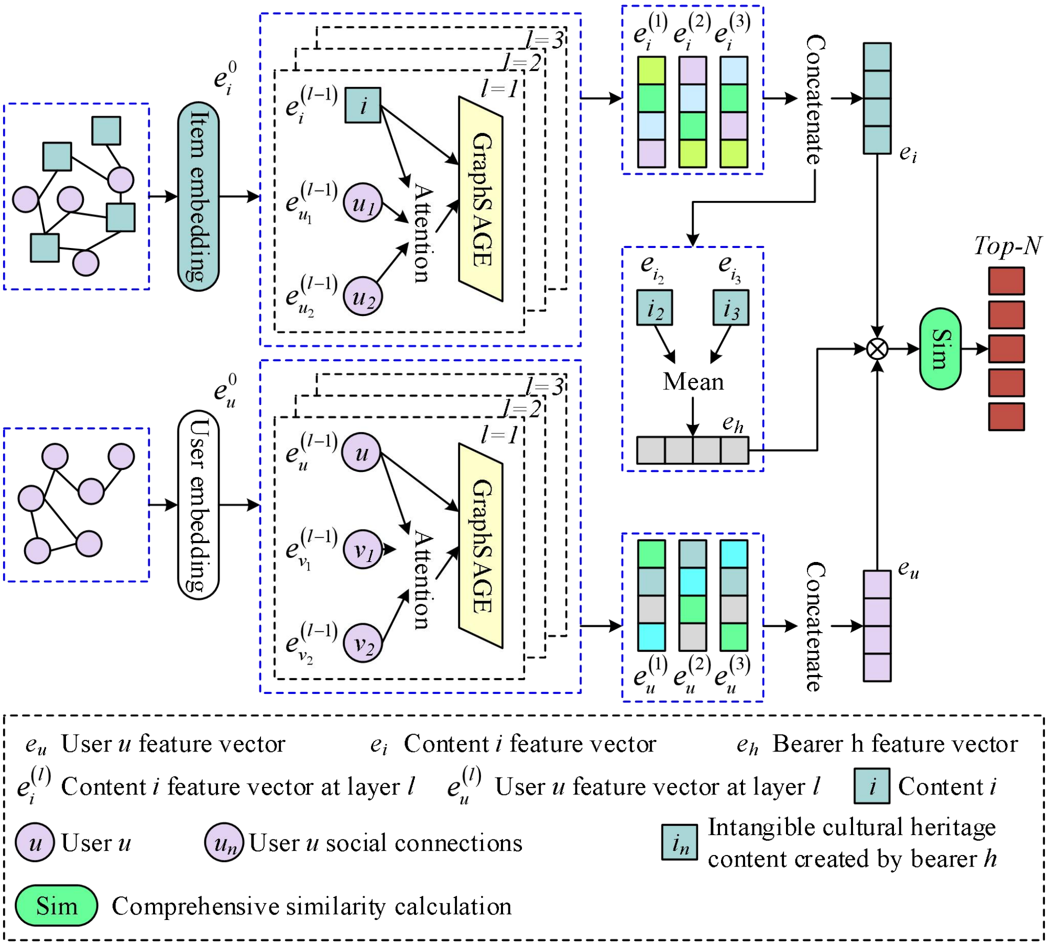


Figure 2. Recommendation model framework.

(2) User-Content Similarity Assessment Methods

In this paper, the inheritor features are incorporated into the similarity metric, which is used to optimize the calculation of similarity. Its calculation expression is:

$$sim(u,i) = \left(e_h^T \cdot e_u\right) \times \left(e_i^T \cdot e_u\right) \tag{24}$$

Where $sim(u,i)$ denotes the similarity value between the content i to be recommended and the target user u, e_i is the feature vector of the non-legacy content i to be recommended, e_u is the feature vector of the target user u, and e_h is the feature vector of the publisher (i.e., inheritor) of the non-legacy content i to be recommended. After obtaining the similarity value, when recommending the content for users, Top-N is recommended to users according to the similarity value in ascending order.

3. Results and analysis

3.1. Analysis of the traditional sports culture image space exploration of minority nationalities

3.1.1. Image Matching Analysis

In the preliminary stage of this paper, 200 images of horse racing (A1), archery (A2), wrestling (A3), dragon dance (A4), dragon boat rowing (A5), snatching firecrackers (A6), solo bamboo drifting (A7), high-footed race (A8), pearl ball (A9), playing Bulu (A10), polishing autumn (A11), and coconut-climbing race (A12), each of which is a traditional minority sports and culture image, have been collected. In this paper, when verifying the image matching, any one of the 200 images of each kind is selected as the template for matching, and then the remaining 199 are matched, and the image matching results are analyzed as shown in Fig. 3. The experimental results can be found that the improved SIFT algorithm has a more obvious effect on the enhancement of images that are more sensitive to edge information, such as solo bamboo drifting (A7), archery (A2), stiletto competition (A8), polished autumn (A11), and coconut climbing competition (A12). And some images that are less sensitive to edges such as playing Bru (A10), wrestling (A3) and dragon boat rowing (A5) have less obvious enhancement effects. However, in general, BP-SIFT algorithm is better than SIFT algorithm as feature matching, and it also verifies that BP algorithm optimizes SIFT algorithm.

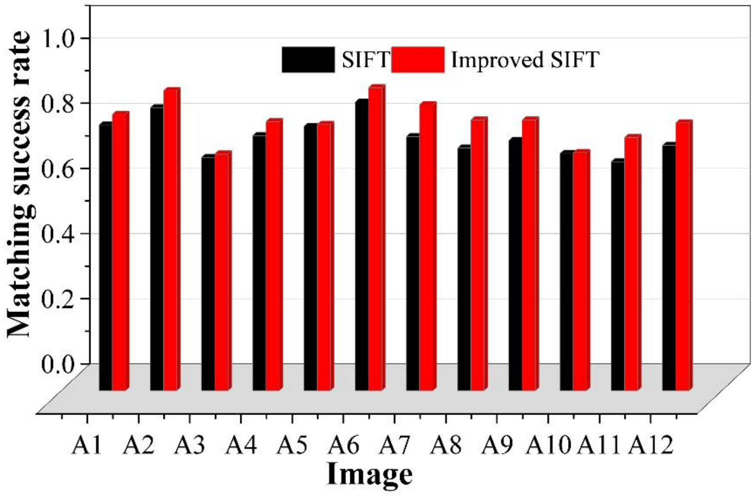


Figure 3. Image matching result.

In order to further verify the priority of this paper's image matching algorithm, image matching algorithm comparison analysis, algorithm comparison analysis results shown in Figure 4. It can be seen that the algorithm in this paper is better than the BRISK algorithm in the comprehensive recognition of images.BRISK algorithm from the recognition principle is also the use of traditional SIFT scale transformation method for feature extraction, this paper is the use of the BP algorithm to make up for the mis-matching due to the SIFT features. Therefore, the feature points extracted in this paper are more advantageous at local edges. The DBN-LTP algorithm, on the other hand, uses deep learning to classify images, relying on the algorithm's own learning degree of a large number of sample samples, due to the limited sample samples of this paper's algorithm, it is better than the BRISK algorithm from the point of view of recognition efficiency, but lower than this paper's algorithm. As of now, it is difficult to obtain a large number of traditional minority sports culture samples, so it is easier to use traditional feature extraction methods to solve such problems.

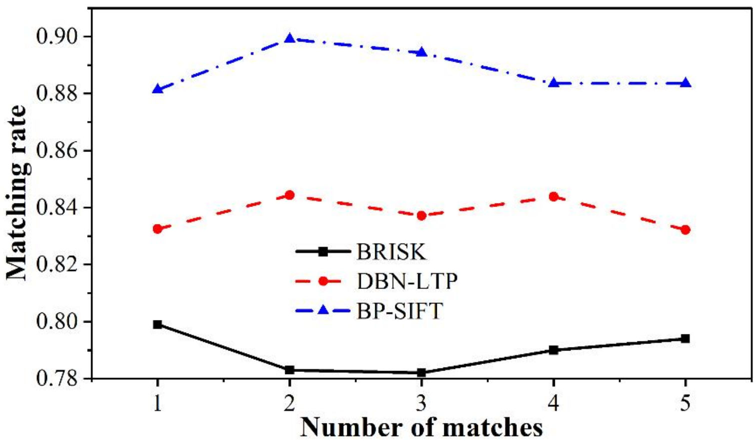


Figure 4. The results of algorithm comparison and analysis.

3.1.2. Image fusion analysis

Various methods of minority sports culture image fusion are realized through software programming, and here the overlapping region linear transition method is compared and analyzed with the mean value method, the weighted average fusion method, and the multi-resolution spline method, and the image fusion analysis is shown in Table 1. The results show that among the 12 ethnic minority sports and culture image fusion, the average time consumed for image fusion of the mean value method is 98.67ms, the average time consumed for image fusion of the weighted average fusion method is 82.17ms, the average time consumed for image fusion of the multi-resolution spline method is 55.50ms, and the average time consumed for image fusion of the overlapping region linear transition method is 28.08ms.From this, it can be seen that, compared with the This shows that compared with the average value method, weighted average fusion method, and multi-resolution spline method, the overlapping region linear transition method has the highest priority in the fusion of ethnic minority sports and culture images, which ensures the smoothness of the subsequent image space and the virtual scene, and can bring a better visual enjoyment to the experiencers.

Table 1. Image fusion analysis

Image	Average value method (ms)	Weighted average fusion method (ms)	Multi-resolution spline method (ms)	Linear transition method for overlapping regions (ms)
A1	105	78	64	24
A2	104	80	58	26
A3	83	89	50	27
A4	86	82	42	35
A5	103	87	68	21
A6	111	86	61	21
A7	89	75	63	36
A8	93	85	57	29
A9	84	79	44	24
A10	112	85	48	40
A11	117	85	63	23
A12	97	75	48	31
Mean	98.67	82.17	55.50	28.08

3.2. Interaction testing

3.2.1. Participants

A total of 200 ethnic minority sport and culture bearers were invited to participate in the user test, 100 of them were male and 100 were female. 100 had experience with computer graphics or 3D computer games, 50 students had experience interacting with immersive VR devices, and 50 had participated in the touch-screen interaction user test. Their ages ranged from 20 to 40 (mean age M = 33, standard deviation SD = 3.42). 170 users were all right-handed in their habitual use of the hand, and 30 were left-handed in their habitual use of the hand.

3.2.2. Tasking

In the case of grabbing the firecracker (A6), one of the 12 ethnic minority sports and cultures, for example, a total of 12 placement tasks were set up to manipulate the object by panning and rotating it according to the target position, which was given by a wireframe model with the same shape as the manipulated object. These 12 tasks are timed tasks, and to prevent users from getting too tired, each task is limited to a maximum of 120 seconds. There are three ways to move to the next task, the user matches the object to the target position successfully and automatically moves to the next task, the task time is up and automatically moves to the next task, and the user chooses to abandon the current task. An error threshold is set for the placement task, when the user places the object within the error threshold of the target location, the color of the object will change to green, indicating the success of the task and moving to the next task. In order to improve the accuracy of placement, the error threshold was set to 0.004 meters for the x,y,z directions. If the task time is up and the user has not placed the object to the target position, the task fails and the position of the manipulated object at the last second is saved.

3.2.3. Analysis of test results

Setting the control model as an eye-tracking interaction model, each user needs to adopt two models (this paper's model: natural gesture interaction model based on FOB location information data, and the control model: eye-tracking interaction model) to complete the 12 tasks, and verify the effectiveness of this paper's model in terms of both completion time and placement error.

(1) Completion time comparison

With the help of data analysis software, the task completion time of the interaction model is compared and analyzed, and the results of the task completion time comparison are shown in Fig. 5, which uses grouped violin plots to show the task completion time data of different models, with the lines indicating the median, upper quartile, and lower quartile, and the O and C indicating the model of this paper and the control model, respectively. Among the 12 tasks, the task completion time of this paper's model is controlled at 10 s ~ 80 s, while the task completion time of the control model is 40 s ~ 120 s. This intuitively demonstrates that the natural gesture interaction model based on the incremental data of FOB location information is prioritized in the interaction test of the ethnic minority's sports and culture, which provides favorable technical support for the work of the dissemination and inheritance of non-heritage culture.

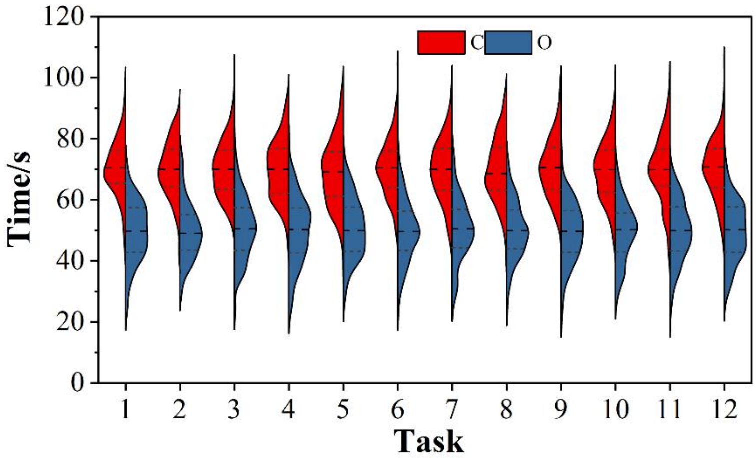


Figure 5. Comparison results of task completion time.

(2) Placement error comparison

Using the same method described above, the placement task error results of the model are analyzed, and the placement error comparison results are shown in Figure 6. Based on the data performance in the figure, it can be seen that the placement error range of the model in this paper is 0~75mm, however, the placement error range of the control model is 25~110mm, which can be concluded that the model in this paper shows more excellent interaction accuracy, which can bring a better experience to the user, and enable the user to better integrate into the virtual ethnic minority sports activities, and further promote the dissemination of non-heritage culture and the cause of heritage. The model in this paper shows better interaction accuracy, which can make the user feel better, make the user better integrated into virtual minority sports activities, and further promote the dissemination and inheritance of non-heritage culture.

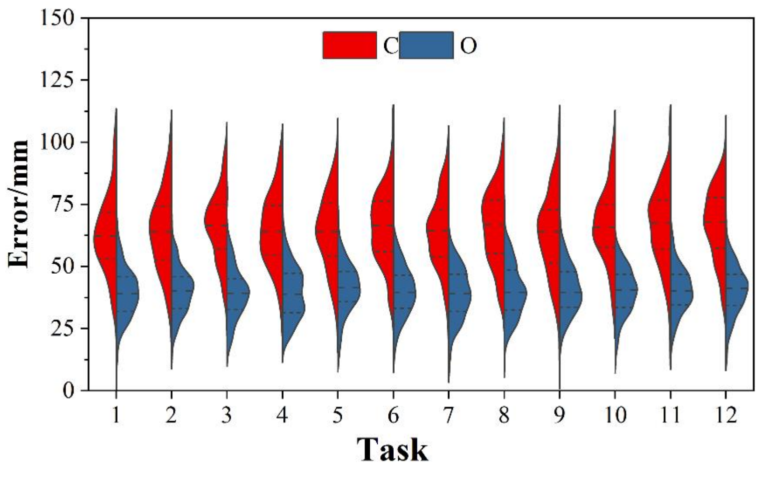


Figure 6. The comparison results of placement errors

3.3. Exploratory Analysis of Communication Models

3.3.1. Experimental data

In order to test the effectiveness and practicality of the GCHS recommendation algorithm for the dissemination of ethnic minority sports and culture, we distributed forms containing detailed information of ethnic minority sports and culture programs to users for simulation experiments, and asked users to select the ethnic minority sports and culture programs they were interested in in the forms, and organized the collected user data, which was regarded as the user's click data in the recommendation algorithm. In order to facilitate the user to fill in the minority sports and cultural programs as much as possible, the author in the form, as detailed as possible to the minority sports and cultural programs, the form content mainly contains the minority sports and cultural program ID, minority sports and cultural program name, minority sports and cultural program declaration area, minority sports and cultural program ethnicity, as well as minority sports and cultural programs Cultural Programs' pictures and detailed descriptions of minority sports and cultural programs, which are shown in the Appendix. Valid data were collected including a total of 12,341,658 user data from 13,456 users for 12 ethnic minority sports and culture programs, and this dataset was used to build a user-program feedback set. The dataset is divided into training set and test set according to the ratio of 7:3, and combined with the similarity of minority sports and culture programs calculated in the previous section to conduct minority sports and culture recommendation experiments.

3.3.2. Experimental results

The effectiveness of minority sports and culture recommendation is usually measured using three indicators: precision rate, recall rate and F-Measure, where precision rate indicates the probability that a user is interested in an item recommended by the system, and recall rate indicates the probability that an item that a user is interested in is recommended. Because the precision rate and recall rate sometimes appear contradictory situations, resulting in the inability to effectively evaluate the effectiveness of the recommendation, it is necessary to have an indicator to synthesize them, the most common method is the F-Measure, that is, the precision rate and the recall rate weighted and averaged, usually take the parameter 1, that is, the most common F1. The calculation formula is as follows:

$$\Pr ecision = \frac{\sum_{u \in U} \left| R(u) \cap T(u) \right|}{\sum_{u \in U} \left| R(u) \right|} \tag{25}$$

$$\operatorname{Re} call = \frac{\sum_{u \in U} \left| R(u) \cap T(u) \right|}{\sum_{u \in U} \left| T(u) \right|} \tag{26}$$

$$F1 = \frac{2 precision * recall}{precision + recall} \tag{27}$$

Where U is the set of all users, $R(u)$ is the list of recommendations made by the recommendation algorithm to the user based on the click behavior of the user u on the spin and $T(u)$ is the list of the user's u behavior on the test set. In all experiments, we set the number of recommendations to be $N = 15$, and the number of neighbors K is taken as 15~150, and the precision under different number of neighbors is shown in Fig. 7, the recall under different number of neighbors is shown in Fig. 8, and the F1 value under different number of neighbors is shown in Fig. 9. From Fig. 7~-Fig. 8, it can be seen that the precision rate of the GCHS recommendation algorithm proposed in this paper for the dissemination of minority sports and culture is between 0.85 and 0.96, the recall rate is between 0.86 and 0.95, and the F1 value is between 0.87 and 0.96. Under the comprehensive comparison, when the K value is taken as 45, a higher precision rate, recall rate and F1 value can be obtained, and the minority sports culture recommendation is the best.

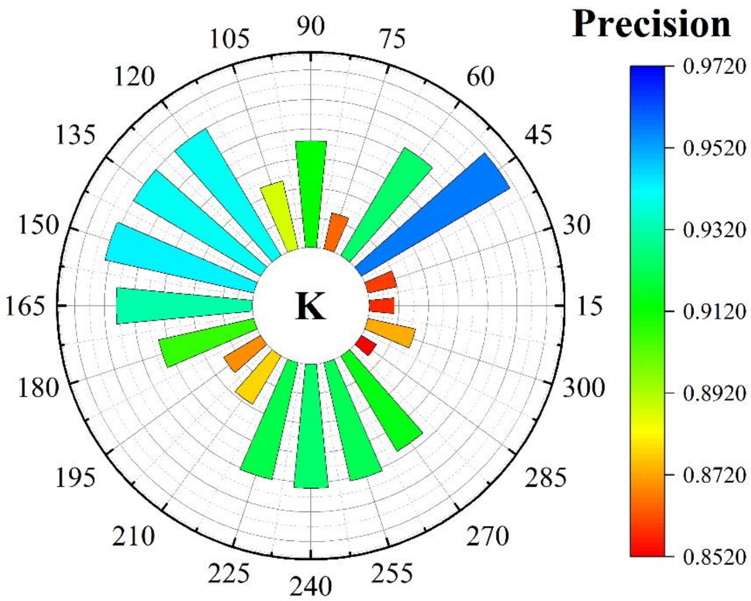


Figure 7. Precision under different numbers of neighbors.

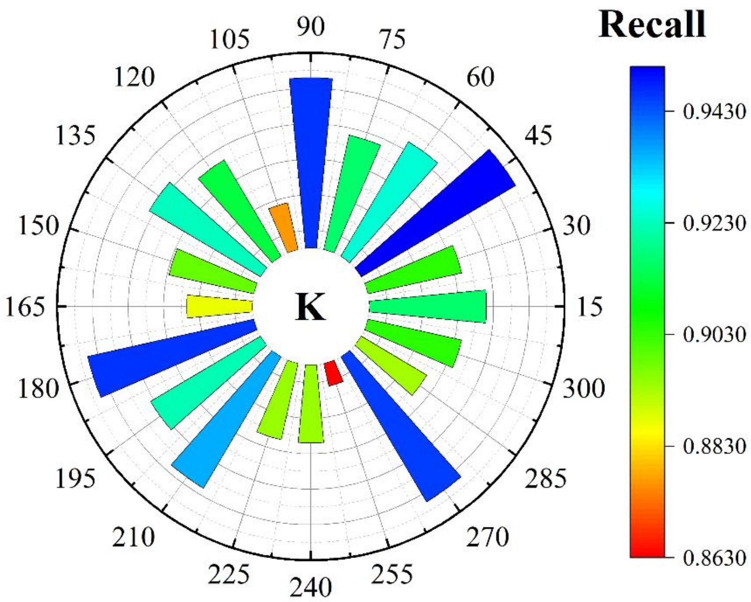


Figure 8. Recall rates under different numbers of neighbors.

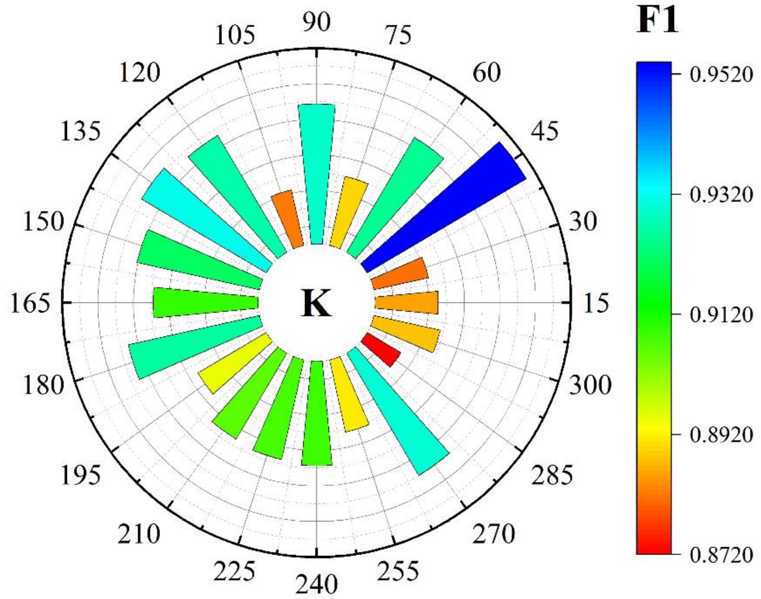


Figure 9. F1 rates under different numbers of neighbors.

Based on the experimental results, the feasibility of the GCHS recommendation algorithm for the dissemination of minority sports culture is verified, and the algorithm in this paper is able to recommend minority sports culture to individual users in a timely manner, which is conducive to the production of traditional minority sports programs into a series of pages, and the continuous updating of the content, which is conducive to the dissemination of its complete connotation. In the secondary dissemination, the algorithm in this paper will timely recommend to the users who make feedback (likes, comments, concerns, etc.), which can locate the specific users, targeted dissemination, and further consolidate the cause of the dissemination and inheritance of non-heritage culture.

4. Conclusion

With the rapid development of the economy, people's thinking is also advancing with the times, and the rapid change of their values has led to a crisis in the inheritance and dissemination of traditional minority sports. For this reason, this paper combines the virtual reality communication technology and GCHS recommendation algorithm to construct a cultural communication model of minority sports and discuss the practical application value of the model. The research results of this paper are as follows:

(1) Compared with BRISK algorithm and DBN-LTP algorithm, BP-SIFT algorithm has superiority in minority sports image feature matching, and its ratio is 0.88~0.91. In addition, overlapping region linear transition method is excellent in image fusion, with an average time consuming of 28.08 ms. In summary, the algorithm in this paper can maximize the guarantee of minority sports virtual The algorithm in this paper can maximize the authenticity and smoothness of the virtual scene of minority sports, so that it can better serve the cause of non-heritage dissemination.

(2) In the 12 interaction tasks, compared with the eye-tracking interaction model, the natural gesture interaction model based on FOB position information data has superiority, its time control is 10s~80s, and the corresponding error range of object placement is 0~75mm, which not only brings users a high-quality virtual experience, but also improves the users' cognitive level of the minority sports culture, which leads to the users' recommendation and dissemination effect.

(3) When the number of neighbors is 45, the minority sports culture model based on the GCHS recommendation algorithm has the best efficacy, with a precision rate of 0.85-0.96, a recall rate of 0.86-0.95, and an F1 value of 0.87-0.96. The algorithm in this paper can make more audience groups come into contact with minority sports culture, and then promote the development of non-heritage culture dissemination and inheritance.

About the Author

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