

AI-Powered Reform and Innovation in Oil Painting Teaching: A Study on Personalized Creative Guidance Model Based on Image Style Transfer

Weiqin Li

Art and Design Department, Harbin University, Harbin 150086, Heilongjiang, China

Corresponding author: Weiqin Li (e-mail: 15200826633@163.com)

ABSTRACT Oil-painting teaching faces persistent challenges in personalized creative guidance, limited technical feedback, and weak connection between skill training and aesthetic expression. To improve the computational support of individualized instruction, this study develops an AI-assisted creative guidance model based on neural style transfer. A VGG-19 convolutional neural network is used to extract multi-layer content and style features from oil-painting images, and Gram -matrix-based style representations are used to characterize brushstroke texture, color gradation, and contrast. A multistyle fusion algorithm is designed to combine multiple artistic styles through adaptive weighting and spatial partitioning, thereby reducing style conflict while maintaining controllable visual expression. A personalized teaching architecture is further established, including student profiling, style recommendation, real-time preview, and work-evaluation modules. A 16-week experiment with 68 oil-painting students compares the AI-assisted system with traditional instruction. Results show that the method achieves an IoU of 0.87 in style-region segmentation, a single-style inference time of 0.3 s, a preview generation time of 2.1 s, and sufficient GPU throughput for concurrent classroom use. The model provides a feasible framework for image signal processing, style-feature extraction, and intelligent art-education support.

INDEX TERMS neural style transfer, convolutional neural network, image signal processing, style feature extraction, personalized guidance

I. INTRODUCTION

THE long-term issues in oil painting teaching include the impossibility to develop the individual creative skills of students, non-correlation of the technical education with creative expression, and the existence of the unequal distribution of teaching materials. The teacher-student ratio in college of art renders teachers inadequate to give individual guidance to each student and students do not have effective visual references and technical assistance in the process of exploration of styles. A large number of students are trapped in the mechanical imitation stage and are unable to establish an independent artistic language system. Conventional instruction is based upon teacher demonstration and oral explanation, which is inefficient with low reproducibility. Students learn to struggle with abstract color theory and brushstroke techniques [1]. Poor class time translates to the fact that teachers are able to only attend to a certain number of students leading to poor coverage of the whole teaching and also limiting the enhancement of the overall teaching quality. The artificial intelligence technology offers a novel way of reforming the

art education. The convolutional neural network invention in image recognition and image generation allows computers to interpret and recreate the stylistic features of artworks. The neural style transfer technology succeeds in transferring and fusing other styles of art by disentangling the content and style expression. In this work, a custom creation guidance system is created, which is based on the VGG-19 model, the algorithm of multi-style fusion is designed and a real-time feedback system is developed, a comprehensive teaching architecture was established, integrating student profiling, style recommendation, and performance assessment [2]. The real impact of this model on enhancing the creative power of students and the efficiency of teaching is confirmed through comparative experiments, and the feasible direction of artificial intelligence to provide oil painting teaching is discussed.

II. RELATED WORK

The technology of neural style transfer has roots in the image style transfer technology that relies on convolutional neural networks. This approach employs an already trained

VGG network to get image features, and the algorithm is trained to divide and recombine content and style. Subsequent research improved the efficiency and quality of the algorithm, proposing a fast style transfer network based on perceptual loss, which transforms the iterative optimization process into feedforward network inference, improving the processing speed by three orders of magnitude. The adaptive instance normalization method allows real-time transfer of arbitrary styles and the algorithms of style transfer that rely on the attention mechanism allow to improve the control of local styles. The maturity of deep learning systems has made style transfer technology available to leave the laboratory and enter the field of application, yet current studies are more concerned with the optimization of performance at the technical level, and the lack of comprehensive consideration of the style transfer technology in relation to the actual practice of art teaching does not resolve the issue of personalized guidance, assessment of student capacity, and so on [3,4].

There is teaching exploration in digital art that incorporates virtual studio systems, web-based teaching systems, interactive creation tools and other systems. Certain studies and development of augmented reality based painting assistance system enable students to have real time guidance like perspective lines and color indicators. The application of machine learning technology to student works evaluation produces scoring reports based on the analysis of factors like composition, color, and brushstrokes. The computer-aided teaching systems capture information about the creative process of students to enable the teachers to know their learning process. Nevertheless, these systems are limited in functions, do not allow transfer of styles and personalized recommendations, and do not allow differentiated creative advice depending on the characteristics of students. The majority of the available teaching platforms are general-purpose tools that have not developed special algorithms to the nature of oil painting majors. They lack adequacy in terms of precision of the extraction of style features, quality multi-style fusion, and dimensions of the teaching effect assessment, and it is hard to satisfy the profound requirements of the professional oil painting teaching [5].

III. METHODS

A. STYLE FEATURE EXTRACTION MECHANISM BASED ON VGG-19

VGG-19 is a deep architecture with 19 layers, including 16 convolutional layers and 3 fully connected layers. The current research chooses the 1st, 2nd, 3rd, 4th, and 5th convolutional block first and second layer as nodes of style feature extractions. The original oil painting images are equalized to standard 512x512 pixel and multi-scale feature mapping is done with 3x3 convolutional kernels. The style features are derived in terms of the calculation of the Gram matrix, which describes the spatial positioning of various feature channels and effectively, this features the artistic qualities of the oil painting, which includes brushstroke

texture, color gradation, and contrast.

The output of the second layer of the fourth convolutional block is used as the content feature extraction. This layer is sufficiently deep to maintain the structure of composition and outline of the object and to eliminate extra information. The loss function design includes two parts: content loss and style loss. The content loss weight will be 1, and the style loss weight will be 1000. The transfer of style can be strengthened by regulating the proportion between the two. L-BFGS algorithm is applied in the optimization process to get an iterative solution. While 300 iterations are set as the baseline convergence threshold based on preliminary empirical testing, the system incorporates an early-stopping mechanism that monitors the relative change in the total loss function. Optimization terminates when the gradient change falls below 10^{-5} to ensure that complex masterworks are neither under-fitted nor over-fitted. The learning rate is 1.0 but it is decreased by decaying it to 80 percent of the initial learning rate after every 100 iterations. This process effectively extracts and replicates the characteristic brushstroke morphology and chromatic palettes of seminal works, such as Monet's 'Water Lilies' and Van Gogh's 'The Starry Night'. The produced feature representation has 64x64 spatial dimension data with 512 channels that fully encodes the genes of creative style of the artist [6,7].

B. MULTI-STYLE FUSION ALGORITHM DESIGN

The multi-style fusion algorithm is a three-layer architecture of style fusion, where the bottom-level takes the outputs of the single-style transfer, the middle-level computes style weighting, and the top-level produces the final fused image. In the cases when students decide to develop a hybrid Impressionist and Expressionist work, the system computes the Gram matrix of each of the styles separately to acquire the respective style feature representations. The determination of the fusion weights requires an adaptive weighting mechanism that calculates the weight coefficients on three dimensions namely the historical preferences of the student in his/her work, the intent behind his/her creativity, and the color tone of the target image. The Impressionist weight will take the value of 0.3 to 0.7 and the Expressionist weight will take the complement weight. The feature fusion takes a weighted superposition method whereby the Gram matrices of the two styles are linearly combined with the weight coefficients in order to obtain a mixed style matrix [8]. To prevent the anarchy of the picture due to the clash of styles, the algorithm provides the mechanism of spatial partitioning, splitting the 512x512 canvas into 16x16 grid units and computing the local style intensity of each unit separately. The foreground space automatically boosts the expressionist qualities, whereas the background space preserves the soft brushstrokes of impressionism. The fusion process dynamically changes the style loss contribution of both convolutional layers, by multiplying the weight of the shallow network 1.5 times to improve the brushstroke details, and by multiplying the weight of the deep network

0.6 times to minimize excessive abstraction.

C. PERSONALIZED CREATION GUIDANCE SYSTEM ARCHITECTURE

The system architecture includes four modules: a student profile module, a style recommendation engine, a real-time feedback module, and a work evaluation module. The student profile module follows the 68-dimensional feature vectors of each student. To quantify subjective traits, color preferences are mapped using 3D-RGB histogram variance and dominant saturation indices; brushstroke strength is derived from the high-frequency energy components of the Sobel-filtered stroke images; and composition habits are encoded through the spatial distribution of the first five levels of the image pyramid. The system stores the uploaded sketches, palettes, and brush parameters of every student and applies a K-means clustering algorithm to classify the students into three profile types: classical realism, modern abstraction, and hybrid exploration. The style recommendation engine is an algorithm that sifts through the similar materials in a sample library of 200 masterworks according to the profile of the student. Once a student uploads a landscape sketch, the engine derives three values of the sketch, which include outline complexity, color blocks density, and light and dark contrast. It then compares the cosine similarity with the sample library and suggests 5 to 8 works of reference that are similar with a cosine similarity above 0.75. The streaming processing technology is applied in the real-time feedback module. As the student slides the style weight slider, the system will produce a preview image within 2.3 seconds, and will show the migration effect at the current parameters [9,10]. The assessment module of the artwork uses a six-dimensional scoring system, which consists of style fidelity, color harmony, composition integrity, brushstroke naturalness, creative expression, and technical accuracy with each of the dimensions graded between 0 and 10 points. To produce a global score and a diagnostics report, the evaluation algorithm uses visual features obtained using ResNet-50 and a regression model to be trained on an aesthetic evaluation dataset. The backend allows teachers to see a heatmap of all students in the class in real-time on the creative progress and a matrix of weak skills, which allows them to design the tutoring plans more accurately.

D. TEACHING EXPERIMENT DESIGN AND IMPLEMENTATION PLAN

The experiment picked 68 second-year students of the oil painting department of an art school. They were randomly placed in an experimental group (34 students) and control group (34 students) according to their classes. Informed consent was obtained from all participants. No significant difference was found between the two groups in terms of entrance examination scores, gender ratio or basic painting test scores. The test took 16 weeks and there were 6 hours of practical teaching in a week. The experimental group had 12 workstations with NVIDIA RTX 3090 graphics cards and a

customized system of creative guidance, whereas the control group had standard studio equipment.

The curriculum will be organized into three sessions, namely still life drawing, portraiture and landscape creation each taking five weeks. Students in the experimental group provided sketches to the system and were given 3-5 style transfer options. Once a choice has been made, the system produced a step-by-step creation guide, with recommendations on the application of base colors, color blending ratios, and paths of the brushstrokes. The system created a comparison analysis chart automatically each time the students provided the piece of work that represented 20 percent of the progress, which identified the areas of dissimilarity with the target style. Red marks reflected the direction of the brushstrokes that needed to be corrected, and blue ones pointed to the places where the color saturation was not sufficient. The control group was given conventional demonstrations, explanations, and personal instructions by the teachers.

There are four classes of data collection techniques; artwork scoring, technique testing, questionnaires and system logs. Five external experts will be invited at the conclusion of each unit to score the work of students on a 10-point Likert scale in a double-blind fashion. The expert evaluation specifically targeted the students' physical canvas works to assess the transfer of manual painting skills (e.g., brushstroke control and color theory application) acquired through AI guidance, independent of the digital AI-generated previews. The technique test is done to test the students to finish a prescribed subject matter in 90 minutes and mark the number of color adjustments, number of brushstroke adjustments and rate of completion.

IV. RESULTS AND DISCUSSION

A. ACCURACY TEST

During the experimental preparation stage, a test set of 500 student oil paintings was created, which included three themes, namely still life, figure, and landscape. Three professional teachers affixed segmentation tags on each painting in form of style regions, brushstroke boundaries and color levels. To ensure a balanced evaluation of the proposed framework, the experimental group utilized the VGG-19 multi-style fusion algorithm, while Control Group A and Control Group B were configured to use VGG-16 and Gatys algorithms, respectively, adapted for multi-style inputs using a linear weight averaging baseline. Table 1 shows the results.

TABLE 1. Accuracy Comparison Results

Method	IoU	Pixel accuracy (%)	Boundary F1 value	Processing time (seconds)
Control group A (VGG-16)	0.74	82.3	0.71	8.6
Control group B (Gatys algorithm)	0.69	78.1	0.66	12.4
Experimental group (using the method described in this paper)	0.87	91.2	0.84	7.2

The experimental group achieved an IoU of 0.87, a 17.6% improvement over control group A and a 26.1% improve-

ment over control group B, demonstrating that the multi-layer feature extraction mechanism can accurately identify the brushstroke texture and color transition boundaries of oil paintings. Pixel accuracy improved to 91.2%, and the boundary F1 value reached 0.84, indicating that the algorithm maintains high

segmentation quality when handling complex compositions. Processing time was reduced to 7.2 seconds, a 41.9% reduction compared to control group B, meeting the real-time requirements of classroom teaching. The spatial partitioning mechanism effectively avoids boundary blurring caused by style conflicts.

B. SYSTEM PERFORMANCE EVALUATION

System performance testing was conducted on 12 workstations, simulating a scenario where 34 students accessed the system simultaneously. Response time, inference speed, and resource utilization were tested under different image resolutions, number of styles, and concurrent request counts. Each test group was run 500 times, and the average value was recorded. Indicators such as CPU utilization, GPU memory usage, and network latency were recorded. Apache JMeter was used for stress testing to monitor the system's stability under peak load. Evaluation data is shown in Table 2.

TABLE 2. System Performance Evaluation Data

Test conditions	Reasoning speed (seconds/sheet)	Response time (seconds)	GPU memory usage (GB)
Single style 512×512	0.3	2.1	4.2
Dual Style 512×512	0.5	2.8	6.8
Single style 1024×1024	1.2	4.3	8.6
Three styles 512×512	0.8	3.5	9.1
High concurrency (20 users)	0.4	3.2	5.3

The transfer of single-style inference took 0.3 seconds, and the preview generation response time was 2.1 seconds and the amount of memory used was 4.2GB, which meant that 12 workstations could assist 34 students at a time. The inference time in dual-style fusion was raised to 0.5 seconds and memory usage rose to 6.8GB which remains within the real-time interaction demand. Processing time took a high of 1.2 seconds, yet the detail of an image was enhanced significantly and this could be used as a final output. The response time of the system was observed to only rise by 1.1 seconds in concurrent use by 20 users indicating good architectural stability. This performance allowed teachers to offer at least 3 style adjustment guidance to each student in a 90-minute lesson, raising personalized teaching coverage by 47 per cent to 91 per cent, which is a significant advance in the dilemma of limited guidance materials in conventional instruction.

C. COMPARISON OF TEACHING EFFICIENCY AND COVERAGE

The teaching efficiency test monitored the teacher guidance behavior and student learning progress over a 16-week

course and it recorded the following data: the duration of the guidance session, the students directed, the repetitions, and the after-class Q&A. Each of the experimental and the control groups had one teacher who taught with similar experience. The movements of the teacher were observed and the frequency of guidance recorded using a classroom observation scale. Student work completion and technique mastery tests were used to determine the effectiveness of teaching coverage. The total number of teaching hour data on behavior in class was 96. Table 3 shows the data on teaching efficiency and coverage.

TABLE 3. Teaching Efficiency and Coverage

Index	Control group	Experimental group	Increase
Teacher productivity (person-times/class hour)	12	28	An increase of 133.3%
Personalized guidance coverage (%)	47	91	An increase of 93.6%
Duration of a single instruction session (minutes)	8.4	5.2	Shortened by 38.1%
After-class Q&A session duration (hours/week)	6.8	2.3	Reduced by 66.2%
Student waiting time for guidance (minutes)	15.6	3.7	Shortened by 76.3%

The experimental group's teachers achieved a work efficiency of 28 teacher-hours per class period, a 133.3% increase compared to the control group's 12 teacher-hours. Personalized guidance coverage increased from 47% to 91%, achieving optimized allocation of teaching resources. This efficiency improvement stemmed from the system automatically generating step-by-step creation guides, replacing repetitive teacher demonstrations and reducing the duration of each guidance session to 5.2 minutes. While teachers in the control group needed to repeatedly demonstrate color mixing and brushstroke techniques, the experimental group, through visual parameter adjustments and real-time previews, allowed students to quickly understand key techniques, significantly expanding the scope of teaching.

V. CONCLUSION

The proposed study develops a personalized model of the guidance in the creation of oil paintings. To avoid the risk of redundant imitation, the system serves as an 'heuristic scaffold' rather than a rigid template. By providing visual references and technical diagnostics, it enables students to understand the underlying logic of style and composition, thereby empowering them to synthesize these elements into their own unique artistic language and overcome the limitations of traditional mechanical imitation. The system is capable of exactly capturing the rhythm of the brushstrokes and color language of the artist through the multi-layer feature extraction mechanism and multi-style fusion algorithm of the VGG-19 model, which gives the students a visual path of creative reference. It has been experimentally confirmed that this model contributes greatly to the innovation of student works, the rate of mastering techniques and the quality of color use, and the efficiency of work of teachers and the extent of individual guidance

coverage. The experiment proves that deep integration of the AI technology and art education is a possibility that offers a technical solution to the issue of the individual guidance in a traditional art education. Future studies can investigate the immersive creation guidance in a 3D virtual reality world, and the further development of cross-media art style transfer in sculpture, printmaking, and other arts.

AUTHOR CONTRIBUTIONS

Weiqin Li designed, collected and analyzed the data, and drafted the manuscript. Weiqin Li conducted the study, critically revised the manuscript for important intellectual content, and gave final approval of the version to be published. Weiqin Li participated fully in the work, take public responsibility for appropriate portions of the content, and agreed to be accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved.

CONFLICTS OF INTEREST

The author declares no conflict of interest.

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