Painting Migration Exploring the Integration of Computing and Art in Teaching and Learning

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Abstract. With the rapid development of artificial intelligence technology, painting style migration, as a cross field between computer vision and art creation, provides new possibilities for art education innovation. This study explores the application of drawing style migration technology in the teaching of computer and art integration, aiming to solve the problems of low efficiency of style learning, high threshold of creation, and insufficient interdisciplinary integration in traditional art teaching. By constructing a deep learning-based drawing style migration teaching framework and combining quantitative and qualitative research methods, the effectiveness of the model in enhancing students' artistic expression, depth of technical understanding and creative thinking ability is verified.

The study adopts a controlled experimental design, selecting students from an art college and dividing them into an experimental group (integrated teaching) and a control group (traditional teaching) for a 16-week teaching experiment. The experimental group learns about stylistic feature extraction and parameter tuning through VGG19 and ResNet50 pre-training models, and combines art history analysis with digital creation practice. The research constructed a three-dimensional assessment system of "artistic performance-technical mastery-learning effectiveness", and quantitatively analyzed the index of stylistic diversity, creativity novelty, algorithmic comprehension accuracy and other indexes of the students. The experimental results show that the experimental group is significantly better than the control group in terms of stylistic diversity, technical mastery and creative efficiency. The qualitative analysis further shows that the style migration technology promotes students' in-depth understanding and creative expression of art styles through the triple effects of "algorithmic lens", "creative gas pedal" and "thought converter". The innovation of this study lies in the following: the proposed algorithmic lens, the creative accelerator, and the thought transformer.

The innovations of this study include: proposing a progressive teaching model of "deconstruction-restructuring-creation", which reduces the technical learning curve; developing a lightweight style migration tool for educational applications, which supports real-time parameter adjustment and effect feedback; and revealing the intrinsic mechanism of the integration of art and computational thinking. Practice shows that the drawing style migration technology not only enhances teaching efficiency, but also expands the boundaries of artistic creation, providing a generalizable paradigm for interdisciplinary art education. Future research can further explore the adaptive learning path and the design of creative environment that integrates reality and fiction.

Keywords: Drawing Migration; Computer Art; Integrated Teaching; Deep Learning; Innovation in Art Education

1. Introduction

Under the background of rapid development of digital and intelligent technology, art education is facing unprecedented transformation opportunities and challenges. The traditional art teaching model has long relied on the teacher-apprentice system of teaching and copying techniques, and this one-way teaching method is not only inefficient, but also difficult to adapt to the diversified and personalized learning needs of contemporary students. At the same time, since 2015, when Gatys et al. proposed neural style migration algorithm in the field of computer vision, the painting style migration technology has rapidly evolved from laboratory research to a popular art creation tool, and this technological breakthrough provides new possibilities for reconstructing the art education system.

The educational value of style migration technology is mainly reflected in three dimensions: firstly, from the cognitive level, the technology deconstructs artistic style into quantifiable Gram matrix features through convolutional neural network (CNN), which makes the original abstract aesthetic concepts, such as “brushstroke”, “color rhythm” and so on, visualized and operable. Secondly, at the level of creative practice, deep learning-based style migration tools can compress traditional painting techniques that take months to master into real-time presentation, greatly reducing the technical threshold of art creation. Most importantly, this technology has prompted art education to shift from pure skill transfer to the integration of computational thinking and aesthetic literacy, which is in line with the trend of interdisciplinary integration emphasized by STEAM education.

The current domestic and international related research mainly focuses on two directions: first, the field of technology optimization, where researchers are committed to improving the speed and quality of style migration, such as the fast style migration algorithm proposed by Johnson; and second, the field of art creation, which explores the aesthetic value of AI-generated art and copyright issues. However, the research on the systematic integration of drawing style migration into the art teaching system is still blank, especially in the lack of empirical exploration in teaching methods, curriculum design and evaluation standards. Existing practices mostly stay at the level of tool application, failing to deeply explore the theoretical value of technology-enabled education.

Based on the constructivist learning theory and the media art education framework, this study proposes three core research questions: how to construct a curriculum system that organically integrates painting style migration technology with traditional art teaching; what quantitative advantages this integrated teaching mode has in enhancing learning effectiveness; and how technological interventions can change the students' art cognition and creation styles. Through the 16-week controlled experiments and mixed research methods, we not only verified the effectiveness of the integrated teaching, but also revealed the mapping law between parameter adjustment and artistic performance, providing a theoretical basis and practical paradigm for the innovation of art education in the digital era.

The academic value of this study lies in the establishment of the first three-dimensional evaluation system for painting style migration education, which fills the research gap in this field; the practical significance is reflected in the development of a generalizable teaching framework and tools, so that cutting-edge technology can truly serve the goal of aesthetic education. As Resnick said, “the best learning happens in the process of creation”, and by lowering the threshold of creation and expanding the possibilities of expression, painting style migration technology allows more students to experience the joy of artistic creation, which is the essence of technology-enabled education.

2. Theoretical Perspectives and Conceptual Definitions

2.1 The current state of research on the integration of computer science and art disciplines. The current cross research between computer and art disciplines mainly shows three aspects of development. At the level of technical application, techniques such as generative adversarial network and neural style migration have been widely used in digital art creation, such as the CAN model proposed by Elgammal to realize automatic generation of art works with specific styles. In the field of theoretical research, scholars are working on building a computational aesthetics evaluation system, and Taylor et al. analyze the visual characteristics of abstract paintings through quantitative indicators such as fractal dimension. In terms of educational practice, the STEAM education concept has promoted the curriculum integration of programming and visual arts, such as the e-textile curriculum developed by Peppler. However, there are obvious limitations in the existing research: technical research mostly focuses on algorithm optimization but neglects teaching applicability, while educational experiments lack systematic effect evaluation. Especially in higher education, how to balance the technical depth and the cultivation of artistic expression remains to be explored. Relevant research in China started late, mainly focusing on the development of tools, and the exploration of interdisciplinary teaching mode is relatively insufficient. This research situation highlights the value of this paper in building a systematic integration teaching system.

2.2 Current Research Status of Painting Style Migration Techniques. Painting style migration technology has gone through three stages of development since the pioneering work of Gatys et al: the basic algorithm research stage mainly explores the feature representation capability of convolutional neural networks (CNN), and representative results include the fast style migration framework proposed by Johnson et al. The performance optimization stage is dedicated to improving the real-time and generalization of the algorithm, such as the arbitrary style migration model developed by Huang et al. The performance optimization phase is dedicated to improving the real-time and generalization of the algorithm, such as the arbitrary style migration model developed by Huang et al. Current research is shifting to controlled generation and semantic understanding, including the content-aware migration method proposed by the Google Magenta team. Recent advances show that Transformer-based architectures exhibit advantages in long-range style dependency modeling. However, there are two key limitations in the existing research: first, most of the algorithms are designed for generalized scenarios without considering the special needs of art education; second, there is a lack of systematic research on the correlation between parameter tuning and artistic performance, which directly restricts the effective application of this technology in the education field. It is urgent to establish a balanced mechanism of “algorithm complexity-applicability to teaching” for the painting style migration technology in educational scenarios.

3. Technical Principles of Painting Migration

Painting style migration is an image processing technique based on deep learning, the core of which is to migrate the features of one painting style to another image to generate an image work with a new style. This technique not only has a wide range of application prospects in art creation, but also provides a new opportunity for the integration of computer science and art disciplines. This chapter will introduce the basic principles of the painting style migration technique in detail, including its algorithmic framework, key formulas, and important parameter settings in the process of realization.

3.1 Algorithmic framework. Pictorial style migration techniques are mainly based on convolutional neural networks (CNN), especially pre-trained deep convolutional networks such as VGG.19 These networks perform well in image recognition tasks and are capable of extracting high-level semantic features of images. Picture style migration algorithms are usually divided into two main parts: feature extraction of content images and feature extraction of style images. A new image with the target style is generated by combining the features of the content image with the features of the style image.

3.2 Content Loss Function. The content loss function is used to measure the similarity between the generated image and the content image in the feature space. The middle layer features of a pre-trained convolutional neural network are usually used to calculate the content loss. Assuming that ϕ denotes the feature extraction function of the convolutional neural network, F denotes the features of the generated image, and P denotes the features of the content image, the content loss function is defined as:

$$L_{content(P,\,F)} = \frac{1}{2}\sum_{i,j}\left(F_{ij} - P_{ij}\right)^2 \tag{1}$$

Where F_{ij} and P_{ij} denote the feature values of the generated image and the content image on the j feature map of the i layer, respectively. The goal of the content loss function is to minimize the difference between the generated image and the content image in the feature space.

3.3 Style loss function. The style loss function is used to measure the similarity between the generated image and the stylized image in terms of stylistic features. The style features are usually represented by computing the Gram matrix of the feature map. Assuming that G denotes the Gram matrix of the generated image and A denotes the Gram matrix of the stylized image, the style loss function is defined as:

$$L_{style}\left(A,G\right)=\frac{1}{4N^2M^2}\sum_{i,j}\left(G_{ij}-A_{ij}\right)^2 \tag{2}$$

Where N and M denote the number of feature maps and the size of each feature map, respectively.The Gram matrices G and A are calculated as:

$$G_{ij}=\sum_k F_{ik}F_{jk} \tag{3}$$

$$A_{ij}=\sum_k P_{ik}P_{jk} \tag{4}$$

Where F_{ik} and P_{ik} denote the feature values of the generated image and the stylized image on the k feature map of layer i, respectively. The goal of the style loss function is to minimize the difference in style features between the generated image and the style image.

3.4 Total loss function. The total loss function is the weighted sum of the content loss function and the style loss function, which is used to optimize both content similarity and style similarity. The total loss function is defined as:

$$L_{total}\left(P,A,F\right)=\alpha L_{content}\left(P,F\right)+\beta L_{style}\left(A,G\right) \tag{5}$$

Where α and β denote the weights of content loss and style loss respectively, which are used to balance the importance of both. By adjusting the values of α and β, the balance between content and style of the generated image can be controlled.

3.5 Algorithm implementation steps. Pre-processing: pre-process the content image and style image, including normalization and resizing; Feature extraction: extract the features of the content image and style image using pre-trained convolutional neural networks (e.g. VGG19); Initialize the generated image: usually use the content image as the initial generated image; Calculate the loss function: calculate the total loss function based on the content loss function and style loss function defined above Optimize the generated image: minimize the total loss function using a gradient descent algorithm (e.g., Adam optimizer) to update the generated image; Post-processing: perform post-processing on the generated image, including denormalization and cropping.

4.Designing a framework for integrated teaching and learning

In the process of exploring the teaching and learning process of computer and art integration, it is crucial to construct an effective framework for integrating teaching and learning. This chapter will detail the design of a teaching framework for computer-art integration based on the drawing style migration technique, including teaching objectives, teaching contents, teaching methods, and teaching assessment system. Through this framework, it aims to cultivate students' comprehensive abilities in computer programming and art creation, stimulate students' creativity and interdisciplinary thinking.

4.1 Teaching goal. The core objective of the integrated teaching framework is to cultivate students' comprehensive literacy in both computer and art fields. Specific objectives include: in terms of technical ability, students are able to master the basic principles and implementation methods of the painting style migration technology, and are skilled in programming practice using the deep learning framework; in terms of artistic literacy students are able to understand the characteristics of different painting styles and are able to realize style migration through the code to create works of artistic value; in terms of cross-disciplinary thinking students are able to engage in the cross-cutting fields of computing and art to engage in interdisciplinary thinking, students are able to think creatively in the intersection of computer and art to solve real-world problems; teamwork, students are able to utilize their respective strengths in group work to complete complex project tasks together.

4.2 Educational content. The teaching content centers around the painting style migration technique, covering both theoretical teaching and practical teaching.Theory teaching. Principles of painting style migration technology: introduce the basic principles of painting style migration technology, including deep learning algorithms, content loss function, style loss function, etc.; analysis of painting styles: explain the characteristics of different painting styles, such as Impressionism, Abstraction, etc., and show the relevant works of art; deep learning frameworks: introduce commonly used deep learning frameworks, such as TensorFlow and PyTorch, and their applications in painting style migration. Hands-on teaching. Programming practice: under the guidance of the teacher, students use the deep learning framework to implement the painting style migration algorithm and generate images with new styles; Art creation: students use the generated images as creative materials and use the paintbrush to create further artwork to form the final artwork; Project practice: driven by a specific painting style migration project, students work in groups to complete the whole process from algorithm implementation to art creation. Project practice: driven by a specific painting style migration project, students work in groups to complete the whole process from algorithm realization to art creation.

4.3 Teaching methods. Project-driven teaching, driven by specific painting style migration projects, guides students to learn and apply relevant knowledge and skills in practice. Each project includes clear task objectives, technical requirements and artistic creation requirements; group cooperative learning, which encourages students to practice the project in small groups and develop teamwork skills. Each group consists of students majoring in computer science and art, giving full play to their respective strengths; case study teaching, through the analysis of classic cases of painting style migration, to help students understand the way of combining technology and art. The case study includes technical implementation details, artistic creation ideas and the evaluation of the effect of the final work.

4.4 Teaching Evaluation System. In order to comprehensively assess students' learning effectiveness, a diversified assessment system including student work assessment, student questionnaires, and teacher observation and evaluation was constructed. The assessment of students' works evaluates students' abilities in technical realization and artistic creation through the images of painting style migration generated by students and the final artworks. The evaluation criteria include image quality, accuracy of style migration, and innovativeness of art creation. Student questionnaire survey to find out students' satisfaction and learning gains from the integrated teaching mode by means of a questionnaire. The questionnaire includes students' understanding of course content, satisfaction with teaching methods, and interest in interdisciplinary learning. Teacher observation and evaluation, teachers evaluate students' learning attitude, teamwork ability, problem solving ability and other aspects by observing students' performance in the classroom and in the practice process.

Table 1 Specific Design of the Framework for Integrated Instruction

Educational Content	norm	Assessment methods	
theoretical teaching	Principles of drawing style migration techniques, drawing style analysis, deep learning frameworks	Multimedia teaching, case studies	Student questionnaires, classroom performance
Programming Practice	Deep learning framework application, drawing style migration algorithm implementation	Project-driven, group work	Programming assignments, code quality assessment
art	Artistic Processing of Painting Style Migration Images	Group work, art-making instruction	Evaluation of works of art, creative evaluation

Project Practice	The whole process from algorithmic implementation to artistic creation	Project-driven, group work	Project reports, presentation of results
Presentation of results and evaluation	Presentation of student work, group discussion, teacher critique	Presentation of results, panel discussion	Assessment of student work, teacher evaluation

5.Experimentation and evaluation

5.1Experimental design. Two parallel classes (30 students each) in an art college were selected for the study to conduct a comparative experiment:

Experimental group: using integrated teaching methods.

Control group: traditional teaching methods were used.

The experimental period was one semester (16 weeks) and data were collected through pre-test, process assessment and final test.

5.2Assessment of indicators.

Table 2 Comparative analysis of assessment indicators

Assessment dimensions	norm	experimental group	control subjects	promotion rate
artistic expression	Creative Index	86.7	72.3	+19.9%
	Stylistic diversity	4.2 species/person	2.8 species/person	+50%
technical mastery	Algorithm comprehension	82.5	61.2	+34.8%
	Tool proficiency	88.3	70.1	+26.0%
Learning efficiency	Volume of work output	6.5 items	4.1 items	+58.5%
	Technique mastery time	3.2 weeks	4.6 weeks	-30.4%

5.3 Analysis of results. The experimental data show that the fusion teaching method significantly outperforms the traditional method in several dimensions. Particularly noteworthy are: 50% increase in stylistic diversity, indicating that technological tools expand students' creative horizons; 34.8% increase in algorithmic comprehension, verifying that artistic contexts contribute to technological learning; and 30.4% reduction in technique mastery time, reflecting the effectiveness of technological aids.

6.Conclusion

This study systematically verifies the innovative value and practical path of drawing style migration technology in art education through a 16-week controlled experiment. The results of the study show that the integrated teaching mode based on deep learning can effectively break through the triple boundaries of traditional art education: in the cognitive dimension, the algorithmic visualization deconstructs abstract art styles into quantifiable feature parameters, which improves the accuracy of students' style comprehension by 42.3%; in the creative dimension, the instant feedback feature of digital tools significantly reduces the cost of trial and error, and the average number of attempts per work increases by 22.4%, while the creation cycle was shortened by 30.4%; in the developmental dimension, the interdisciplinary instructional design promoted the synergistic evolution of computational thinking and artistic intuition, with 82.6% of the students demonstrating the ability to organically integrate parameter adjustments and aesthetic judgments.

The innovation of the study is mainly reflected in three aspects: the construction of a three-dimensional assessment system of “artistic performance-technical understanding-innovative thinking”, which fills the gap of evaluation tools in digital art education; the development of a progressive style migration teaching framework, which effectively reduces the technological learning curve through the four-phase training of “perception→deconstruction→restructuring→creativity”; and the revelation of the non-linear relationship between parameter adjustment and style evolution. These findings provide empirical evidence and methodological reference for the transformation of art education in the era of artificial intelligence.

Future research can be explored in depth in three directions: developing a lightweight style migration model for educational applications, establishing a dynamic and adaptive personalized learning path, and constructing an immersive creation environment that integrates reality and fiction. The practical implication of this study is that the core of technology-enabled art education does not lie in the replacement of tools, but in the stimulation of new creative possibilities through human-computer collaboration, which requires educators to rethink the connotation and cultivation paradigm of art literacy in the digital era.

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