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Article

# Study on the Construction of Immersive Learning Scene in the Construction of “Integration of Large, Medium and Small” Civics Course Based on Virtual Reality Technology

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**Abstract:** The improvement of the integrated construction of ideological and political education promotes the equitable development of education. To enhance the realism and construction efficiency of immersive learning scenarios, this paper proposes an improved registration algorithm (RANSAC) based on the determinant point process (DPP) to optimize the sampling accuracy of image feature points. By establishing a collaborative education platform for primary, secondary, and higher education, a k-DPP sampling strategy is designed to enhance the uniformity of feature point spatial distribution, achieving high-precision learning scenario integration. Through comparative and control experiments, the effectiveness of the constructed immersive learning environment in assisting ideological and political education is validated. The study shows that the constructed technology achieves a maximum mIoU of 0.963 across 10 scenarios, with inference times ranging from 65 to 80 seconds, demonstrating good feature extraction performance and faster scenario construction speeds. The experimental class achieved an average satisfaction score of 9.52 for the immersive learning scenarios, with flow experience scores in all 8 dimensions exceeding those of the control class, and learning psychological states maintained at a high arousal level.

**Keywords:** virtual reality technology; k-DPP sampling strategy; RANSAC algorithm; immersive learning scenarios; integrated ideological and political education courses

## 1. Introduction

Virtual reality, as a cutting-edge information technology, has demonstrated immense potential and value in the field of education [1]. Its unique immersive and interactive nature has brought revolutionary changes to traditional teaching environments [2]. In higher education, particularly in ideological and political education, virtual reality technology not only breaks through spatial and temporal constraints but also provides contextualized learning experiences, thereby enhancing students' learning motivation and outcomes [3]. Immersive concepts are increasingly permeating various fields, and even education and teaching are being empowered by “immersive” approaches, giving rise to new forms of scenario-based learning [4-5]. The application of immersive learning scenarios demonstrates diverse, experiential teaching methods, guiding students to actively perceive, genuinely understand, dare to question, and actively reflect, thereby achieving the visualization of abstract emotions that are otherwise invisible and intangible in teaching [6-7].

The construction of teaching scenarios based on virtual reality technology has garnered significant attention from researchers due to its novelty and practicality. For example, Ling [8] sought to transform the traditional Japanese language teaching method by designing a virtual scene using VRML technology, combined with Java interface technology to enable interactive functionality. The results demonstrated that the optimized teaching method enhanced Japanese language teaching efficiency, making Japanese learning more convenient and efficient. Liu et al. [9] designed an immersive virtual reality-based teaching experiment, incorporating immersive teaching scenarios in the experimental group. The results showed that the experimental group's academic performance and scores in cognitive, behavioral, emotional, and social engagement were significantly higher than those of the control group. Lønne et al. [10] designed two types of virtual scenes—desktop-based and immersive—and conducted a parallel-design randomized controlled trial to study changes in students' emotions under the two scenarios. The results revealed that students' positive emotion scores were significantly higher in the immersive scenario than in the desktop-based scenario.

In ideological and political education, immersive media technologies are increasingly used to enhance teaching effectiveness in theoretical courses [11]. Xu [12] developed an integrated virtual reality (VR) teaching environment based on the Unity3D virtual engine, combining 3D modeling technology and dynamic visual interaction technology to create an immersive, experiential virtual simulation learning environment, thereby enhancing students' interest and engagement in ideological and political education.

Additionally, research has found that integrating intelligent algorithms with virtual reality technology in teaching can better meet students' diverse needs and improve teaching quality. Wang et al. [13] introduced an improved convolutional neural network structure into the layout of immersive virtual learning scenarios and applied a visual attention model in visual interface design, enhancing the visual effects of the learning environment while meeting the personalized instructional environment needs of different learners. Wang et al. [14] used support vector machines and particle swarm optimization algorithms to classify and evaluate students' physical activity performance in virtual sports activity scenarios, effectively enhancing students' enthusiasm for physical education and overall teaching quality. Based on the above research findings, educators can use virtual reality technology to create more attractive, interactive, and personalized learning environments that significantly enhance students' motivation, engagement, and learning outcomes, highlighting the immense potential of the deep integration of technology and education.

This paper leverages the high immersion characteristics of virtual reality technology and employs algorithm optimization to enhance the sense of presence in the construction of ideological and political education learning scenarios. It establishes a collaborative education platform for primary, secondary, and higher education institutions to achieve cross-level adaptation of ideological and political education course resources and promote their effective utilization. We propose an improved RANSAC registration algorithm based on the DPP probabilistic model. To address the limitation of resource waste caused by non-fixed sampling points, we introduce a k-DPP sampling strategy to optimize the spatial distribution of feature points, thereby improving the accuracy and efficiency of scene image feature extraction and fusion. We design an immersive classroom scene image registration example to evaluate the quality of feature point selection in the proposed method.

## 2. Creating Immersive Learning Scenarios for Ideological and Political Education Based on Virtual Reality Technology

### *2.1. Establishment of a Collaborative Education Platform for Ideological and Political Courses in Primary, Secondary, and Higher Education Institutions*

The key to implementing virtual reality technology in education is the creation and use of an intelligent education platform. The integration of virtual reality technology into the unified construction of ideological and political courses across primary, secondary, and higher education institutions necessitates the establishment of a comprehensive, multi-module, integrated collaborative education platform for ideological and political courses across all levels of education. First, the platform should enable users to select and combine modules based on educational stage, student circumstances, and individual needs, thereby creating personalized, modularized learning experiences for students. This approach optimizes the integration of online resources and systematically expands ideological and political education resources in accordance with the characteristics and learning patterns of students at different educational stages, progressing from basic to advanced levels. Second, virtual reality technology should be utilized to achieve the co-construction and sharing of teaching resources on the collaborative education platform, breaking away from the traditional one-way teaching structure of ideological and political education courses. This will enhance the interactive effects between teachers and students on the platform, creating a highly efficient, integrated virtual simulation classroom where each student has their own space and teacher throughout the entire process. Finally, we must master the degree of integration between virtual reality technology and ideological and political education classrooms at primary, secondary, and higher education levels, achieving a blend of virtual and real elements to reshape educational scenarios and optimize students' immersive learning experiences. Algorithm application is the core element of embedding virtual reality technology into ideological and political education. Through specific algorithm programs, online and offline ideological and political classrooms are connected, integrating all stages of ideological and political education across primary, secondary, and higher education, and creating a collaborative education framework that is comprehensive and multi-layered. Additionally, administrative departments need to deepen reforms, fulfill their responsibilities in policy guidance, standard setting, and financial support, and increase support for the development of virtual simulation ideological and political education across all educational levels to ensure the large-scale operation of the collaborative education platform for ideological and political education across primary, secondary, and higher education.

## *2.2. Improved Alignment Algorithm Based on Deterministic Point Process (DPP) (RANSAC)*

In the implementation of the RANSAC algorithm, the sampling method of the subset of feature points is the most important step, and the deterministic point process (DPP) has good global and negative correlation, and will show the perfect nature of wide coverage and "uniform distribution" during the sampling process, which is very important for the traditional RANSAC random sampling process.This has a very positive effect on the defect of uneven sampling in the traditional RANSAC random sampling process.

### 2.2.1. Analysis of the Row-Type Point Process (DPP)

A row and column point process is a special kind of stochastic point process.A stochastic point process is a mathematical model used to describe a special class of physical phenomena characterized by highly localized events randomly distributed in a certain statistical law.That is, the events occur within a very small range in time or space (denoted as $X$ ). Mathematically, when this range is infinitely small, it can be abstractly idealized as a point.This can be roughly summarized by saying that a certain collection of points that are randomly distributed in some space according to certain statistical laws, i.e., forms a stochastic point process.

The deterministic point process (DPP) was first proposed in quantum mechanics and random matrices. The deterministic point process (DPP) is a probabilistic model that first describes a random event using a mathematical model, constructs the kernel matrix of the mathematical model, and calculates the probability of occurrence of a subset of the random event through the determinant of the kernel matrix.Based on its properties, the DPP provides an effective solution for other inference tasks such as sampling and calculating marginal probabilities.In this paper, we mainly utilize its sampling property to improve the RANSAC algorithm.

A point process $P$ on a discrete set $Y = \{x_1, x_2, \ldots, x_n\}$ is probabilistically distributed over all subsets $2^Y$ of $Y$ , and the basis of this process is referred to as a deterministic point process when, and only when, the point process $P$ is determined by a semipositive definite matrix $K$ and the matrix $K$ is indexed by an element in $Y$ .That is, when $A$ is a subset obtained on the basis of the point process $P$ , for any $A \subseteq Y$ , there is:

$$P(A \subseteq Y) = \det(K_A) \tag{1}$$

where $\det(K_A) = [K_{i,j}]_{i,j \in A}$ , and to ensure the validity of the formula, let $\det(K_\phi) = 1$ and when $A = \{i, j\}$ :

$$\begin{aligned}\det(K_A) = [K_{i,j}]_{i,j \in A} &= \begin{vmatrix} K_{ii} & K_{ij} \\ K_{ji} & K_{jj} \end{vmatrix} \\ &= K_{ii}K_{jj} - K_{ij}K_{ji} = P(i \in Y)P(j \in Y) - K_{ij}^2\end{aligned} \tag{2}$$

From the above equation, it can be obtained that the diagonal elements of the matrix $K$ denote the probability of a single element being selected into a subset, and the non-diagonal elements determine the negative correlation of co-occurrence between pairs of elements, and the matrix $K$ contains all the information about the inter-elements.Accordingly $K$ is called the kernel matrix and this global negative correlation is called diversity.So the following conclusion is obtained: a larger value of $K_{ij}$ represents a smaller probability of $i$ and $j$ occurring at the same time.

Since the matrix $K$ contains the probability of occurrence of a subset, $0 \le K \le I$ , but the data in the actual computation cannot guarantee the value of $K$, so it is necessary to weaken the restriction of $K$. The L-ensemble theory simplifies the determinantal point process by defining the determinantal point process using the real symmetric matrix $L$ : $P_L(Y=y) \propto \det(L_y)$, where the $L$ matrix is a semipositive definite matrix not necessarily smaller than $I$. L-ensemble theory proves that any L-ensemble can represent a determinantal point process (DPP) with a kernel matrix denoted as:

$$K = L(L+I)^{-1} = I-(L+I)^{-1} \tag{3}$$

Figure 1 gives an example of the determinant point process to find subset probabilities.

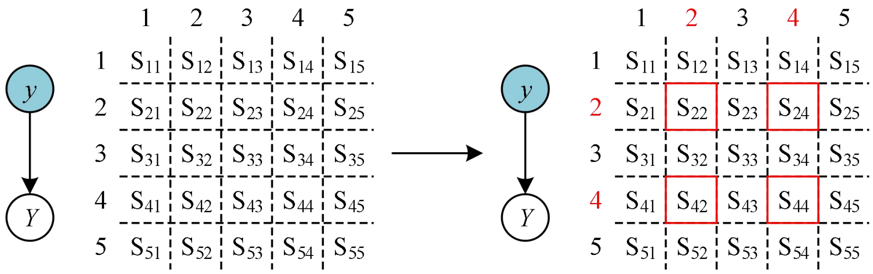


***Figure 1.*** An example of obtaining a subset through the determinant point process.

In the figure $y$ denotes the sequence of feature points in the image, $y=\{1,2,3,4,5\}$.In order to simplify the length of the narrative, the feature points are reduced to 5, and the feature points are arranged according to the index from 1 to 5. $Y$ is a subset of $y$, $Y \subseteq y$, $Y=\{2,4\}$.

$$P(Y=\{2,4\}) = \det\begin{pmatrix} S_{22} & S_{24} \\ S_{42} & S_{44} \end{pmatrix} = S_{22}\cdot S_{44} - S_{24}\cdot S_{42} \tag{4}$$

## 2.2.2. Improved RANSAC Algorithm Based on DPP

In the previous section, the properties of the deterministic point process are discussed, and in this section, the sampling algorithm based on DPP is mainly introduced.And the kernel matrix of the deterministic point process is constructed by using the position information of the feature points in the image to be matched, and finally the input point pairs of the RANSAC algorithm are obtained through the sampling of the deterministic point process.

In the algorithm, the probability of the $j$ th sampling element $i$ is:

$${}_r(i) = \frac{1}{|V|}\sum_{v\in V} v^T e_i^2 = \frac{1}{k-i+1}\left\| \Pr j_{\perp e_1,\ldots,e_{j-1}} B_i \right\|^2 \tag{5}$$

The resulting probability of extracting sequence $1,2,\ldots,k\ (k=|V|)$ is:

$$\frac{1}{k!}\|B_1\|^2 \left\|\Pr j_{\perp e_1} B_2\right\|^2 \ldots \left\|\Pr j_{\perp e_1,\ldots,e_{k-1}} B_k\right\|^2 \tag{6}$$

Since all real symmetric matrices $K$ can be expressed as Gram matrices (Gm), i.e., the real symmetric matrix $K$ can be written as $K = B^T B$, where $B_i$ denotes the elements in the set $Y$.Standard DPP sampling operates exclusively on the basis of probability, so the final number of sampled points is not fixed.If the points obtained from sampling exceed the number of points required by the actual application, it will result in a waste of computational resources because the sampling points are already sufficiently dispersed in the sampling space, and more sampling points will be of little help in improving the computational accuracy.If the number of points obtained from sampling is less than the number of points required by the actual application, the number of parameters for calculating the affine or projective transformations cannot be reached.Therefore, the use of a controlled sampling method is of great significance for image stitching.For the RANSAC algorithm, it is hoped that the number of sampling points can be artificially selected each time to ensure the computational accuracy without wasting computational resources.Therefore, this paper adopts k-DPP sampling. k-DPP is a kind of conditional DPP that only models the base $k$. In practical applications, the base $k$ is the number of sampling points in the sampling set. k-DPP sampling method avoids the drawbacks of inaccurate computational accuracy and waste of resources caused by the unfixed sampling points in the standard DPP sampling method, and achieves the premise of uniformly dispersed sampling to control the number of sampling points.The number of sampling points can be controlled under the premise of uniformly dispersed sampling.The k-DPP sampling can be realized by simply adjusting the standard DPP sampling method.

where $e$ is the basic symmetric polynomial about the eigenvectors, the formula for $e$ is as follows:

$$e_k(\lambda_1,\ldots,\lambda_N)=\sum_{|J|=k}\prod_{n\in J}\lambda_n \tag{7}$$

Compared with the standard DPP sampling method, it is obvious that the k-DPP sampling method has stronger controllability, so it is more in line with the requirements on image applications.

The specific process of purifying feature matching point pairs based on k-DPP improved RANSAC algorithm is as follows:

1) Extract the feature point sets of two images $P_1P_2$ with overlapping scenes using SIFT feature extraction algorithm respectively, denoted as $N_1=\{A_1(x_1,y_1),A_2(x_2,y_2)\ldots A_n(x_n,y_n)\}$, $N_2=\{B_1(x_1,y_1),B_2(x_2,y_2)\ldots B_n(x_n,y_n)\}$.

2) Construct the kernel matrix $K$ required for DPP sampling using the similarity measure function.The similarity measure function is calculated as in equation (8), $d$ is the preset variance of $S(A_m,A_n)$, and $d=5$ is set in this paper.

$$S_m(A_m,A_n)=e^{-\frac{\|A_m-A_n\|^2}{d}} \tag{8}$$

$$K=\begin{vmatrix} S_1(A_1,A_2) & \ldots & S_n(A_1,A_n) \\ \vdots & \ddots & \vdots \\ S_n(A_n,A_1) & \ldots & S_n(A_n,A_n) \end{vmatrix} \tag{9}$$

By the definition of $S$, for any pair of feature points $(A_m,A_n)$, there must be $0\le S(A_m,A_n)\le 1$.Thus the matrix $K$ satisfies the marginal probability distribution and $K$ is the kernel matrix.

3) The matrix $K$ obtained after simulating the probability distribution is eigen-decomposed, and the eigenvalues and eigenvectors are arranged in the order of indexing from the largest to the smallest $\{(v_1,\lambda_1),(v_2,\lambda_2),\ldots(v_n,\lambda_n)\}$. According to the algorithm description of the cyclic judgment, the eigenvectors in the set $J$ that satisfy the conditions are updated.In this paper, the realization of the process $k=4.0$.

4) Repeat the while loop to extract 4.0 feature points from $N_1$ according to the probability $P_r(i)=\frac{1}{|V|}\sum_{v\in V}(v^T e_i)^2$.

5) The image $P_2$ repeats the above operation, and 4.0 pairs of well-dispersed point pairs can be selected from the matched feature point pairs.

Based on the 5 pairs of point pairs extracted by DPP sampling solve the temporary projection matrix $H_i$, calculate the Euclidean distance $L_2$ of the remaining sample points transformed by $H_i$ noted as $d_i$, and if $d_i\le thresho$, then add this sample point to the point set $S_i$, and $d_i$ to $D_i$. After completing a certain number of sampling times, the point set with the highest number of points in the point set $S_i$ is selected as the inner point set $S_i'$ and the projection matrix $H_i'$ obtained at this time is recorded, corresponding to the set of distances $D_i'$. And the projection matrix $H_i'$ obtained at this time is the best image transformation model obtained by the improved RANSAC algorithm.It is worth noting that different numbers of point pairs can be selected for different problems, and the selection of 4.0 pairs of feature point pairs in the algorithm for image stitching is a compromise between the minimum degree of freedom and computational robustness of the projection transform.

### *2.3. Example of image alignment for an immersive classroom scene*

#### 2.3.1. Experimental data collection

A regular digital camera was used to acquire two 650×490 64-bit true-color image data in the classroom in a fixed-point ring shot (in order to see the alignment details), and the camera was slightly skewed and tilted in order to match the column image alignment.

#### 2.3.2. Image Frequency Domain Transform

Let the two neighboring images be $a_1$ ( $W1 \times H1$ rectangular region) and $a_2$ ( $W2 \times H2$ rectangular region), with the upper left corner of the rectangle as the coordinate origin.There is the following formula:

$$a_2(x, y) = a_1(x + \Delta x, y + \Delta y) \tag{10}$$

Fourier transform the above equation:

$$A_2(\xi, \eta) = A_1(\xi, \eta) \cdot e^{-\mathrm{j}2\pi(\xi \Delta x + \eta \Delta y)} \tag{11}$$

The reciprocal power spectrum (energy spectrum) of the two images is:

$$\frac{A_1(\xi,\eta)A_2(\xi,\eta)^*}{\left|A_1(\xi,\eta)A_2(\xi,\eta)^*\right|} = e^{-\mathrm{j}2\pi(\xi Vx + \eta Vy)} \tag{12}$$

where $(\Delta x, \Delta y)$ is a relative translation of the difference between $a_1, a_2$; $A_2(\xi,\eta)^*$ is the covariance function of $A_2(\xi,\eta)$; and the Fourier Transform equation is a one excitation function.After the Fourier inverse transform is performed through the energy spectrum, the inverse transform result is detected to find the position of the function maximum, and $(\Delta x, \Delta y)$ can be found.

## 3. Analysis of the Effect of Immersive civic and Political Learning Scenarios and Application Practices

### *3.1. Analysis of the Effect of Immersive Learning Scene Construction*

#### 3.1.1. Verification of the Effectiveness of Fusion of Scene Image Feature Extraction

In this paper, the sampling characteristics of k-DPP are utilized to improve the RANSAC algorithm, and in order to test the effectiveness of the method, this section sets up a comparison experiment to test the effectiveness of image feature extraction and fusion related to immersive learning scenes.The mean intersection and merger ratio (mIoU) is chosen as the index of image feature extraction and fusion accuracy, and the higher the value of this index, the higher the scene image realism.Ten common Civics learning scenes are selected as sampled images, and the mIoU of PointNet, PointNet++, KVGCN and this paper's method on different scenes are calculated and compared. mIoU comparison results of different methods on 10 scenes are statistically presented in Table 1.The mIoU values of the 10 scene images of this paper's method are 0.928, 0.867, 0.819, 0.157, 0.728, 0.963, 0.191, 0.185, 0.825, and 0.327, which are higher than the other three comparison methods on different scenes, and the highest one is Scene 6, which reaches 0.963. It shows that the sampling feature improvement using the k-DPPRANSAC algorithm can bring better fusion effect of image feature extraction for Civics immersive learning scenes.

***Table 1.*** mIoU comparison of different methods in 10 scenarios.

| Scene number | PointNet | PointNet++ | KVGCN | kDPP+RANSAC |
|---|---|---|---|---|
| 1 | 0.716 | 0.791 | 0.874 | 0.928 |
| 2 | 0.572 | 0.553 | 0.693 | 0.867 |
| 3 | 0.459 | 0.512 | 0.705 | 0.819 |

| | | | | |
|---|---|---|---|---|
| 4 | 0.093 | 0.114 | 0.141 | 0.157 |
| 5 | 0.352 | 0.508 | 0.629 | 0.728 |
| 6 | 0.818 | 0.833 | 0.873 | 0.963 |
| 7 | 0.023 | 0.045 | 0.084 | 0.191 |
| 8 | 0.056 | 0.117 | 0.145 | 0.185 |
| 9 | 0.624 | 0.551 | 0.708 | 0.825 |
| 10 | 0.165 | 0.196 | 0.224 | 0.327 |

### 3.1.2. Reasoning Speed Analysis for Immersive Learning Scenarios

Table 2 shows the reasoning speed of different methods under 10 scenarios.The inference time of this paper's method for the 10 scenarios is between 65s-80s, respectively: 70, 67, 65, 73, 71, 75, 80, 79, 71, 77 s. Compared with the inference speed of other Civic Immersive Learning Scenarios, this paper's method's inference takes less time and is faster, which can realize feature sampling and fusion of the scenario images more quickly and improve the response of the immersive scenariosEfficiency.

***Table 2.*** The reasoning speed of different methods in 10 scenarios.

| Scene number | PointNet(s) | PointNet++(s) | KVGCN(s) | kDPP+RANSAC (s) |
|---|---|---|---|---|
| 1 | 87 | 86 | 83 | 70 |
| 2 | 82 | 81 | 78 | 67 |
| 3 | 79 | 80 | 76 | 65 |
| 4 | 84 | 81 | 80 | 73 |
| 5 | 86 | 83 | 80 | 71 |
| 6 | 89 | 87 | 82 | 75 |
| 7 | 90 | 88 | 85 | 80 |
| 8 | 91 | 90 | 89 | 79 |
| 9 | 79 | 82 | 80 | 71 |
| 10 | 93 | 89 | 85 | 77 |

Take the image of scene 1 as an example.The scene image contains 4 main regions, each region has 2 main feature points, the inference speed of each feature point is calculated separately and compared.Table 3 shows the results of the inference speed calculation for different regions' feature points. The average time for the sampling fusion of 8 main regions' feature points is less than 10s, and the inference speed of each feature point is faster than the other 3 comparison methods.And the inference time of each feature point is more balanced, and there is no situation of high and low.

***Table 3.*** The reasoning speed of feature points in different regions.

| Region-Feature point | PointNet(s) | PointNet++(s) | KVGCN(s) | kDPP+RANSAC (s) |
|---|---|---|---|---|
| A-1 | 13 | 10 | 12 | 9 |
| A-2 | 12 | 12 | 11 | 8 |
| B-1 | 10 | 8 | 10 | 9 |
| B-2 | 10 | 10 | 9 | 9 |
| C-1 | 8 | 10 | 10 | 8 |

| | | | | |
|---|---|---|---|---|
| C-2 | 11 | 14 | 10 | 9 |
| D-1 | 10 | 12 | 10 | 9 |
| D-2 | 13 | 10 | 11 | 9 |
| Average time (s) | 87 | 86 | 83 | 70 |

### *3.2. Controlled Experiments and Analysis of Results*

Two sophomore classes in the School of Marxism of a university are selected as experimental subjects, and a control experiment is set up to study the advantages of the immersive learning scenario based on the improved RANSAC algorithm of k-DPP for practical teaching and learning. class A, as an experimental class, uses the immersive learning scenario of the improved RANSAC algorithm of k-DPP to assist the study of Civic and Political Science, and class B, as a control class, uses the conventional contextualized learningscenarios to assist learning.Both classes consisted of 50 students, and there was no significant difference in the initial Civics learning scores and no other variables, and the control experiment lasted for one academic year.At the end of the experiment, an evaluation questionnaire was set up to collect data on the evaluation of the learning scenarios used by the two classes (on a 10-point scale), and a mind-flow experience scale was set up to examine the elements of the students' mind-flow experience in learning (on a 5-point scale).

#### 3.2.1. Analysis of Satisfaction with Learning Scenarios

The evaluation questionnaire data were analyzed using SPSS23 software.Table 4 summarizes the data of the learning scene questionnaire.In the dimensions related to scene immersion, role experience, cultural infection, interactive communication, ideological consensus, and effect evaluation, the corresponding significance level is 0.05. The overall rating mean of the experimental class reaches 9.52 points, with a standard deviation of 1.45 points, while the overall rating mean of the control class is only 6.71 points, with a standard deviation of 2.59 points.There is a significant difference of 2.81 points between the overall score means of the two classes.From the comparison of scores, it can be analyzed that the experimental class is much more satisfied with the immersive learning scenarios used than the control class, and the satisfaction is more consistent among the students in the class.It shows that the Civics immersive learning scene created based on virtual technology in this paper is more realistic, more natural, and better able to immerse students in it.

***Table 4.*** Questionnaire survey data of learning scenarios.

| Evaluation index | Experimental Class | | Control class | |
|---|---|---|---|---|
| | Mean value | Standard deviation | Mean value | Standard deviation |
| Scene immersion | 9.37 | 1.41 | 7.25 | 2.71 |
| Role experience | 9.65 | 1.48 | 6.55 | 2.87 |
| Cultural infection | 9.24 | 1.94 | 6.14 | 2.62 |
| Interactive communication | 9.42 | 1.41 | 7.23 | 2.38 |
| Ideological consensus | 9.79 | 1.52 | 6.12 | 2.45 |
| Effect evaluation | 9.63 | 0.95 | 6.97 | 2.52 |
| Overall mean | 9.52 | 1.45 | 6.71 | 2.59 |

#### 3.2.2. The Effect of Different Scenarios on Learners' Experience of Mindstreaming

The learning of curriculum Civics in the immersive scene environment is a typical process of mind-flow activity. A more pronounced state of mind-flow will produce a positive emotional experience for the learners, which in turn will promote the learners to actively absorb the elements of Civics and Politics in the teaching and to self-reflect and improve at the ideological level. Table 5 shows the survey data of the two classes on the Heart Flow Experience Scale. Among the eight dimensions of heart flow experience, the minimum scores of the students in the experimental class ranged from [3.35,3.82] and the maximum scores ranged from [4.46,4.91], with the minimum scores being greater than 3.00, and the maximum scores being greater than 4.00, whereas the minimum scores of the students in the control class were not more than 2.50 and the maximum scores were not more than 2.50, and the minimum scores of the control class were not more than 2.50, and the maximum scores were not more than 2.50, and the maximum scores were not more than 2.50.4.00. It indicates that utilizing immersive learning scenarios to assist the teaching of Civics can enable students to achieve an obvious state of mind-flow experience and enhance the performance of Civics learning.

***Table 5.*** The survey data of the flow experience scale of the two classes.

| Flow experience project indicators | Experimental Class (Mean value) | | | Control class (Mean value) | | |
|---|---|---|---|---|---|---|
| | Min-value | Max-value | Standard deviation | Min-value | Max-value | Standard deviation |
| Balance between study and psychology | 3.41 | 4.91 | 0.36 | 2.11 | 3.51 | 0.51 |
| Clarity of ideological and political learning objectives | 3.35 | 4.67 | 0.31 | 1.63 | 3.22 | 0.55 |
| Feedback degree of the learning experience | 3.72 | 4.68 | 0.32 | 1.42 | 3.03 | 0.63 |
| Concentration in study | 3.82 | 4.84 | 0.35 | 1.95 | 2.85 | 0.66 |
| Scene control degree | 3.56 | 4.85 | 0.32 | 1.67 | 3.46 | 0.57 |
| Degree of loss of self-awareness | 3.77 | 4.63 | 0.36 | 2.01 | 3.57 | 0.62 |
| Experience of a sense of time | 3.71 | 4.57 | 0.34 | 1.35 | 2.98 | 0.56 |
| Self-contained experience | 3.63 | 4.46 | 0.27 | 1.76 | 3.15 | 0.56 |
| Balance between study and psychology | 3.41 | 4.91 | 0.36 | 2.11 | 3.51 | 0.51 |

### 3.2.3. Effects of Different Scenarios on Learners' Mental Arousal States

In order to verify the persuasiveness of the survey data from the perspective of learners' physiological data, seven students from each of the two classes were selected to undergo electrocardiogram (ECG) testing, and the data were collected after 30 minutes of class.ECG is an important indicator for the current psychological analysis of learners, including waveforms such as P, Q, R, S and T.Professional ECG analysis focuses on the intervals, peaks and waveform value ratios of the above five waveforms to obtain the learner's psychological state during the learning process.According to the ECG signals are analyzed from two aspects: firstly, the influence of scene environment on the arousal level of learners' psycho-emotions; and secondly, the aspect of the value dimension of arousal.Scene learners with low arousal levels have calmer psychoemotions, less volatility in ECG signals, and lower positive emotions.Scenarios with high arousal levels have learners with higher psychological emotions, higher volatility of ECG signals, and produce higher positive emotional representations.The study of the learning scene with high arousal level shows that the learners' ECG signals have a longer time from high level to low level state, in which the learners' scene immersion is high, their emotions are soothing, they have a feeling of psychological pleasure, they have both a high enthusiasm for learning participation, and they maintain a low level of tension and anxiety.Figure 2 shows a representative sample of the two ECG data tests of the experimental and control classes.As can be seen from the ECG waveform graphs, the ECG signals of the students in the experimental class were basically above 0mV for 7s, reaching a maximum of 5.33mV, which is at the level of high arousal mental state.The ECG signals of the students in the control class, on the other hand, were basically at 0mV, with a maximum of only 2.34mV, which was at the level of low arousal mental state.The experimental class students' learning process in the immersive Civics learning scenario has a longer human ventricular depolarization time course, and their learning experience is characterized by high emotions, comfortable moods, and a higher degree of activity engagement.

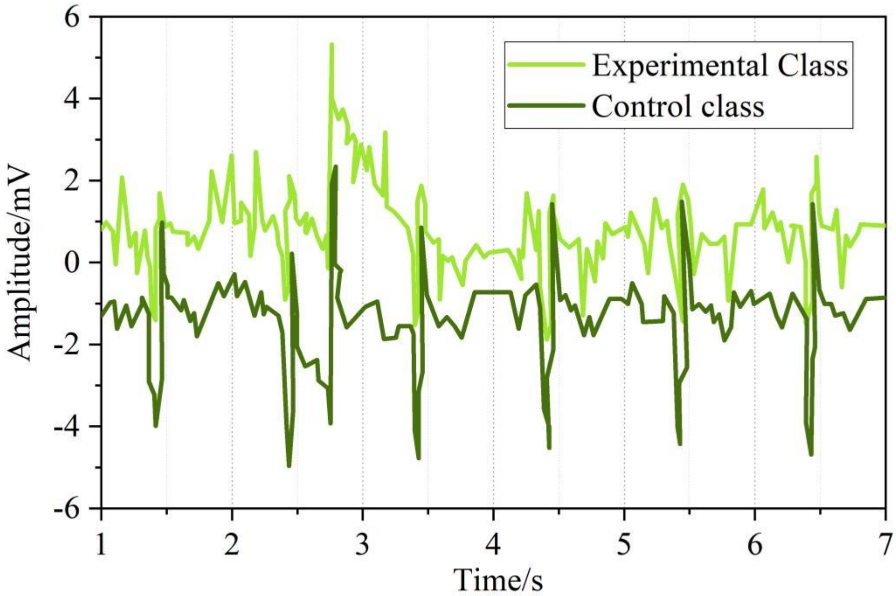


***Figure 2.*** Test samples of electrocardiogram data from two classes.

## *3.3. Subjective Evaluation of Immersive Learning Scenarios for Educational Platforms*

Table 6 shows the subjective evaluation data of 12 Civics teachers on the effect of the construction of immersive learning scenarios on the collaborative education platform.The evaluation was conducted in 7 dimensions such as improving students' learning attitudes, and 3 evaluation options were used: supportive, average, and opposing.Among the 7 subjective evaluation dimensions, 12, 12, 12, 11, 12, 12, 11 chose the support option respectively, with the support rate ranging from 91.67% to 100%.It proves that most of the Civics teachers believe that the Civics immersive learning scenario constructed with the help of the Nurturing Platform can improve the quality of classroom teaching and student learning.

***Table 6.*** Teachers' subjective evaluations of immersive learning scenarios(N=12).

| Evaluation project | Support | General | Oppose |
|---|---|---|---|
| Improve students' learning attitudes | 12 | 0 | 0 |
| Optimize students' previewing and reviewing situations | 12 | 0 | 0 |
| Enhance students' autonomous learning ability | 12 | 0 | 0 |
| Improve the effect of classroom teaching | 11 | 1 | 0 |
| Increase classroom activity | 12 | 0 | 0 |
| Improve the mastery of the classroom | 12 | 0 | 0 |
| Improve the utilization rate of learning resources | 11 | 1 | 0 |

# 4. Conclusion

In this paper, k-DPP sampling strategy is used to improve the sampling effect of RANSAC algorithm to improve the construction of Civics immersive learning scenes.The mIoU values of this paper's method in 10 scene images reach: 0.928, 0.867, 0.819, 0.157, 0.728, 0.963, 0.191, 0.185, 0.825, 0.327, which are higher than the comparison method.And the reasoning time is 70, 67, 65, 73, 71, 75, 80, 79, 71, 77s, which is also faster than the comparison method.The overall satisfaction of the students in the experimental class with the six dimensions of the immersive learning scenario was 9.52 points, which was higher than that of the control class, which was 6.71 points.And the experimental class's mind-flow experience and mental arousal levels were better than those of the control class.Teachers' support for the construction and application of this immersive learning scenario ranges from 91.67% to 100%.In the future, we can study how to realize the cross-platform adaptation ability of the immersive learning scene and improve the diversified level of scene application.

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