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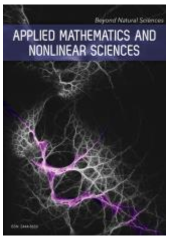

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Application of AI Interaction Design in the Teaching Model of Landscape Topics Course

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Abstract

In this paper, we first define the limb node coordinates through the established limb node coordinate system and evaluate the behavior of the human body through the constructed posture sequence to analyze the human body's body characteristics, such as the area of concern and the emotional level. Then, a new model of landscape theme course teaching was designed based on AI interaction design technology, the human-computer interaction learning needs were analyzed, and a human-computer interaction landscape course learning system was established. Finally, the differences in students' cognitive ability, learning motivation, and learning emotion under the AI interactive teaching environment and traditional teaching methods were compared, and the advantages of AI interactive teaching were analyzed. The results show that the SD value of students' behavioral attitudes in the teaching mode based on interactive technology is 27.78±2.34, which is more than the SD value of the ordinary teaching mode.2 In terms of goal attitudes, the SD value of the experimental class is about 4.05 more than that of the control class, and the difference is significant. The interactive teaching mode of AI effectively promotes students' learning of the landscape topic course, and this study provides positive reference value.

Keywords: AI interaction design; Limb node characteristics; Postural sequence; Behavioral assessment; Landscape thematic course.
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1 Introduction

In the course of educational development, there is no lack of a series of problems that need to be solved, such as how to use technology to reform teaching methods, what kind of relationship mode should be between teachers and students, and how to be able to carry out high-standard classroom teaching activities [1-2]. Thus, in the era of the smooth development of emerging technologies such as artificial intelligence, big data, virtual reality, cloud computing, augmented reality and so on, they not only affect people's material life and spiritual and cultural life but also receive great attention from the state and all sectors of society [3-4]. Similarly, the state and all sectors of society are considering how these emerging technologies can contribute to the iterative renewal of educational development. Among them, virtual reality technology, as one of the hot topics in the field of technology application in education and teaching, is gradually attracting the close attention of groups in academia, industry, and the front line of education practice.

In terms of landscape interaction design, Xie, X. et al. studied the green urban garden landscape design method based on a virtual visualization system, explored the importance of landscape design to with people's happiness and urban development, and emphasized the importance of landscape design to people's life [5]. A, J. L. et al. studied the ethics and privacy of AI, analyzed the change in society's interest in the ethics of AI over time, and proposed that the ethics and privacy of AI should be emphasized [6]. Song, X. introduced the theory of sustainable development and the green development model to study the development of eco-design and proposed that eco-landscaping is important for people's lives [7]. Mccomb, C. et al. researched the artificial intelligence system construction method involving design and proposed that the artificial intelligence interaction system is of great significance to landscape design [8]. Evensen, K. H. researched the relationship between landscape architectural design and human well-being, looked forward to the prospect of the use of virtual reality technology, and proposed that advanced intelligent technology should be used to assist landscape design [9]. Yang, W. et al. studied the planning and design of a digital cityscape in Guangzhou based on the perspective of a smart city and summarized the design method of Guangzhou's smart cityscape according to the connotation of smart city [10]. Ru, Y. H. et al. proposed the importance of ecological landscape infrastructure in improving the overall quality of the urban environment, and at the same time, the creation of an ecological landscape is conducive to the sustainable development of the city [11]. Erbe, H. H. investigated intelligent interaction techniques in human-computer systems and discussed a newly developed support for intelligence that improves the problems in traditional human-computer interaction [12]. Shun-Hui et al. studied the construction method of a dynamic interactive system of urban landscape information based on PHP technology, which provides a new innovative power for the development of the urban landscape industry [13]. Kempenaar, A. et al. researched the strategic issues in regional landscape design, emphasizing that the regional landscape should be designed from a more dynamic perspective in landscape design [14]. Yan, L. et al. proposed that innovation should be the main color of urban landscape design and should be more innovative in culture and art, science and technology application, environmental protection, etc. [15]. Zhang, X. et al. researched the use of virtual reality technology in the interactive landscape and investigated the realization method of virtual landscape design [16].

In the area of intelligent interaction and curriculum teaching, Karadeniz, A. et al. explored the use of AI technology in the field of education from 1970 to 2020 and analyzed the impact of AI technology on education [17]. Wenjing, Y. et al. constructed an integrated teaching model for colleges and universities based on AI, explored the paradigm of instructional design in the context of AI, and analyzed the impact of AI on higher education [18]. Huang, J. et al. investigated the instructional design specification under AI technology and explored the impact of AI on teaching activities and instructional design [19]. Tan, X. et al. proposed that AI technology improves the problem of imbalance in China's educational resources and emphasized that AI technology is conducive to enhancing the interactivity of student learning [20]. Chun, H ...et al. proposed that artificial intelligence is of great significance to the development of education, and should pay attention to the combination of education and modern technology to actively reform and upgrade modern education [21]. Hughes. et al. researched affective computing and intelligent interaction technology, analyzed the scenarios of the technology's use in the development of education and its development prospects, and emphasized that intelligent interaction technology will surely be the development trend of future science and technology [22]. Huang, G. R. X. et al. explored the impact of AI technology on instructional design, and the results showed that AI technology affected all aspects of instructional design, including instructional content, instructional media, instructional environment, and instructional evaluation [23].

In this paper, we first studied the implementation method of AI interaction design technology to establish the limb node coordinate system, define the limb node characteristics, identify the body movements, evaluate the behavior and perception of the human body, and analyze the departure of one of the human body and the emotional level under AI interaction. Then, a human-computer interaction learning system is established based on AI interaction design technology, and the landscape design course is assisted in teaching based on the learning system, which analyzes the data generated in the learning state and detects the students' interest level and learning state. Finally, the comparison of the effect of AI interactive teaching and traditional teaching is used to analyze the differences in the cognitive ability, learning motivation and emotional level of students under the two teaching environments. This paper carries out an in-depth study on the course teaching mode of human-computer interaction and constructs a landscape topic course teaching mode based on the AI interactive system through the study, which promotes the integration of AI interactive technology and landscape course teaching and lays a solid foundation for the development of landscape topic courses.

2 AI interaction design technology model

2.1 Body movement recognition

2.1.1 Limb node coordinate system establishment

In order to eliminate individual user differences as much as possible, it is necessary to transform the spatial description of user actions from the device spatial coordinate system to the user spatial coordinate system and to establish the interaction action characteristics that conform to the user's attributes. FIG. 1 shows the spatial coordinate system transformation, FIG. 1(a) depicts the user spatial coordinate system, O' represents the origin of the user spatial coordinate system $o'x'y'z'$, FIG. 1(b) depicts a top view of a user rotating around y axes under the Kinect spatial coordinate system, $L(x_1, z_1)$ represents the user's left-shoulder-mapped coordinate point in the Kinect spatial coordinate system, $R(x_r, z_r)$ represents the user's right-shoulder-mapped coordinate point, and θ represents the user's rotation angle with respect to the device xoy plane. $(-45° < \theta < +45°)$ the angle of rotation of the user relative to the plane of the device 7.

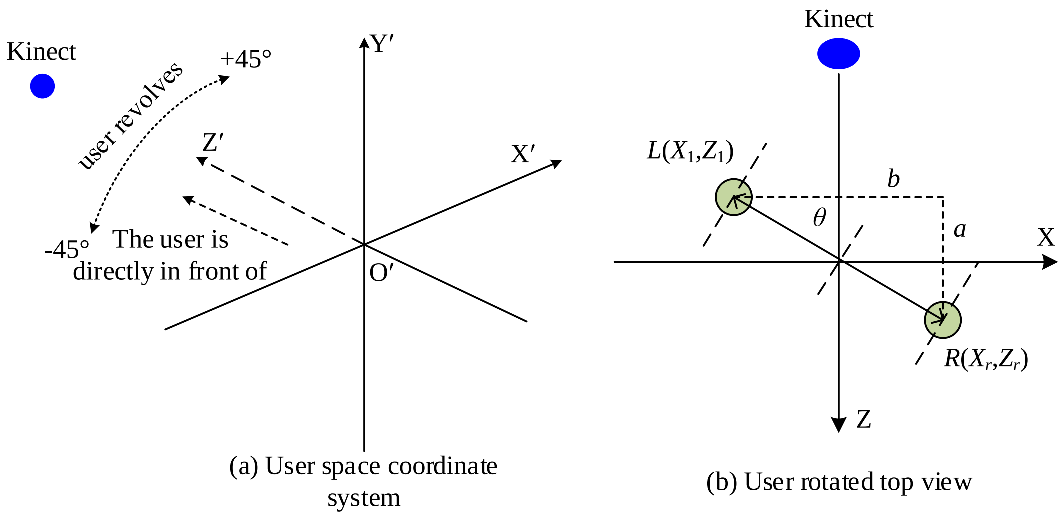

Figure 1. Space Coordinate System Transformation

Since the acquired limb node data is mirror-symmetric, the transformation relationship between coordinate point $P(x,y,z)$ under Kinect spatial coordinate system $oxyz$ and coordinate point $P'(x',y',z')$ under user spatial coordinate system $o'x'y'z'$ can be described as equation (1):

$$(x',y',z',1)=(x,y,z,1)\begin{pmatrix}1&0&0&0\\0&1&0&0\\0&0&-1&0\\-x_0&-y_0&z_0&1\end{pmatrix}\begin{pmatrix}\cos\theta&0&-\sin\theta&0\\0&1&0&0\\\sin\theta&0&\cos\theta&0\\0&0&0&1\end{pmatrix} \tag{1}$$

In Eq. (1), $O'(x_0,y_0,z_0)$ denotes the coordinates of the origin of the user's spatial coordinate system $o'x'y'z'$, θ is the angle of rotation of the user with respect to the plane of the sensor xoy, $\theta=\arctan\left((x_r-x_1)/(z_r-z_1)\right)$, where $x_r>x_1,-45°<\theta<+45°$.

After the transformation of the coordinate system through the formula (1), the current user-specific spatial mesh model is established in the user coordinate system, and in this paper, the mesh model is divided into a 3D cubic mesh of w^3. Fig. 2 shows the cross-section diagram of the spatial mesh division in the xoy plane. The upper and lower anterior and posterior directions are meshed with a uniform distance in d. The human joint skeleton is shown in green. After establishing the 3D meshing model, the region in the user's coordinate system can be described in the form of a cubic grid, which ensures that an independent user's limb node coordinate system is always established with the user as the center, thus eliminating the user's differences as much as possible.

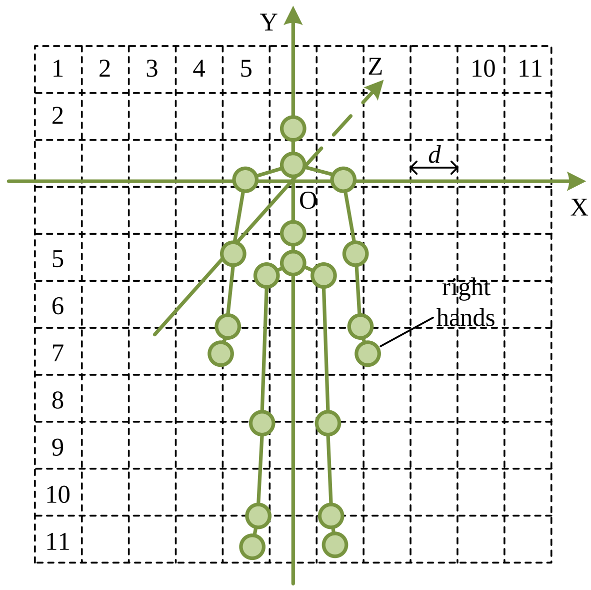

Figure 2. Space grid is divided into the section diagram of the y plane

2.1.2 Limb node feature vector definition

The state of the action at a point in time is the static pose, and the motion sequence of joint or multiple joint points of the human body in space is the dynamic behavior. Before recognizing the action, it is necessary to describe the generic feature data under the user's spatial coordinate system, and the generic feature data generally includes the three-dimensional coordinate information of the relative joint points, the spatial motion vectors of the joints, and the spatial distances between the joints, etc., and Fig. 3 shows a description of the feature data of the limb action. Among them, the green circle indicates the relative joint point, the arrow indicates the relative motion vector, D1 is the motion distance from the hand movement to the head direction, and D2 indicates the motion distance between the hands.

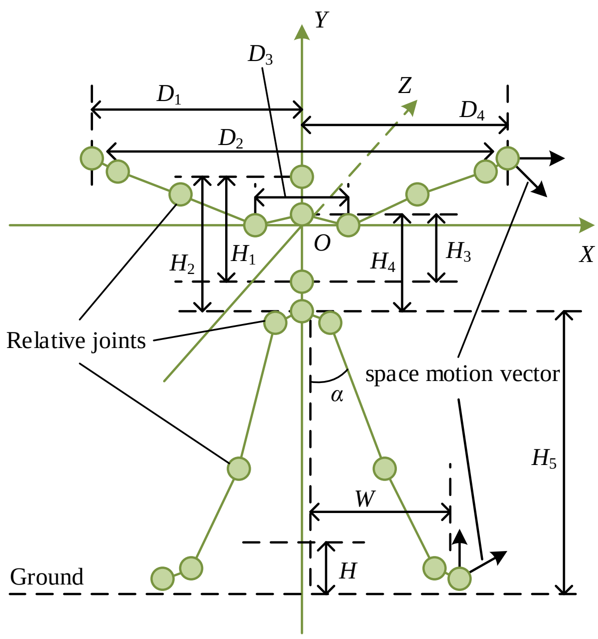

Figure 3. Data representation of user space coordinate system

In this paper, limb node feature vectors are defined to describe the action feature data, and the recognition of dynamic sequences formed by the combination of multiple specific poses, i.e., the recognition of limb actions, is realized through the calculation and analysis of limb node feature vector parameters. The limb node feature vectors include joint point spatial motion vector, joint point motion time interval and joint point spatial distance, and the limb node feature vector V is defined in equation (2):

$$V(T,k)=\left[\bigcup_{i-0}^{s-1} J_k^i J_k^{i+1}, \Delta t_k^s, |P_m P_n|\right] \tag{2}$$

In Eq. (2), T denotes the action type, $k(0 \le k \le 19)$ denotes the index of the joint point, $i(i=0,1,\cdots,s)$ denotes the current sampling frame, s denotes the end frame in which the corresponding joint point reaches the next specific sampling point, $J_k{}^i J_k{}^{i+1}$ denotes the spatial motion vector of the joint point k moving from the current sampling frame i to the next frame $i+1$, $J_k{}^i$ denotes the spatial coordinate point $\left(x_k{}^i, y_k{}^i, z_k{}^i\right)$ of the joint point k in the i th frame, $\Delta t_k{}^5$ denotes the time interval for the movement of the joint point k through the trajectory from the $J_k{}^0$ coordinate point to the $J_k{}^s$ coordinate point, and $|P_m P_n|$ denotes the spatial distance between the specific joint points of the human body, which serves as a proportionality feature calibration quantity in the grid model.

Each joint point defines the spatial motion vector $J_k{}^i J_k{}^{i+1}$, which calculates the motion direction and trajectory of the limb node, and the length of time used for each step of sample point transfer of the action can be described by the time interval $\Delta t_k{}^5 = t_k{}^5 - t_k{}^0$. where $t_k{}^0$ and $t_k{}^5$ correspond to the moments of articulation point k in each set of start sampling frames and end sampling frames, respectively. From the definition of Eq. (2), $J_k{}^i = \left(x_k{}^i, y_k{}^i, z_k{}^i\right)$, $J_k{}^{i+1} = \left(x_k{}^{i+1}, y_k{}^{i+1}, z_k{}^{i+1}\right)$, then the spatial motion vector $J_k{}^i J_k{}^{i+1}$ is expressed as Eq. (3):

$$J_k^i J_k^{i+1} = \left(x_k^{i+1} - x_k^i, y_k^{i+1} - y_k^i, z_k^{i+1} - z_k^i\right) \tag{3}$$

In $|P_m P_n|$, P_m and P_n denote the joints at both ends of the human limb parts, m and n denote the index numbers that will start and end the set of joints, respectively, where $m<n$, point $\left(x_j, y_j, z_j\right)$ denotes the spatial coordinates of the corresponding joints of the human limb parts, and $j(m \le j \le n-1)$ denotes the index variable of the corresponding joints in the computation, then the spatial fixed distance between the joints of the limbs is computed by the formula (4):

$$|P_z P_n| = \sum_{j=-}^{n-1} \sqrt{\left(x_j - x_{j+1}\right)^2 + \left(y_j - y_{j+1}\right)^2 + \left(z_j - z_{j+1}\right)^2} \tag{4}$$

According to Eq. (2), the definition can represent 3 classes of limb node feature vectors representing actions $V(T,k)$. When the joint point k reaches the next specific sampling point, the end frame s is determined, the current feature vector is analyzed as an input parameter to the state transfer function, and the sampling frame i is set to zero and waits for the next end frame, which is analyzed again, and then set to zero again, until the last sampling point.

1) For the right leg side kick action, the generic feature data of the right foot joint point $(k=19)$ is extracted, thus defining the limb node feature vector: $V(\text{"Right leg side kick"},19)=\left[\bigcup_{i=0}^{s-1} J_{19}^{i} J_{19}^{i+1}, \Delta t_{19}^{s}, L\right]$, where, L is the leg length.

2) For the right-handed circle-skimming action, the generic feature data of the right-handed joint point $(k=11)$ is extracted, thus defining the limb node feature vector: $V(\text{"Right hand in a circle."},11)=\left[\bigcup_{i=0}^{s-1} J_{11}^{i} J_{11}^{i+1}, \Delta t_{11}^{s}, D\right]$, where D is the arm length.

3) For the horizontal unfolding action of both hands, the generic feature data of the left/right hand joint point $(k=7,11)$ is extracted, thus defining the limb node feature vector.

2.1.3 Pose sequence FSM construction

In this paper, we propose the pose sequence FSM method to recognize predefined limb actions. A pose sequence represents a set of motion sequences in which an action is described by multiple poses on the time axis, and the pose sequence FSM describes a finite number of states for each action and the transfer process between each state. In this paper, we define the pose sequence FSM as Λ, and its quintuple representation is shown in Equation (5):

$$\Lambda=\left(S,\Sigma,\delta,s_0,F\right) \tag{5}$$

In Eq. (5), S denotes the state set $\{s_0,s_1,\cdots,s_n,f_0,f_1\}$, which describes the postural state for each particular should of the action. Σ denotes the set of input limb node feature vectors and the alphabet of restriction parameters $\{u,\neg p,\neg t\}$, where the symbol "$\neg$" denotes logical negation. δ is the transfer function, and the path restriction $p=\left\{\mathrm{xyz} \mid \mathrm{x}\in[x_{\min},x_{\max}],\mathrm{y}\in[y_{\min},y_{\max}],\mathrm{z}\in[z_{\min},z_{\max}]\right\}$ controls the range of critical points for a particular pose, and in any case outside the predefined path range, i.e., when $\neg p$ is true, it is labeled as an invalid state.

In the table, $k,x=0,1,2,\cdots,n$, and $k\neq k+x,, n,n$ denote the total number of intermediate valid states required to recognize the action. This pose sequence FSM accepts a point domain rule of $L(\Lambda)=\left\{\left(u^n\left|u^*\neg p\right|u^*\neg t\right)\mid n\geq 1\right\}$.

A regular expression for the trajectory of an action can be extracted from the eigenvector point domain string of the action. In the alphabet Σ, $\Sigma_{i(1-i)}=\Sigma_i\wedge\Sigma_{1-i}$, where $i=0,1$, denotes the spatial point domain symmetric along the yoz-plane holds simultaneously. The regular expression for the trajectory of the action is collapsed and simplified in equation (6):

$$R=a_i c_i\left|d_i e_{1-i} f_i g_i h_i\right| d_{i(1-i)} e_{i(1-i)} h_{i(1-i)} \tag{6}$$

Finally, the semantics and uses of the interaction actions are defined by the user, and the user is given new semantics by the obtained action types, e.g., lifting the left and right leg represents scene roaming, sliding the left and right hand represents document page turning, and horizontally unfolding the both hands represents pulling back the curtain, etc., so as to realize the natural human-computer interaction applications.

2.2 User perception of interaction subjects based on behavioral features

2.2.1 Overview of human behavior estimation

The field of intelligent video surveillance and intelligent human-computer interaction has focused on human behavior estimation as a research hotspot. The methods of human behavior estimation are roughly divided into two categories: one is to model a large number of video or image samples using deep learning methods, and the other is the behavior estimation method based on the human skeleton.

Extracting robust human behavior features is the key to effectively recognizing human behavior. In order to identify the interactive subject users with interactive behaviors, this paper proposes an interactive behavior perception method based on stage behavioral features for identifying whether the users in an interactive scene have interactive behaviors. The method utilizes human torso displacement features to determine if the human body is standing or not. To analyze the motion state of the arm of the human body in the standing state, the arm displacement feature is utilized. Figure 4 shows the flowchart of perception of interaction behavior based on stage behavior features. For the user in the standing state and the arm remains static, the relative position of the hand joint features are used to identify whether the user indicates interaction behavior. On the basis of the realization of the perception of the user's interaction behavior, the spatial proximity algorithm is used to locate the interactive subject user from the group of users with interaction behavior. Different from other human skeleton-based behavior recognition algorithms mentioned above, the main contributions of the method proposed in this paper include: only the key points of the human skeleton that play a role in each stage of the behavior are feature extracted and normalized, which eliminates the interference of the other key points of the skeleton in recognition of the interaction behavior. The rigidity of the torso in the upright human body is exploited to ensure consistency of the normalized feature units.

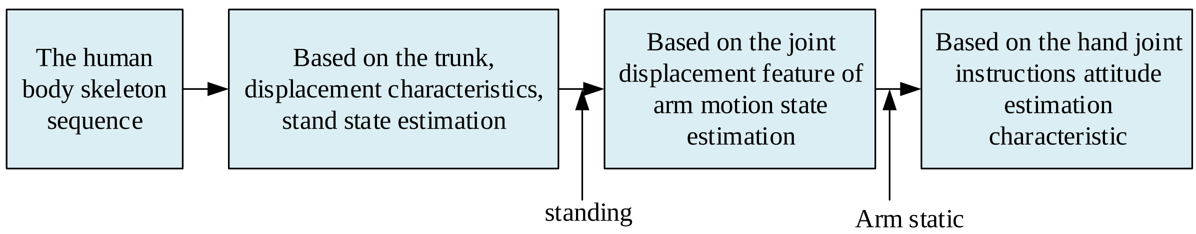

Figure 4. Interaction behavior sensing process based on stage behavior characteristics

2.2.2 Interaction Subject User Perception

Based on the above realization of perception of interaction behavior, it is necessary to distinguish the interaction subject user from the other users who interact in the scene. The interaction subject user refers to the individual or group with the intention of engaging in interaction behavior that the machine needs to respond to in a timely manner. In order to determine the interaction subject user, this paper adopts the following rule: if only a single user with interaction behavior attributes is obtained, then the user is the interaction subject user. Otherwise, there are multiple users with interaction behavior in the interaction scene. If the users have interaction priority, then respond to the highest interaction priority user. If these users do not have interaction priority, then calculate the distance from the center of the interaction interface for each user, and the closest user is defined as the current interaction subject user.

Assuming that the pixel distance from the interactant to the centerline of the image is x, and the depth value of the interactant's neck is z, the distance from the center of the interactive interface is d, which is calculated as follows:

$$d_r = \sqrt{(\frac{x}{pd})^2 + (\frac{z}{lb})^2} \tag{7}$$

2.3 Context-aware human-computer interaction

2.3.1 Focus on area-aware human-computer interaction

Based on the realization of user perception and tracking of the interaction subject, the interaction system judges whether the human interaction action is effective and responds accordingly. Since human interaction methods and habits are so varied and diverse that it is difficult to be all-inclusive, this paper focuses on discussing and studying the most commonly used human-computer interaction methods and strategies based on human eyes, human hands, and eye-hand coordination.

This paper focuses on how to use face orientation to approximate the direction of attention of the human eye in the previous chapters, and this chapter will further penetrate the scope of things that the human eye looks at based on face orientation, i.e., how to locate the interaction area where the interaction object is located on the basis of the previous research. Figure 5 shows a schematic diagram of the attention area localized to face orientation.

In the figure, the installation position of the camera is defined as the center point of the interaction interface, assuming that the center point coordinates are the origin $(0,0)$, $(x_r y_r)$ denotes the coordinates from the center point of both eyes to the center of the interaction interface, z_r denotes the depth distance from the head to the interaction interface, and α_h and α_v denote the angles of the human face orientation in the horizontal and vertical directions, respectively. (x_d, y_d) denotes the coordinate from the center of the attention area to the center of the interaction interface, and β denotes the visual divergence angle of the human eye when attention is focused, which is experimentally defined as $15°$ in this paper.

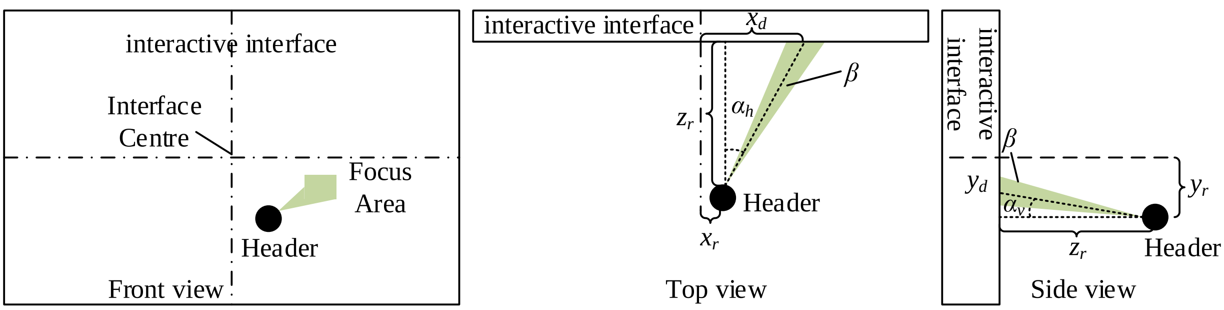

Figure 5. Faces orientation to locate the area diagram

In the 3D skeleton estimation model of the human body, the torso length of the sample, which is the actual length from the neck to the centers of the two hips, is included. Assuming that the torso length of the human body is lb, and the pixel distance from the neck to the centers of the two hips is pb, the length of the human body per pixel at the current position is lb / pb.

Assuming that the pixel distance from the center point of both eyes to the center point of the image is $\left(x_p, y_p\right)$, there is:

$$\begin{cases} x_r = \dfrac{x_p \cdot lb}{pb} \\ y_r = \dfrac{y_p \cdot lb}{pb} \end{cases} \tag{8}$$

The coordinates of the center of the area of interest $\left(x_d, y_d\right)$ are:

$$\begin{cases} x_d = x_r + z_r \cdot \tan\left(\alpha_h\right) \\ y_d = y_r + z_r \cdot \tan\left(\alpha_v\right) \end{cases} \tag{9}$$

Concerned about the coordinates of the region's borders can also be used in a similar way, respectively, assuming that the coordinates of the diagonal points of the border for the upper-left corner $\left(x_s, y_s\right)$, the lower-right corner $\left(x_x, y_x\right)$:

$$\begin{cases} x_s = x_r + z_r \cdot \tan\left(\alpha_h - \beta\right) \\ y_s = y_r + z_r \cdot \tan\left(\alpha_v + \beta\right) \end{cases} \tag{10}$$

$$\begin{cases} x_x = x_r + z_r \cdot \tan\left(\alpha_h + \beta\right) \\ y_x = y_r + z_r \cdot \tan\left(\alpha_v - \beta\right) \end{cases} \tag{11}$$

This gives the region of interest of the interacting subject.

2.3.2 Posture tracking and human-computer interaction

The traditional non-negative matrix decomposition decomposes the data into the product of two matrices and does not allow negative values in the data, which limits the scope of application of non-negative matrix decomposition in practical scenarios. Chris Ding proposed a convex non-negative matrix decomposition algorithm for this purpose. The algorithm takes the data matrix as a factor of the decomposition result, and decomposes the matrix into the product of the data matrix, the basis matrix and the encoding matrix, as shown in equation (12):

$$X_{\pm} = X_{\pm} U_{+} V_{+} \tag{12}$$

Since the sign of the data features is preserved in the decomposition result, the nonnegativity of the basis and coding matrices can still be guaranteed even if the features are negative, i.e., the nonnegativity constraint of nonnegative matrix decomposition is loosened, so that the data matrices can still be decomposed in the presence of negative numbers.

Describing the decomposition error in terms of Euclidean distance, the cost function $OCNMF$ of the CNMF is defined as:

$$O_{CNAF} = \left\| X_{\pm} - X_{\pm} U_{+} V_{+}^{T} \right\|^{2} \tag{13}$$

Similar to the multiplicative iteration rule of NMF, CNMF has multiplicative iteration rule as follows:

$$\begin{aligned} u_{ik} &\leftarrow u_{ik} \sqrt{\frac{\left(\left(X^T X\right)^{+} V + \left(X^T X\right)^{-} U V^T V\right)_{ik}}{\left(\left(X^T X\right)^{-} V + \left(X^T X\right)^{+} U V^T V\right)_{ik}}} \\ v_{jk} &\leftarrow v_{jk} \sqrt{\frac{\left(\left(X^T X\right)^{+} U + V U^T \left(X^T X\right)^{-} U\right)_{jk}}{\left(\left(X^T X\right)^{-} U + V U^T \left(X^T X\right)^{+} U\right)_{jk}}} \end{aligned} \tag{14}$$

GCNMF relaxes the non-negative constraints of NMF while preserving the flow structure feature of the data space by minimizing the graph regularization term. GCNMF is based on Laplacian feature mapping and constructs the adjacency graph G, the weight matrix W and the Laplacian matrix L to obtain the graph regularization term $\mathrm{R}(V)$ and integrates it into the objective function $O\mathrm{CNMF}$. Its objective function O^* is shown in Eq. (15):

$$\begin{aligned} & O^*(U,V) = O_{CNMAF}(U,V) + R(V) = \left\| X - XUV^T \right\|^2 + \lambda \operatorname{Tr}\left(V^T L V\right) \\ & s.t. U_{ij} \geq 0, V_{ij} \geq 0 \end{aligned} \tag{15}$$

3 AI interaction-based learning system for landscape thematic courses

3.1 Requirement Analysis of Human-Computer Interaction Learning System

Design and implement a multi-channel intelligent learning system, which includes student registration and login, teacher registration and login, learning activity module and multi-channel integration, and system functions include student function, teacher function, teaching function and multi-channel integration.

The HCI learning system equipment should include a computer equipped with a touch screen, a camera, and an electrical skin activity sensor. The computer equipped with a touch screen creates a natural and harmonious interactive environment for the students and provides a richer interactive experience, while the camera and the electrical skin activity sensor provide multi-channel fusion data to help analyze the learning status of the students and to detect the level of interest in their learning.

The system employs a relational database to record student information and interaction data. The purpose of using a platform programming language is to provide a foundation for porting between system platforms. Student interest level detection requires the use of multi-channel data fusion based on dermatoelectric activity and face recognition.

3.2 HCI Learning System Architecture

3.2.1 System framework

The framework of the HCI learning system consists of a database, a computer, and multi-channel sensors. The multi-channel sensors include a camera and a sensor for electrical skin activity.

As can be seen from the framework diagram of the system, the students carry out human-computer interaction learning activities through the computer equipped with a touch screen, and the learning activity data and student information come from the database. The system acquires students' learning status data through multi-channel sensors, skin activity sensors and cameras, and after detecting the level of interest, analyzes the results and stores the students' learning status in the database.

3.2.2 System architecture

The structure diagram of the HCI learning system is depicted in Figure 6. The system structure diagram is a tool for visualizing the relationship between different modules in the HCI learning system, and students can query student information via HCI devices. The student information comes from the student database, while the learning status information comes from the learning status database. Through the HCI device, students can also access learning activities, where the information on the learning activities is obtained from the learning activity database. During students' HCI learning process, learning status data are generated, including interest level detection results, students' learning activities, learning time and grades, and other information stored in the learning status database and the following describes each module in the system structure diagram.

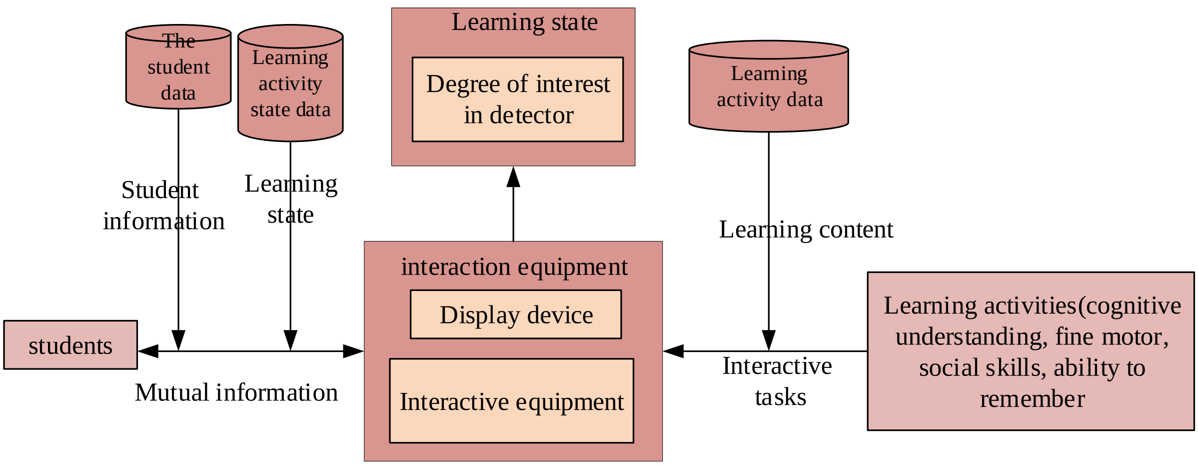

Figure 6. System structure diagram of interactive learning system

Students are the user objects of the system, following the guidelines of human-computer interaction, and by analyzing the characteristics of the students themselves, such as their ages, learning styles and learning contents, etc., the human-computer interaction learning system is designed with the "human-centered" design idea.

The student database is used to store student information, which is an important basis for the comprehensive management of teaching in the learning system, including the following contents: student age, gender, class, learning advantages, learning disadvantages, etc. Student learning information is stored in the learning activity status database.

The learning activity status database is used to store student learning status information and is an important basis for student learning status assessment, which includes the following content: learning content, time, scores and student interest level detection results.

Learning status refers to the data generated from students' learning activities, such as learning content, time and score, etc., as well as the data on students' learning interest level detected by the module for detecting students' interest level, which is the raw data for detecting the interest level are derived from the data on skin electrical activity and smiley face recognition in the human-computer interaction interface.

The human-computer interaction interface refers to the physical medium for information transfer between the user and the system, and the interaction devices in this system include computers, tablet PCs, cameras, and various sensor facilities such as electric skin activity sensors etc. The learning activity database stores information on learning activities, and the learning activity database stores information on learning activities.

The learning activity database stores the information on learning activities, which is the important basis for the system to call learning activities, including the following contents: the name of the learning activity, the class of students, the limitation time and the difficulty level.

The learning activities are designed according to cognitive psychology, student development theory and human-computer interaction theory, and they are divided into six categories according to the learning objectives, which are cognitive understanding, fine motor skills, social skills, memory skills, visual discrimination and classification concepts.

4 Analysis of the teaching effectiveness of the AI interactive landscape course

4.1 Cognitive Ability Analysis

This study will analyze the experimental results around the three lower-order thinking level levels of students in terms of memorization, comprehension, and application to facilitate a full understanding of whether there is a significant difference in the impact of using different teaching styles on the cognitive level of students' knowledge of landscape design. Thus, the pre-and post-landscape design test scores of the experimental and control classes were subjected to an independent sample t-test to observe the differences between the pre- and post-test scores of the two classes.

Table 1 shows the results of the independent samples t-test for knowledge of pre- and post-landscape design in the experimental and control classes. From the results of the processed data, the differences between the two in the three dimensions of memorization, comprehension and application were not significant before the experimental intervention, thus indicating that there was no difference in the mastery of landscape design and its related knowledge between the two groups of subjects before the experiment. However, in the process of comparing and analyzing the teaching process using two different teaching methods, traditional and AI interactive teaching, it was found that AI interactive teaching based on AI can promote students' mastery of the knowledge of the landscape course to a certain extent. In the post-test of landscape topic knowledge, the mean score of the experimental class on the comprehension dimension was higher than that of the control class by 1.721. The ability to apply knowledge was also higher in the experimental class than in the control class, with 3.075. It can be seen that after the teaching intervention, there is a significant difference between the experimental class and the control class in the three dimensions of memorization, comprehension and application, with $p = 0.075$. There is a significant difference, $p=0.000<0.015$. Meanwhile, the experimental results also show that interactive teaching can guide students' memory and understanding of landscape topic knowledge to a certain extent and can be applied to practical topics, which can help to promote the effective construction of students' knowledge of landscape topics.

Table 1. Landscape design knowledge independent sample t test

Test type	Capacity dimension	Mean		Standard deviation		T value
		Laboratory class	Cross-reference class	Laboratory class	Cross-reference class	
Pre-measure	Memory	2.532	2.324	0.625	0.723	1.383
	Understand	2.255	2.191	0.770	0.805	0.44
	Applied	1.753	1.704	0.885	1.159	0.304
	Total score	6.533	6.197	1.712	1.768	0.905
Post-test	Memory	2.125	1.497	0.789	0.955	3.393**
	Understand	2.789	1.068	0.555	0.655	5.544**
	Applied	3.075	2.601	0.854	0.760	2.735**
	Total score	6.985	5.178	1.264	1.696	5.726**

4.2 Learning Motivation Differences and Analysis

4.2.1 Results and analysis of learning attitudes in the experimental class after the experiment

After the experiment, Figure 7 displays the learning attitude of the experimental class. In this paper, through the longitudinal analysis of the experimental class students before and after the experiment in the behavioral intention, emotional experience and subjective criteria of the three paired samples t-test, $p < 0.05$, there is a significant difference. The results of the experiment show that there is a significant difference between students' behavioral intention, emotional experience and subjective judgment in the AI interactive education mode, which promotes the formation of good learning attitudes among students. The SD value of behavioral attitudes of students based on interactive technology teaching mode is 27.78±2.34, and the SD value of behavioral attitudes of students in ordinary teaching mode is 25.89±3.36. In terms of emotional experience, the SD value of students based on interactive technology teaching mode is about 16.67 more than that of students in ordinary teaching mode, which is a significant difference. Through the application of the program in teaching practice, it is found that the AI interactive education mode has a different degree of promotion effect on the formation of learning attitudes in different dimensions.

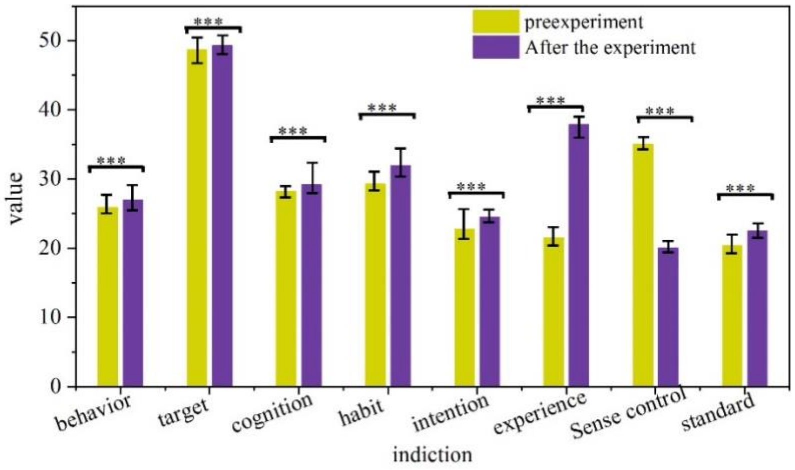

Figure 7. Experimental class learning attitude after experiment

4.2.2 Results and Analysis of Comparison of Exercise Attitudes between Control and Experimental Classes after the Experiment

The analysis of differences in students' learning attitudes after the experiment is shown in Figure 8. According to the experiment's results, the experimental class has an SD value of about 6.78 more than the control class in terms of line study habits. In terms of goal attitude, the SD value of the experimental class is about 4.05 points higher than that of the control class, and the difference is significant. And there is a 5%-10% difference in the level of attitude between the two classes at all levels. It indicates that the AI-based interactive education model is more conducive to promoting the formation of good learning attitudes, especially when students' behavioral intentions are reflected significantly. The implementation of this program has a greater effect on the formation of students' behavioral attitudes and the development of behavioral habits in teaching than the teaching model used in the control class.

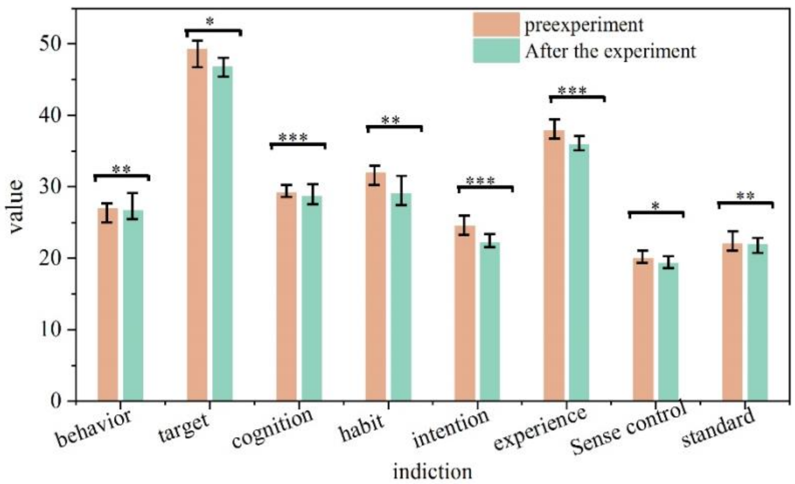

Figure 8. Analysis of different attitudes of learning

4.3 Significance Analysis of Differences in Students' Emotions

Independent samples t-tests were used to explore whether the use of instructional interactive devices with or without the use of instructional interactive devices affects mood, and then one-way ANOVA was used to investigate the effects of the different variables on the seven moods and Welch's test was used when variances were not homogeneous. The statistical significance of differences was determined using the Least Significant Difference and Dunnett's T3 methods when the variances were equal and when they were different, respectively. Specific heterozygotes were explored using post-hoc tests.

Table 2 shows the results of the independent samples t-test to determine whether or not the Ai interaction affected student mood. According to the independent samples t-test, there is a significant difference in anger and calm emotions between using an instructional interactive device and not. The p-value for the anger emotion on whether or not to use the instructional interaction device was 0.004, which is less than 0.05. The coefficient of significance for the calm emotion and the decision to use the AI interaction was also less than 0.05, suggesting a difference between these emotions.

Table 2. Taching interaction equipment - independent sample t test results

Condition	Anger	Bore	Fear	Pleasure	Peace	Sad	Surprise
Yes	1.152±1.343	0.194±1.113	0.44±0.885	1.223±1.342	3.65±2.44	1.613±1.483	0.9394±1.173
No	0.833±1.185	0.832±1.122	0.33±0.765	1.14±1.401	3.13±1.253	1.835±1.753	1.142±1.284
t	3.193	0.453	1.522	0.722	4.014	1.943	1.945
p	0.004	0.652	0.123	0.464	0.000	0.055	0.057

A more in-depth step of analysis was then carried out, in terms of instructional interaction devices, the emotions of anger, fear, calmness, and frustration were significantly different between the different instructional interaction techniques. Table 3 shows the results of the ANOVA on the effect of instructional interactive devices on students' emotions. Table 4 shows the results of Welch's test regarding the impact of instructional interactive devices on students' emotions. There is a significant effect of instructional interactive devices on the emotion of anger, and the effect of AI interactive teaching on the emotion of anger of the students has a significant difference between the non-use of interactive methods,α=8.442,p=0.008. The effect of AI interactive teaching on the emotion of fear of the students has a difference between traditional teaching and learning, with a significant coefficient of significance of less than 0.05.In the case of the emotion of calmness, p=0.017, which means that There is a significant difference between the effect of AI interactive teaching on students' calming emotions and the use of interactive devices. Instructional interactive devices have a significant impact on the emotions of frustration, while the emotions of happiness, boredom, and surprise do not differ significantly between different instructional interactive techniques.

Table 3. The result of the "anova result" for the students' emotions

Variable	Emotion		Sum of squares	Freedom	Mean	F	p	Significant
Teaching interact	Pleasure	Intergroup	10.943	3	3.454	1.943	0.114	
		Within group	1408.525	235	2.666			
		Total	1419.453	567				

Table 4. Teaching interaction affects student sentiment - Welch test results

Variable	Emotions	Statistical a	Freedom 1	Freedom 2	p	Significant difference
Interactive teaching equipment	Emotions	8.442	3	83.667	0.008	No interaction
	Anger	1.965	3	80.443	0.442	
	Revulsion	3.753	3	88.954	0.134	No interaction
	Fear	7.642	3	78.553	0.017	No interaction
	Peace	3.743	3	79.531	0.028	Have interaction
	Despondency	1.995	3	80.452	0.128	

5 Conclusion

This paper studies AI interaction-related technology and, too long, the use of this technology in the landscape topic teaching mode, based on the student's cognitive ability learning motivation, and emotional differences to analyze the teaching effect of AI interaction landscape topic course. The main conclusions are as follows:

To a certain extent, interactive AI teaching can improve students' mastery of landscape course knowledge. The control class has a memorization level of 2.125, while the course knowledge points have a level of 0.628 higher. After the teaching intervention, there is a significant difference between the experimental class and the control class in the three dimensions of memorization, comprehension, and application, $p=0.000<0.005$.

By longitudinal analysis of students' behavioral intention, affective experience and subjective criteria in three paired-sample t-tests, $p < 0.05$, there is a significant difference. That is, the AI interactive education model has a different degree of promotion effect on the formation of learning attitudes in different dimensions.

In terms of calm emotions, $p=0.017$. In terms of angry emotions, $\alpha=8.442, p=0.008$, AI interactive teaching mode has a significant effect on students' emotions.

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