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Transforming Art Design Education Through Information Technology

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ABSTRACT

In an era of rapid technological advancement, this paper examines the integration of information technology into art design education to meet contemporary demands. Traditional methods often fall short in equipping students with necessary digital-age skills. By incorporating technologies, such as virtual reality, augmented reality, and artificial intelligence, educators can enhance spatial understanding, foster creative thinking, and bridge digital content with the physical world. These advanced tools diversify teaching methods and prepare students for a tech-driven industry. Personalized graphic design represents a shift in information art, driven by emotional and technological convergence. It extends beyond visual content to include material and media selection, inspired by individual differences. Technology becomes crucial for expressing unique identities and fostering deeper consumer engagement. The research highlights the need to align educational practices with industry need, emphasizing image literacy and personalized learning platforms.

KEYWORDS

Information Technology, Art Design Education, Virtual Reality, Augmented Reality, Artificial Intelligence, Image Literacy, Personalized Learning Platforms, Graphic Design, Digital Age

INTRODUCTION

With the dawn of the information age, societal values have shifted profoundly, where the most cherished assets are no longer merely monetary or material possessions but rather intangible experiences—those that touch, stimulate, and evoke deep emotional responses. This shift underscores a growing preference for the intangible over the tangible, reflecting a broader human desire for meaningful connections and experiences. In this context, the widespread adoption of new technologies has facilitated unprecedented levels of resource sharing across various sectors of human society, leading to significant advancements and transformations (Casciani & Vandi, 2022; Sharma & Kohli, 2024).

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The emergence of images as a dominant form of communication in the modern era has redefined how we perceive and interact with the world around us. The ability to interpret and create visual content has become crucial in the 21st century, essential for navigating the vast sea of information and extracting valuable insights (MacDowall & Budge, 2021). Images, as a powerful tool for human communication, play an indispensable role in conveying thoughts, emotions, and intentions. We have entered what is often referred to as the “era of reading pictures,” where image literacy is not just a desirable trait but a fundamental necessity for both adults and the younger generation (Meng & Zhao, 2023).

Possessing the literacy to read and understand images enables individuals to discern and access healthy and beneficial information from myriad visual stimuli, thereby enriching their spiritual lives and fulfilling their material needs. In today’s design practices, the integration of text and imagery is a prevalent method used by designers to convey information efficiently. This approach not only facilitates rapid and accurate absorption of information by the public but also reduces the time and effort required for information processing (Mujtahid et al., 2021; Tinmaz et al., 2022).

Education, particularly art education, is the bedrock upon which the growth of science and technology is built. As such, art education must evolve to align with the demands of the information age. Traditional art education, characterized by rigid structures and outdated methodologies, is ill-equipped to compete with the dynamic and innovative educational paradigms of the digital era. Therefore, transforming conventional art education into a more technologically integrated and adaptive form is crucial (Freedman & Hernández-Hernández, 2024).

Aesthetic experiences, encompassing both the appreciation and critique of artistic works, are enriched by moral and intellectual dimensions. The synthesis of truth, goodness, and beauty elevates consumption to a quasi-artistic activity, fostering deeper engagement and interaction among consumers (Horng & Hsu, 2020; Wanzer et al., 2018). In this new paradigm, consumers become active participants, engaging in rich imaginative activities that transcend mere consumption and promote a sense of communal connection (Dagalp & Hartmann, 2021; Gorman, 2024).

In the context of the information age, foundational aspects of design education are increasingly exposed as inadequate. Evolving trends in information art design necessitate that educators adopt new strategies and approaches tailored to contemporary societal contexts, incorporating essential components of information art education, and effectively transitioning from traditional to modern educational practices (Meyer & Norman, 2020; Mohamed Hashim et al., 2022; Tusiime et al., 2022; Wong et al., 2023).

This study focuses on enhancing students' skills in assessing and improving image quality through advanced tools, like the structural similarity index (SSIM) algorithm, emphasizing its role in learning and understanding visual communication principles. Integrating immersive virtual reality (VR) into traditional art design curricula is explored to highlight its benefits and challenges, aiming to enrich learning experiences and optimize student engagement and creativity. The curriculum integrates image literacy and artistic expression literacy, equipping students with critical analysis and creative manipulation skills necessary for digital media navigation.

Addressing the gap between theoretical knowledge and practical application, the proposed educational models combine technical instruction with hands-on, project-based learning. This ensures students can apply their skills effectively in real-world scenarios. By integrating SSIM and VR into education, alongside a hybrid learning model, this approach fosters creativity and practical skills. It prepares students for the digital age by bridging theory and practice, signaling a shift from rigid educational practices to more adaptive, technologically integrated frameworks essential for nurturing future artists and designers. This modernization of art design education leverages technology to enhance both learning outcomes and student preparation for the information age.

LITERATURE REVIEW

The integration of information technology (IT) into art design education has become increasingly crucial in recent years, signaling a significant shift from traditional teaching methodologies. This transformation is driven by evolving demands in visual communication design, necessitating the incorporation of new technologies to enhance the quality and relevance of art design education.

Traditional art design education often suffers from rigid thinking patterns and a lack of alignment with contemporary societal needs. However, it has been undergoing substantial changes recently, focusing on integrating new technologies and innovative teaching methods. For instance, Som et al. (2021) explored the use of immersive VR technology in art and design classes to improve creative learning methods, hypothesizing that VR could enhance students' knowledge and skills in these areas. Xie (2021) emphasized the importance of integrating traditional culture into modern art design education in China, highlighting its necessity for the development of Chinese contemporary design.

Innovative educational forms in art and design have gained attention, as noted by Alyabieva et al. (2021). These programs aim to strengthen practical and research skills while bridging theoretical knowledge with practical applications. The trend toward practice-based Ph.D. programs reflects changing perceptions about graduate study standards. Saleh & Sabri (2023) compared the quality of studio learning experiences in traditional and online settings during the COVID-19 pandemic, underscoring the need to adapt to new learning environments.

Huang (2021) examined practical teaching methods in art design education based on new media technology, stressing the need for curriculum reform to align with technological advancements. Souliotou (2021) investigated the application of new technologies in traditional crafts to enhance sensory experiences, demonstrating the potential for combining traditional techniques with modern approaches in higher education.

Li (2020) pointed out that traditional methods fail to bridge the gap between theoretical knowledge and practical application, leaving students unprepared for real-world design challenges. Yue (2020) further elaborated on this issue, advocating for a more practical and industry-oriented approach in higher private colleges. By integrating industry, academia, and research, Yue proposed a teaching innovation model aimed at enhancing students' employment and innovation abilities.

Recent technological advancements, particularly deep learning methods, like convolutional neural networks (CNNs), have transformed image processing and analysis by enabling more accurate feature extraction and classification (Archana & Jeevaraj, 2024; Zangana et al., 2024). These technologies are being integrated into educational curricula to enhance students' technical and creative skills. Generative adversarial networks (GANs) also offer new possibilities for generating realistic images and designs, fostering innovative digital art expressions (Bansal et al., 2024).

Compared to traditional techniques, which often involve manual feature extraction and subjective evaluations, deep learning models automatically learn hierarchical features from large datasets, improving efficiency and accuracy (Chiu et al., 2022). GANs further facilitate experimentation and creativity by allowing the generation of high-quality synthetic data (Fang & Jiang, 2024). Studies by Xu et al. (2024) and Vijendran et al. (2024) highlight the potential of hybrid models combining deep learning and GANs to optimize both feature extraction and content generation, providing a robust framework for modern art design education.

To align with these advancements, art design education must evolve. Research underscores the importance of incorporating cutting-edge technologies into curricula. For instance, Zailuddin et al. (2024) discuss integrating artificial intelligence-driven tools in design courses to enhance innovation and problem-solving. Wang & Huang (2025) explore using VR and augmented reality alongside deep learning methods to create immersive learning environments that promote deeper engagement and understanding. These approaches emphasize adapting traditional teaching methods to include modern technologies, preparing students for the dynamic field of art and design.

By adopting these advanced methodologies, art design education equips students with the necessary skills to thrive in the digital age. The shift toward deep learning and GANs fosters an environment where creativity and technical proficiency coexist, ensuring future artists and designers can meet the multifaceted challenges of their profession and leverage technological innovations to expand artistic expression. The integration of IT into art design education is vital for addressing the demands of the digital age. Liu et al. (2022) discuss innovative teaching modes in furniture design, encouraging students to use various IT sources and technologies to reinterpret old furniture, enhancing both their skills and readiness for real-world challenges. This approach aims to improve art design education quality through IT.

Despite its benefits, integrating IT into art design faces challenges. Liang's (2021) survey identifies poor cultural literacy, monotonous teaching methods, and a lack of practical skills among Chinese college students as key issues. Liang suggests a hybrid learning model that incorporates IT and innovative teaching methods to bridge theory-practice gaps and enhance core literacy.

Hong (2020) focuses on improving Thangka art talent education in China, emphasizing the need for better training quality and a deeper understanding of design aesthetics and ethics. Strengthening educational functions and technical training can significantly improve Thangka art education.

"Information design," a relatively new concept with diverse global interpretations, reflects the interdisciplinary nature of the field. Terms, like "media design," "network design," and "virtual reality design," highlight varying perspectives on its application across Japan, the United States, and Europe.

In summary, integrating IT and innovative teaching methods is crucial for enhancing art design education. Embracing new technologies, fostering creativity, and improving practical skills prepare students for success in the evolving art and design field. The literature underscores the importance of a flexible, adaptive approach to design education, incorporating technological advancements and promoting creative and practical competencies. This review paves the way for further exploration and innovation in information design.

METHOD

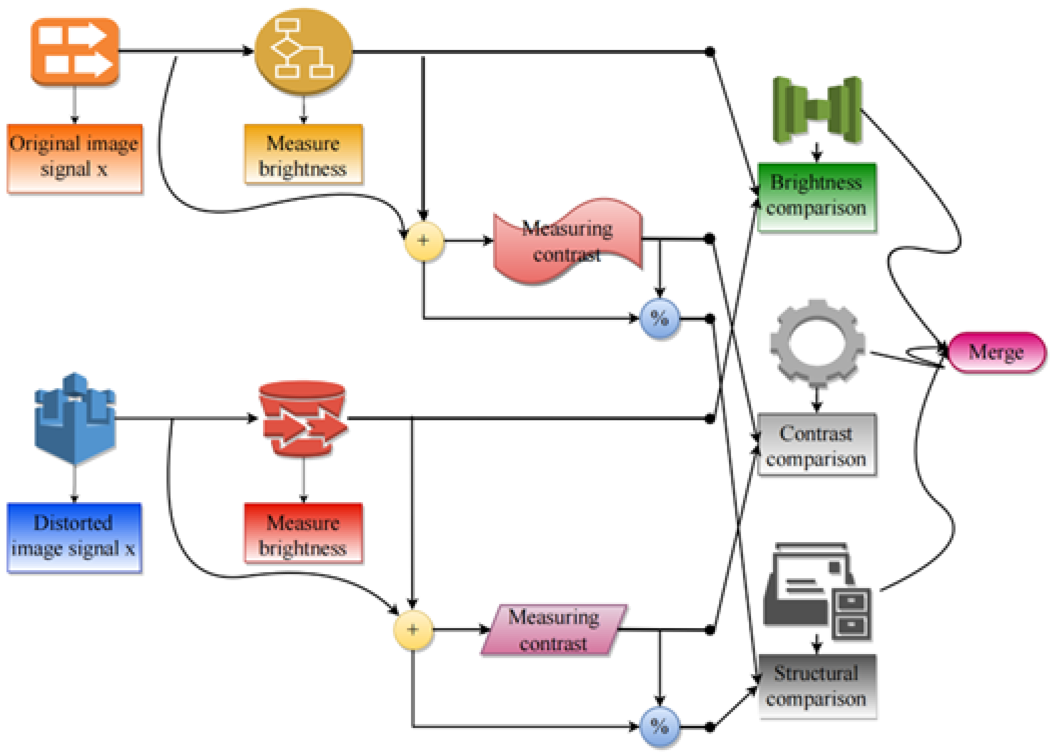
An Overview of IT Combined With Art Design

When perceiving images, the human eye primarily evaluates structural information. The SSIM assesses distorted image quality by measuring the structural similarity between the distorted and original images. Unlike bottom-up models that simulate low-level structures of the human visual system (HVS), SSIM adopts a top-down approach, simulating the overall function of the HVS. This method focuses on the input-output relationship of the HVS, modeling it holistically to avoid limitations associated with specific human physiological and psychological thresholds.

The SSIM model diagram for image quality evaluation is shown in Figure 1.

This paper aims to provide a comprehensive understanding of how information impacts modern life, the evolution of information design, and the necessary adaptations in art design education. By addressing these areas, it lays the groundwork for developing more effective and innovative design practices suited to the information age. This foundation supports advancements in design education and practice, emphasizing the integration of technology and creativity.

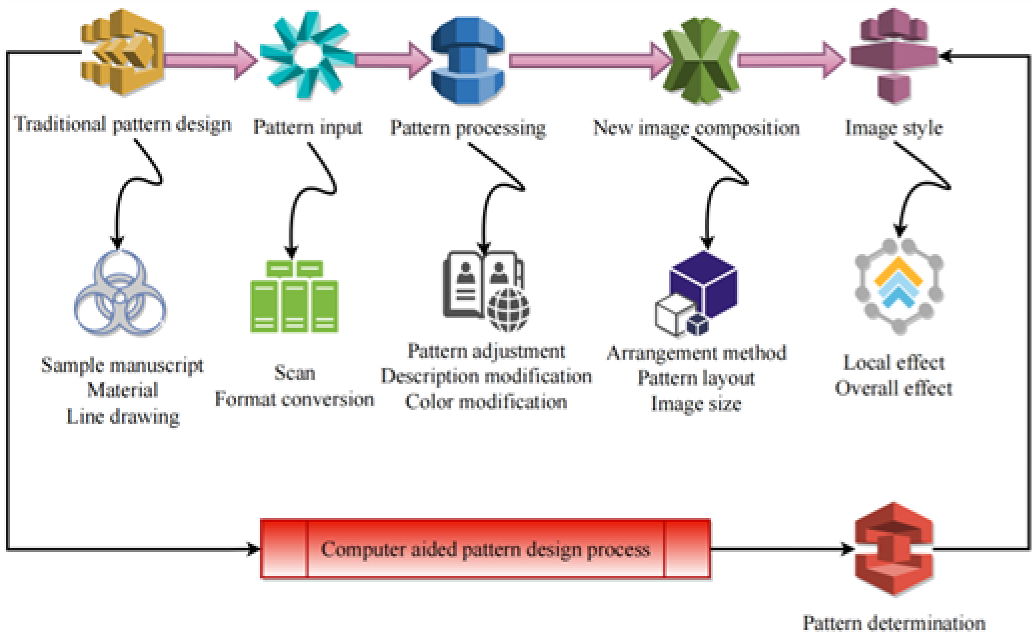
Figure 1. Model diagram of image quality evaluation method based on structural similarity



Enhancing Color Expression and Pattern Design With Computer-Aided Systems

Traditional images often fall short in color richness, limiting their visual appeal and effectiveness. Computer-aided systems provide powerful tools for modifying and harmonizing image colors, offering a practical solution when hand-drawn modifications are impractical. Compared to traditional methods, computer-aided pattern design excels by enabling a broader exploration of themes and motifs, creating complex compositions with precision, enhancing color harmony and vibrancy, and refining patterns through local and global adjustments. This results in more visually appealing and functional designs, as illustrated in Figure 2.

Figure 2. Computer-aided pattern design process



The computer-aided pattern creation system is integral to Jacquard computer-aided design, especially during the graphic design phase. It offers a robust vector drawing environment and comprehensive image processing tools, supporting the creation of high-quality graphics. Utilizing an object-oriented structure, the system leverages Visual C++ controls for its user interface and includes input/output interfaces for file handling and external interactions. Advanced modules for mathematical morphology processing and geometric transformations enhance image manipulation capabilities, facilitating the creation of dynamic and complex compositions.

Image literacy involves recognizing and interpreting various forms of visual media, understanding elements, like material, color, shape, and texture. Art expression literacy focuses on students' ability to use artistic skills to address problems across studies, life, and work. Mastery of both traditional and modern media and techniques is crucial for personal development, fostering creativity and problem-solving skills.

Integrating computer-aided systems into design education not only overcomes traditional limitations but also promotes creativity and innovation. By developing image literacy and art expression literacy, students are better prepared to thrive in a visually rich and technologically advanced world. This approach ensures that design education remains relevant and effective in the digital age.

Path Improvement of Design Quality Based on Art Image

In the era of big data, ordinary visual design struggles to meet sophisticated information transmission needs. Information design aims not only to fulfill social needs but also to develop designers' integrative capabilities. Its primary goal is to organize complex information into a coherent format and convey it through suitable visual language, ensuring effective presentation. Four key visual elements—color, graphics, text, and annotations—are fundamental in information visualization. These elements transmit information engagingly and informatively, with adaptability to match specific content requirements. Text, as a unique visual element, combines descriptive accuracy with visual variation through font, size, and color, enhancing readability and experience.

Diagrams are essential in visual communication due to their imagery and memorability. Figurative diagrams, more recognizable and memorable than abstract figures, integrate textual content visually. Color, transcending cultural boundaries, symbolically enriches designs and aids immediate recognition, exemplified by faucet color-coding for hot and cold water. Graphic information design offers a concrete, intuitive, and aesthetically pleasing way to present information, enhancing reader experience and ensuring effective communication. This form of design overcomes language barriers, facilitating widespread information dissemination.

Sparse representation, a significant research area in signal processing, represents signals in a sparse domain to solve linear equations with the fewest non-zero terms. This concise representation enables efficient extraction and further processing of information within signals, offering a powerful method for managing complex data. The core model of sparse representation is a simple linear system equation that has been studied for a long time in the field of linear algebra. The purpose of sparse representation is to find a linear combination of the least atoms to express the signal in the redundant dictionary, in which each column in the dictionary represents an atom. For any signal $y \in R^n$ and redundant dictionary $D \in R^{n \times m}(n < m)$, the signal can be represented by a linear combination of dictionary atoms, as shown in (1):

$$Da = \sum_{j=1}^{m} a_j d_j = y \tag{1}$$

where $m_\alpha \in R$ is the signal representation, a_j is the j element of a, D is an over-complete redundant dictionary, and atom d_j is the j column of dictionary D. In (1) are infinite solutions, of which the solution α that satisfies the least non-zero terms is the sparse representation of signal Y in redundant dictionary D. In order to find the sparse representation of signal, we construct the following optimization problem:

$$\hat{a} = \arg\min_a \|a\|_o s.t. \|Da - y\|_2^2 = 0 \tag{2}$$

Among them, $\|a\|_0$ is called the l_0 norm of the vector α, which represents the number of non-zero elements in the signal a, that is, the sparsity, and (2) is the sparse representation model of the norm.

Also, (2) is transformed into an unconstrained optimization problem using the Lagrange multiplier method, as follows:

$$\hat{a} = L(a, \lambda) = \arg\min_a \|Da - y\|_2^2 + \lambda \|a\|_1 \tag{3}$$

Neural networks are computational models inspired by the human brain's neural structure, featuring interconnected nodes or neurons. Each neuron applies an activation function to process inputs, and the connections between neurons have associated weights. Various connection methods lead to different neural network architectures. CNNs, featuring convolutional and pooling layers, are particularly effective for image processing due to their ability to manage high-dimensional data.

A typical CNN architecture includes four main types of layers: convolutional layers, pooling layers, nonlinear mapping layers, and fully connected layers. The convolutional layer, central to a CNN, extracts features from input images using convolution kernels that slide over the image to produce feature maps. This process mimics biological visual receptive fields, with each neuron responding to stimuli within a specific area. Weight sharing in these layers reduces parameter numbers, enhancing efficiency and mitigating overfitting. For example, a 2×2 convolution kernel applied to a 3×4 image produces a 2×3 feature map, effectively capturing key features while reducing dimensionality.

However, large input images can still result in significant feature dimensions post-convolution, increasing computational complexity and overfitting risks. Pooling layers address this by downsampling feature maps, summarizing outputs from groups of neighboring neurons. This retains crucial features while reducing overall dimensionality, making the network more efficient. The specific operation of the convolution layer is illustrated in Figure 3.

Figure 3. Operation process of convolution layer

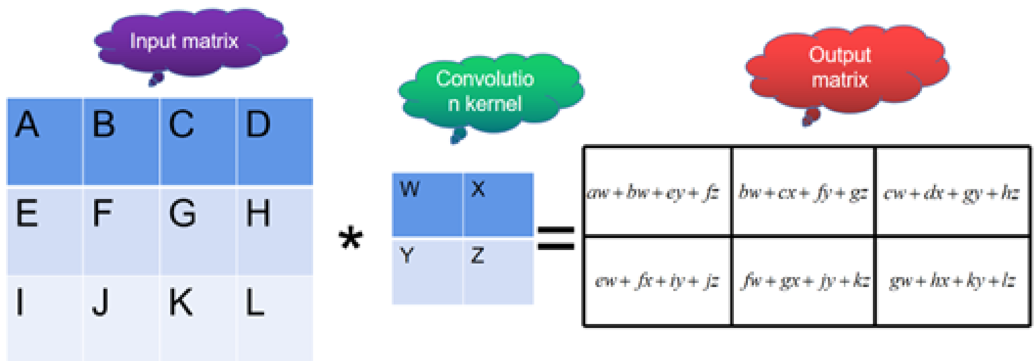


Image Quality Improvement Design Algorithm Model Based on Sparse Representation

Teaching materials in art colleges predominantly emphasize technical aspects, particularly computer knowledge, often at the expense of fundamental design principles. This imbalance results in visually impressive but soulless designs and fosters a misconception among students about the omnipotence of computer technology, hindering critical and creative thinking. The rapid growth of the service sector economy underscores the importance of creative industries, with art design playing a pivotal role in national innovation and corporate development. In this context, contemporary design education faces the challenge of nurturing designers equipped with the appropriate qualities and skills for the information age.

Traditional teaching methods have failed to bridge the gap between design education and practical application, necessitating reforms in information art design education. Creativity is recognized as the essence of design, regardless of the specific area. Encouraging students to think creatively and apply their ideas practically becomes crucial. Software should not be seen merely as a tool for design expression but as an active assistant in the design process. Teaching students to leverage software effectively enhances creative outcomes and supports the design process. It remains essential for students to understand both the limitations and potential of computer technology, viewing computers not only as tools for design but also as aids that enhance the design process.

Selecting suitable software tailored to specific tasks emphasizes the importance of training students based on merit and suitability. In an era characterized by information overload, equipping students with the ability to identify and filter useful information becomes crucial for effective information art design. Additionally, fostering the development of unique expressive styles encourages individuality and creativity in design. These reforms aim to adapt design education to meet the demands of the information age, ensuring students are well-prepared for the challenges and opportunities they will face. Through these adjustments, design education can better align with societal needs and guide students in applying their knowledge to solve practical design problems.

By addressing these areas, art design education can better prepare students to meet the challenges of the information age and contribute meaningfully to the creative industries.

First, assume that x and y are the original image signal and the distorted image signal, respectively, and then calculate the brightness comparison function $l(x, y)$, the contrast comparison function $c(x, y)$, and the structure comparison function $s(x, y)$ of the two signals, respectively, and finally the image structure similarity evaluation result is obtained through weighted and combined calculation. The luminance mean value μ_x of the original image signal x and the luminance mean value μ_y of the distorted image signal y are, respectively, defined as:

$$\mu_x = \frac{1}{N}\sum_{i=1}^{N} x_i \tag{4}$$

$$\mu_y = \frac{1}{N}\sum_{i=1}^{N} y_i \tag{5}$$

where n is the total number of pixels of the image; x_i and y_i represent the gray value of the i th pixel in the original image signal x and the distorted image signal y, respectively. Therefore, the brightness comparison function $l(x, y)$ is defined as:

$$l(x, y) = \frac{2\mu_x\mu_y + C_1}{\mu_x^2 + \mu_y^2 + C_1} \tag{6}$$

Among them, in order to prevent instability when the denominator $\mu_x^2 + \mu_y^2$ is close to zero, a constant is introduced here, which is the value range of the image grayscale (when the image is 8-bit, L is 255), and k1 is a constant far less than 1.

The luminance standard deviation σ_x of the original image signal x and the luminance standard deviation σ_y of the distorted image signal y are, respectively, defined as:

$$\sigma_X = \left[\frac{1}{N-1}\sum_{i=1}^{N}(x_i - \mu_x)^2\right]^{1/2} \tag{7}$$

$$\sigma_y = \left[\frac{1}{N-1}\sum_{i=1}^{N}(y_i - \mu_x)^2\right]^{1/2} \tag{8}$$

Therefore, the definition of the contrast comparison function $c(x, y)$is similar to that of the luminance comparison function:

$$c(x, y) = \frac{2\sigma_x\sigma_y + C_2}{\sigma_x^2 + \sigma_y^2 + C_2} \tag{9}$$

Among them, in order to prevent instability when the denominator $\sigma_x^2 + \sigma_y^2$ is close to zero, the constants C_ψ, $C_2 = (k_2 L)^2$ and K_ψ are also introduced here, which are constants far less than 1.

First, the correlation coefficients (CCs) of the two image signals are defined as:

$$\sigma_{xy} = \frac{1}{N-1}\sum_{i=1}^{N}(x_i - \mu_x)(y_i - \mu_y) \tag{10}$$

According to the mathematical theory, the correlation of unit vectors $(x - \mu)/\sigma_x$ and $(y - \mu_y)/\sigma_y$ is consistent with the CC of image signals x and y. Therefore, the structure comparison function $s(x, y)$ of the two image signals is defined as follows:

$$s(x,y)=\frac{\sigma_{xy}+C_3}{\sigma_X\sigma_y+C_3} \tag{11}$$

Similar to the definition of brightness comparison and contrast comparison function, a small constant C is introduced into the expression of structure comparison function to prevent the occurrence of instability.

According to the SSIM evaluation model diagram, the SSIM is obtained by combining and weighting three kinds of structural information. Therefore, by synthesizing (9), (10), and (11), the SSIM of images is defined as follows:

$$SSIM(x,y)=[l(x,y)]^{a}\cdot[c(x,y)]^{\beta}\cdot[s(x,y)]^{y} \tag{12}$$

The local quality calculation initially uses the 8×8 window, which moves point-by-point from the upper left corner to the lower right corner of the image and calculates the SSIM value of each area corresponding to the local window. However, after the simulation test, it is found that this design has certain defects, e.g., it will make SSIM score chart appear "block effect."

In order to prevent the existence of this defect, an effective method is to use the 11×11 cyclic symmetric Gaussian weighting function $W = \{\omega_i | i = 1,2,...,N\}$ to calculate the three types of local statistical values of μ_x and σ_{xy}. The standard deviation of the Gaussian weighting function is set to 1.5, and it is normalized by $(\sum_{i=1}^{N}\omega_i = 1)$. Then, (13) is the Gaussian weighting function expression:

$$\omega(x,y)=\frac{1}{2\pi\sigma_x\sigma_y}\exp(-\frac{(X-X_0)^2}{2\sigma_x^2}-\frac{(y-y_o)^2}{2\sigma_y^2} \tag{13}$$

Among them, the values of σ_x and σ_y are 1.5 and (x_0, y_0) is the coordinate of the center point. The calculation of local statistical values μ_x, σ_x, and σ_{xy} is modified accordingly as follows:

$$\mu_x=\sum_{i=1}^{N}\omega_i x_i \tag{14}$$

$$\sigma_x=\sum_{i=1}^{N}\left[\sum_{i=1}^{N}\omega_i(x_i-\mu_x)\right]^{1/2} \tag{15}$$

$$\sigma_{xy}=\sum_{i=1}^{N}\omega_i(x_i-\mu_x)(y_i-\mu_y) \tag{16}$$

Parameters K_1 and K_2 in the SSIM model are set as 1k0.01 and 2k0.03. These values are arbitrary. In the current experiment, the evaluation effect of SSIM model is less affected by these values.

Study Design

This study aims to construct an efficient system specifically designed for image fusion and quality assessment. To support high-resolution image processing tasks, the system requires robust computing resources. Processors should be at least Intel Core i7 or equivalent, with memory recommended to be 16 gigabytes or more to ensure smooth data handling capabilities. Given the need for large-scale data storage, solid state drives are preferred as the primary storage medium due to their fast read/write speeds.

For software components, Linux Ubuntu (long-term support version) serves as the development platform owing to its open-source nature and strong community support. Python 3.x combined with OpenCV libraries handles general image processing tasks, while MATLAB is utilized for specific algorithm implementations, such as the adaptive trilateral wavelet transform (ATWT) algorithm. MySQL manages experimental data, including original images, distorted images, and corresponding evaluation results, ensuring organized and accessible data management.

The interface design adheres to user-friendly principles, employing a graphical user interface. Developed using the Qt framework, the front-end allows users to easily upload images, select parameters, and view processing results. Communication between the back-end and front-end occurs via RESTful application programming interfaces, enabling asynchronous data transmission and real-time processing status updates. This design philosophy maximizes the utilization of existing resources while ensuring operational simplicity, allowing researchers and technicians to focus on algorithm optimization, rather than system maintenance. By integrating these elements seamlessly, the system ensures smooth operation and enhances overall efficiency in image fusion and quality assessment tasks.

In building this system, specific technologies were selected based on detailed considerations. The ATWT algorithm was chosen over other potential options due to its superior edge preservation capability and high robustness against noise. This algorithm particularly excels when handling images with complex textural characteristics, outperforming traditional methods. Comparative experiments demonstrated that the ATWT algorithm achieved the highest scores on the overall quality (Q4) metric, indicating it produced the best quality of fused images among all tested methods.

For dictionary learning processes, the K-SVD algorithm was employed with specific settings, such as 20 iterations and a maximum sparsity level of 8. These parameters enhance the efficiency of redundant dictionary training, accelerating the entire image processing workflow. By optimizing these settings, the system achieves faster processing times without compromising on the quality of output, making it highly efficient for large-scale data analysis.

Global relative dimensionless synthesis error (ERGAS) serves as a key metric for assessing the quality of image fusion. Lower ERGAS values indicate better fusion outcomes, guiding adjustments in parameters, like the number of layers and filter size, to achieve optimal results. Through systematic experimentation and parameter tuning, optimal combinations can be identified to further improve the quality of image fusion. This approach ensures that the final outputs are not only technically sound but also visually superior, meeting the high standards required for advanced image processing tasks.

Data Collection Techniques and Analysis

Data collection involved downsampling original multispectral and panchromatic images and recording the ERGAS values obtained from each experiment. Further analysis included calculating statistics, such as the CC, root mean square error (RMSE), and others, under different evaluation metrics to assess the accuracy and reliability of the algorithms. For subjective evaluations, a panel consisting of over 20 participants rated each distorted image, leading to the calculation of mean opinion scores (MOS).

Validation and Reliability

To ensure the credibility of the research findings, several measures were implemented, including outlier elimination, setting a 95% confidence interval, and employing nonlinear fitting methods (such as logistic functions) to establish relationships between algorithm scores and subjective quality scores. These steps collectively ensured the rigor of the data analysis process, making the conclusions both statistically significant and reflective of true human perception.

RESULTS

Evaluation of Image Quality Algorithms

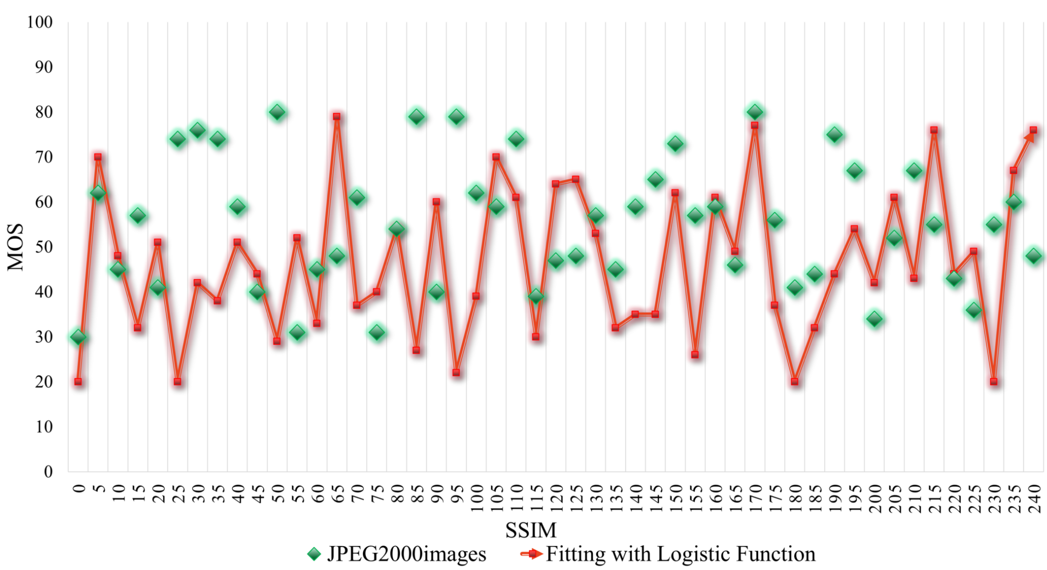
In the digital age, the effectiveness of visual content is crucial, making image literacy a vital part of modern art design education. Advanced tools, like the SSIM algorithm, enhance students' understanding and manipulation of visual information by providing an objective assessment method that simulates human visual perception. This approach not only improves technical skills but also offers a scientific foundation for teaching.

A study using SSIM to evaluate images from the LIVE Image database's JPEG2000 distortion class demonstrates the algorithm's ability to quantitatively assess image quality by measuring structural similarities between distorted and original images. The LIVE database, with its diverse collection of natural scene images and their distortions, serves as an ideal platform for testing image quality assessment models. Engaging with this resource allows students to experiment with different types of distortions and learn methods for enhancing image quality, such as adjusting parameters in JPEG2000 compression exercises.

By incorporating specific cases from the LIVE database into hands-on tasks, students can explore relationships among image elements, like color, shape, and texture, while learning precise editing techniques. Encouraging innovation in solving image quality issues fosters creativity without compromising artistic expression. Image quality assessment plays a key role in developing critical thinking and attention to detail during the creative process.

Introducing scientific tools, like SSIM, elevates technical proficiency and user experience awareness, aiming to cultivate professionals who are adept at both the technical and artistic aspects of design. Through detailed exploration of SSIM and its applications, a comprehensive framework for image quality assessment can be established in art design education. This framework aims to improve teaching quality and contribute to industry development by equipping students with essential skills and perspectives.

Figure 4. Simulation scatter plot of structural similarity index (SSIM) Algorithm in JPEG2000 distortion gallery



Note. MOS = mean opinion scores; SSIM = structural similarity index.

Figure 4 illustrates how different network parameters affect image fusion quality, using the ERGAS metric. The chart compares two variables: the number of layers (purple line) and filter size (red line). The X-axis represents various parameter settings or experiment iterations, while the Y-axis shows ERGAS values, with lower values indicating better fusion quality.

The purple line demonstrates that varying the number of layers significantly impacts ERGAS scores, influencing fusion quality. Similarly, the red line indicates that changes in filter size also substantially affect these scores. By optimizing parameters, such as the ATWT algorithm's decomposition levels and the K-SVD algorithm's iteration counts and sparsity, researchers can identify the best configuration for image fusion.

Additionally, Figure 4 presents a scatter plot where the X-axis represents SSIM algorithm scores and the Y-axis corresponds to human subjective quality scores. Each point on the plot represents a distorted image from the LIVE database. A central curve, derived from nonlinear fitting using the logistic function, correlates algorithmic scores with subjective quality assessments.

Over 20 evaluators assessed each distorted image, rating quality on a scale from 1 to 100. MOS were calculated after statistical processing, including outlier removal and setting a 95% confidence interval. Difference MOS were introduced to quantify distortion levels, with lower difference MOS values indicating better image quality.

Using the LIVE database, detailed in Table 1, simulation experiments provided structured comparisons between original and distorted images, highlighting the effectiveness of the SSIM algorithm in assessing image quality. This approach ensures reliable data reflective of true human perception and supports the validation and enhancement of image processing algorithms, ultimately improving image fusion outcomes.

Table 1. Brief description of five distortion types in LIVE database release 2

Distortion Type	Distortion
JPEG2000	Kakadu (V2.2) coding, bit rate 0.028-3.13bpp
JPEG	The application of MATLAB in mwrite {fnsimheibord 1shad1pos (200,288)} It's my fault {fnsimheibord 1shad1pos (200,288)} My fault, Wu Jingsheng 0.15-3.34bpp
White noise	Gaussian white noise, standard deviation 0.012–2.0
Gaussian blur	Gaussian, the standard deviation of 2D Gaussian function is 0.42–15
Fast fading	Kakadu (V2.2) coding, bit rate 2.5bpp, simulation transmission environment: RSNR 15.5–26.1DB

Note. RSNR = rate and signal-to-noise ratio.

Table 1 outlines five types of distortions applied to images within the LIVE database release 2. Each type has a brief description that specifies the method or conditions under which the distortion was applied:

JPEG2000: Uses Kakadu software for compression with varying bit rates.
JPEG: Involves MATLAB application for creating distortions with specified parameters.
White noise: Adds Gaussian white noise with a range of standard deviations.
Gaussian blur: Applies a blur using a two-dimensional Gaussian function with specified standard deviations.
Fast fading: Simulates a transmission environment with specific bit rate and signal-to-noise ratio.

This table sets the foundation for understanding the types of distortions used in the experiments, which is crucial for evaluating how well different algorithms perform under these conditions.

Analysis of Evaluation Algorithms

In a study on JPEG image compression and its impact on image quality, researchers explore how varying compression ratios affect perceived image quality by calculating the peak signal-to-noise ratio (PSNR) and gathering MOS through user surveys. This dual approach combines objective measures of image fidelity with subjective human perception to understand the effects of compression.

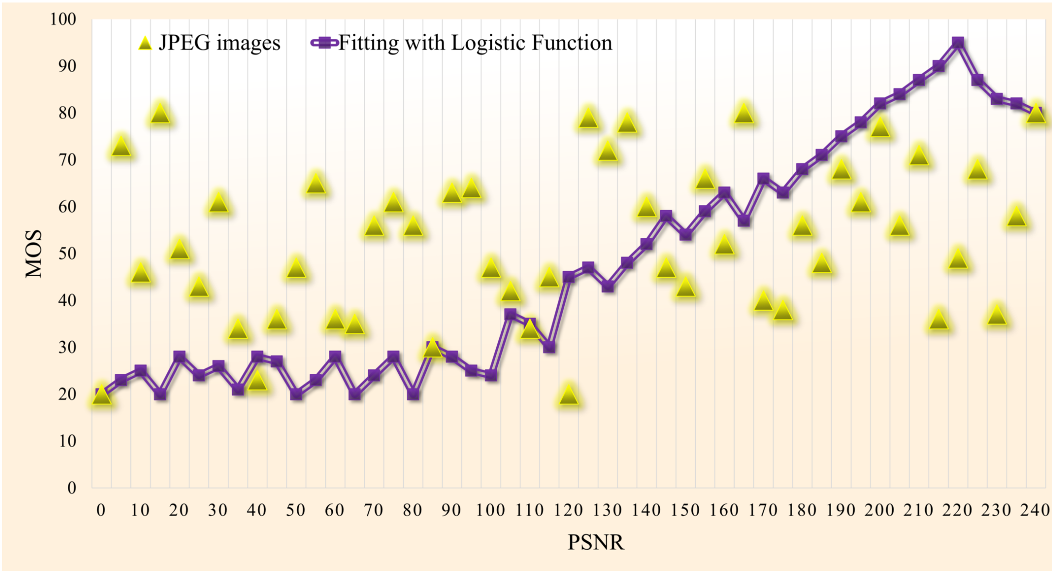
JPEG images compressed at various rates are used as test samples. For each image, PSNR is calculated to quantify image fidelity compared to the original. MOS values are collected from users to capture subjective quality assessments. The results, illustrated in a figure, show that MOS generally increases with higher PSNR values, indicating better perceived quality at lower compression levels. Yellow triangles represent individual MOS scores for each tested JPEG image, while a purple logistic curve models the overall trend between PSNR and MOS, showing diminishing returns in perceived quality improvement at higher PSNR values.

The analysis reveals that beyond a certain PSNR threshold, further improvements do not significantly enhance subjective image quality. This suggests that striving for extremely high PSNR values may be unnecessary when balancing image quality against storage space and transmission efficiency. Instead, finding an optimal compression ratio that maintains satisfactory quality while minimizing file size is more practical.

Figure 5 compares four evaluation algorithms—PSNR, SSIM, GSSIM, and DS-SSIM—using scatter plots and fitting curves based on the JPEG distortion library. While all algorithms show increasing trends in high-quality ranges, SSIM exhibits a decreasing trend in low-quality ranges, failing to meet expected monotonicity requirements for objective evaluation metrics, as detailed in Table 2.

This study underscores the importance of considering both objective and subjective evaluations in assessing image quality. It highlights the need to balance compression efficiency with visual integrity, providing insights for optimizing compression strategies without compromising image quality. These findings can guide researchers and students in making informed decisions about appropriate compression settings for specific applications.

Figure 5. Scatter plot comparison of evaluation algorithm in JPEG distorted image library



Note. MOS = mean opinion scores; PSNR = peak signal-to-noise ratio.

Table 2. Comparison of evaluation indexes of evaluation algorithms in JPEG distortion image library

Algorithm	CC	ROCC	MAE	RMSE	OR
PSNR	0.9242	0.82455	4.6125	6.4152	0.0646
SSIM	09464	0.84223	3.4215	4.2456	0.3481
GSSIM	0.9647	0.9027	2.4564	3.4865	0.4466
DS-SSIM	0.9842	0.9102	4.5677	3.4164	0.0415

Note. CC = correlation coefficient; ROCC = receiver operating characteristic curve; MAE = mean absolute error; RMSE = root mean square error; OR = outlier rate; PSNR = peak signal-to-noise ratio; SSIM = structural similarity index; GSSIM = ; DS-SSIM = .

Table 2 compares the performance of four algorithms (PSNR, SSIM, GSSIM, DS-SSIM) for evaluating JPEG-distorted images using metrics, such as CC, receiver operating characteristic curve, mean absolute error, RMSE, and outlier rate. DS-SSIM stands out with the highest CC and one of the lowest outlier rate values, indicating superior reliability in assessing image quality under JPEG distortion. Specifically, DS-SSIM achieves CC over 98% and receiver operating characteristic curve of 91.02%, along with low errors (mean absolute error below 2.5 and RMSE of 3.1), making it the most accurate among the tested algorithms.

In design education, fostering collaboration between teachers and students is essential, especially during the creative stage where hand-drawn sketches should be emphasized. Specific requirements based on actual teaching situations help guide students, supported by a design text plan that leverages network information and computer production to enhance design efficiency. Providing practical opportunities allows students to develop methods for solving real-world problems, ensuring design education meets the demands of the information age.

Additionally, encouraging the use of network resources to study exemplary design works helps students learn effective design methodologies. This includes promoting modern information network resources and enabling students to showcase their work. Adjustments to the original syllabus have been made to integrate IT fully into basic courses, balancing traditional content with contemporary needs, as detailed in Table 3. These changes aim to prepare students adequately for the evolving field of art and design.

Table 3. Objective evaluation of fusion results and promotion results of different methods

Method	Fusion Results	Promotion Results	Fusion Results	Promotion Results	Fusion Results	Promotion Results
ATWT	5.54321	3.4156	8.16413	5.7321	0.4564	0.4415
BT	7.7912	3.4521	6.4452	5.1234	0.1418	0.4152
GIHS	5.5722	3.4822	6.1243	5.4732	0.7215	0.4755
SAM	5.54321	3.4156	7.7912	3.4521	5.5722	3.4822
Q4	8.16413	5.7321	6.4452	5.1234	6.1243	5.4732
CC	0.4564	0.4415	0.1418	0.4152	0.7215	0.4755

Note. ATWT = adaptive trilateral wavelet transform; BT = ; GIHS = ; SAM = ; Q4 = overall quality; CC = correlation coefficient.

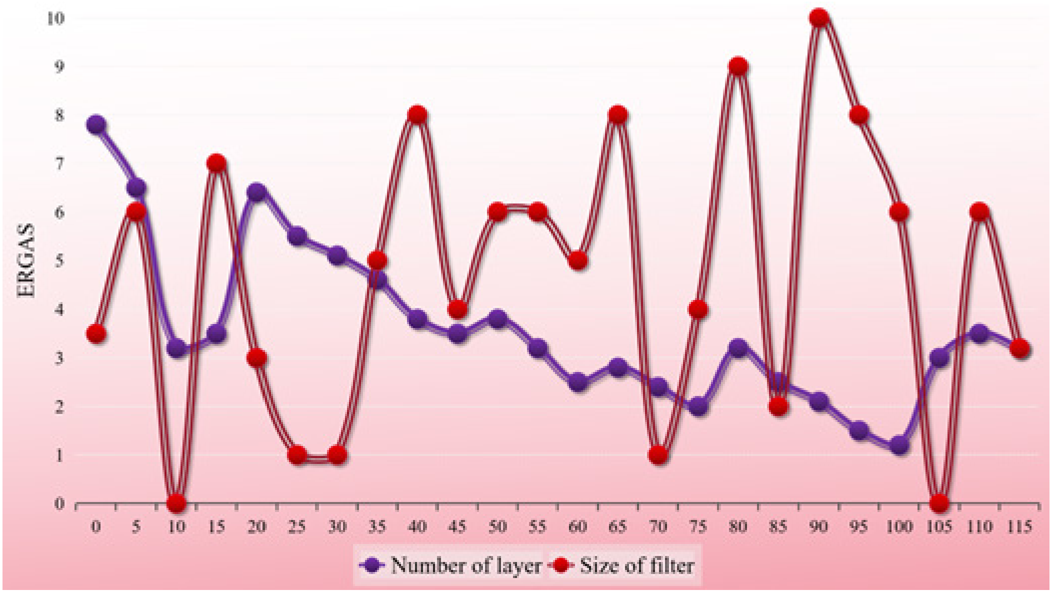
Table 3 presents an objective evaluation of fusion results from three methods (ATWT, BT, and GIHS) and the associated promotion results. The table also includes metrics, such as SAM, Q4, and CC, to evaluate the effectiveness of each method.

Fusion results indicate the outcome quality of the image fusion process, while promotion results suggest improvements or enhancements achieved by the respective methods.

Each metric provides insight into different aspects of the fusion process, such as structural similarity (SAM), Q4, and CC. For example, ATWT scores higher in Q4 for fusion results, indicating better quality in fused images compared to other methods.

To further verify the advantages of this algorithm, we compare the SVT lifting results with those of CS, DRPNN, and PNN, as shown in Figure 6.

Figure 6. Influence of different network parameters on global relative dimensionless synthesis error (ERGAS)



Note. ERGAS = global relative dimensionless synthesis error.

The Quickbird satellite provides high-resolution multispectral images (2.88 meters per pixel, four channels) and panchromatic images (0.7 meters per pixel). For an experiment, both types of images were downsampled by a factor of 4, resulting in low-resolution versions with dimensions of 125×125 for the multispectral image and 500×500 for the panchromatic image. The original multispectral image serves as a reference for training the redundancy dictionary.

Figure 6 illustrates how different network parameters affect image fusion quality using the ERGAS metric. Two variables are considered: the number of layers (purple line) and the filter size (red line). The X-axis represents various parameter settings or iterations, while the Y-axis shows ERGAS values, where lower values indicate better fusion quality. The figure reveals that both the number of layers and filter size significantly impact ERGAS scores, with certain configurations yielding improved fusion quality.

Parameter adjustments aim to optimize the ATWT and K-SVD algorithms for image fusion. The ATWT algorithm uses three decomposition levels, and the K-SVD algorithm sets 20 iterations and a maximum sparsity of 8. By comparing ERGAS values across different settings, researchers can identify the optimal parameter combination for the best fusion results.

After downsampling, images were divided into three sizes. The ATWT algorithm was chosen for fusion, with default settings including a dictionary size of 1024, a balance term of 2048, and a neighborhood size of 0.1. These parameters' influence on performance is shown in Figure 7. This process offers a robust framework for enhancing image processing algorithms, ultimately improving image fusion quality. This approach helps students and researchers understand how to optimize these algorithms through parameter adjustment, contributing to advancements in the field.

Figure 7. Parameters' influence on performance

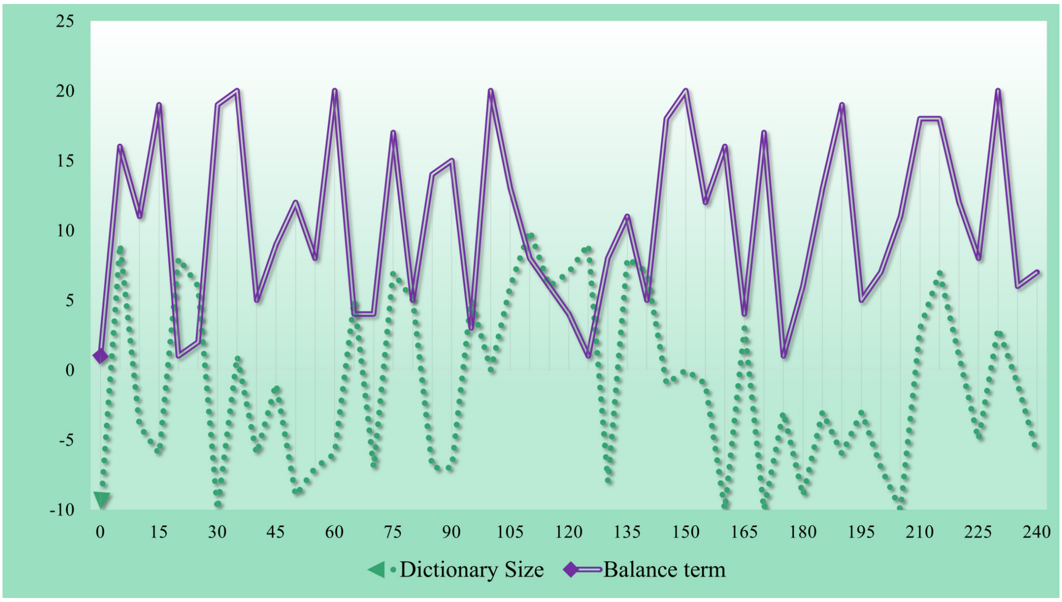


Figure 7 illustrates the effects of varying parameters on the performance of an image fusion algorithm, focusing on dictionary size and balance term metrics. The green dotted line with triangle markers represents dictionary size, while the purple solid line with diamond markers indicates the balance term. The X-axis denotes different parameter settings or experiment iterations, and the Y-axis shows the values for these parameters, where a lower balance term typically signifies better performance.

The fluctuation in dictionary size, as depicted by the green dotted line, reflects changes in model complexity used for image fusion. Meanwhile, the purple solid line demonstrates that the balance term significantly impacts image fusion quality, with certain parameter settings yielding improved performance indicated by lower values, whereas higher values suggest poorer outcomes.

These adjustments aim to optimize the ATWT and K-SVD algorithms for image fusion. Specifically, ATWT employs three decomposition levels, and K-SVD is configured with set numbers of iterations and maximum sparsity. By comparing these values across various settings, researchers can identify the optimal parameter combination. For instance, the combination achieving the lowest balance term value suggests the best performance.

Experimental steps include downsampling original multispectral and panchromatic images, applying the ATWT algorithm for fusion, and adjusting the dictionary size and balance term. Each experiment records balance term values, facilitating data analysis to pinpoint the optimal parameter combination.

In summary, Figure 7 visually demonstrates how different parameter settings influence image fusion quality. This aids researchers and students in understanding how to optimize image fusion algorithms through parameter adjustment, thereby enhancing image processing algorithms' performance and improving overall image fusion results.

DISCUSSION

Limitations

Despite exploring the importance and methods of integrating technology into art education, the adaptability of this framework across various educational settings has not been fully addressed. Differences in curriculum design, student backgrounds, and institutional resources present unique challenges that a one-size-fits-all approach to technological integration cannot adequately meet. Each educational institution possesses distinct teaching objectives, resource allocations, and needs of its student body, indicating the necessity for tailored approaches.

Enhancing the broad applicability of this framework involves customizing curricula according to educational stages and subject requirements. In foundational art education, emphasis might be placed on developing students' image literacy and basic technical skills. Conversely, higher education or specialized training programs could introduce more advanced tools and technologies, such as the SSIM algorithm and CNNs, catering to the sophisticated needs of advanced learners.

Considering the varying levels of technological proficiency and interests among students, it is essential to design tiered educational plans that cater to diverse learner needs. For students less familiar with technology, beginning with fundamental skill training before progressing to complex project practices can be beneficial. Meanwhile, for those with more experience, offering challenging projects stimulates creativity and innovation. This approach ensures all students are engaged and supported according to their individual capabilities.

Given the disparities in resources among institutions, developing a modular educational resource library is crucial. Such a library would include online tutorials, case studies, and interactive platforms, allowing educators to select materials and technological tools best suited to their specific circumstances. By doing so, this not only optimizes the use of available resources but also facilitates effective technology integration even in settings with limited resources.

Through these measures, not only does it enhance the effectiveness of merging technology with art education, but it also ensures this integration model can be implemented across diverse educational environments, truly achieving educational equity and fostering comprehensive student development. These strategies collectively provide a robust foundation for the widespread application of technology in art education and pave the way for future educational innovations.

Whilst parameter tuning has been demonstrated to have a significant impact on fusion results, the optimal settings for each scenario are not universally applicable. Different types of images and fusion tasks may require further research to determine the most appropriate parameter configurations. For instance, when using the SSIM algorithm to assess image quality, although the method is effective in modeling the perception of structural information by the HVS, the effectiveness of its specific application is highly dependent on the accuracy of the selected parameters. For images with rich colors and complex patterns, different parameter settings may be required to achieve optimal visual results compared to processing simpler images. Furthermore, understanding and optimizing these parameters becomes particularly important when it comes to specific application scenarios, such as pattern creation in art design or information visualization design.

To address the above issues, future research should focus on exploring the optimal set of parameters for different types of images and tasks. This will not only enhance the performance of existing algorithms but also enable the development of a more extensive range of application areas. By experimentally comparing the effectiveness of different algorithms with different parameter settings, users will be provided with guidelines to inform their choices when confronted with specific design challenges. Concurrently, such research will further reveal the potential of image processing techniques and drive continued innovation in the field.

Future Directions

To enhance understanding of industry readiness and job market impact, further exploration into theoretical depth is essential. Integration of advanced image processing techniques, such as SSIM, GSSIM, and DS-SSIM, into existing workflows necessitates a thorough examination of their foundational principles. Aligning these metrics with human perception models provides insight into their applicability across various industries including healthcare, entertainment, and remote sensing. Empirical validation through large-scale studies using diverse datasets from different sectors can confirm the effectiveness of these algorithms. Practical applications in medical imaging or environmental monitoring demonstrate real-world benefits beyond academic settings, highlighting areas for improvement.

System modeling plays a crucial role in identifying potential bottlenecks and optimizing performance. Detailed models that simulate real-world applications should consider hardware constraints, software limitations, and user interaction patterns. This ensures proposed solutions are both theoretically robust and practically feasible. Rigorous comparative analysis between proposed methods, like ATWT and K-SVD, and existing industry standards offers valuable insights. Metrics, such as ERGAS, PSNR, and subjective evaluations, like MOS, provide clarity on which methods perform best under varying conditions, guiding practitioners in technology adoption. Clarifying research methodologies involves specifying data collection procedures, experimental designs, and analytical frameworks used throughout the study. Transparent methodologies enable replication and refinement by other researchers, contributing to collective knowledge.

Addressing sustainability within digital art education requires elaboration on sustainable practices promoting resource efficiency, environmental responsibility, and long-term viability. Encouraging the use of open-source software and tools reduces financial barriers for students and educators, while cloud-based solutions minimize local storage needs and energy consumption. Incorporating lessons on digital footprints and environmental impacts of digital media creation educates students about eco-friendly design practices. Optimizing file sizes without compromising quality fosters a more sustainable approach to digital art. Developing curricula focused on emerging trends in digital art prepares students for a rapidly evolving field, integrating topics, like artificial intelligence-driven design, VR, and augmented reality, into traditional courses. These efforts ensure relevance and sustainability in digital art education, bridging the gap between theoretical advancements and practical applications. Fostering collaborations between academia and industry facilitates knowledge exchange and accelerates innovation, benefiting both sectors significantly.

CONCLUSION

The research has addressed the challenge faced by art and design education in adapting to the information age, where intangible experiences are increasingly valued over material wealth. The focus has been on how environmental art education can integrate IT to meet the growing importance of image literacy and the evolving role of images in communication. Additionally, the exploration covered the potential for personalized graphic design enabled by technological advancements and examined the implications for art education practices.

The study revealed that traditional approaches in environmental art education have been slow to adopt IT but show significant potential for transformation. The integration of text and imagery as a method for conveying information has proven effective, enhancing both efficiency and accessibility of communication. Advancements in technology have facilitated the personalization of graphic design, extending beyond visual elements to include material and media selection, thereby offering new avenues for individual expression. Genetic art, influenced by genetic differences, exemplifies the convergence of biotechnology and creative expression, suggesting that future graphic design will be closely linked to technological progress. Surveys among educators highlight consensus on the necessity of integrating interdisciplinary studies and modern technology to better prepare students for a rapidly changing world. The emphasis should be on developing students' technical skills alongside their creative vision, equipping them to thrive in the digital era.

The implications of these findings suggest that art education must adapt to incorporate the latest technologies and interdisciplinary methods, ensuring it remains relevant and impactful. As aesthetic experiences enriched by moral and intellectual dimensions evolve into quasi-artistic activities, they promote deeper consumer engagement and interaction, fostering shared values and mutual understanding. This shift underscores the importance of interactive design in creating platforms that facilitate meaningful interactions between creators and consumers. In summary, the research supports the notion that the future of information art design lies at the intersection of emotion and technology. For art education to remain pertinent, embracing innovation and adaptability is essential, fostering an environment where creativity and technology converge. By doing so, art education can empower individuals to express unique identities and contribute meaningfully to society's cultural landscape. The findings underscore the critical need for educational reform that integrates technology and interdisciplinary approaches, preparing students for the challenges and opportunities presented by the information age.

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