A Study on the Application of Visual Perception in Art Design Based on Industrial Mathematics Models

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To study the beautification of art design and analyze the application of visual perception in art design, this paper proposes an image beautification processing technique based on multiple chromatic aberration compensation of illumination. The paper will then investigate the task of classifying styles, genres, and artists based on deep learning methods on fine art design images. The proposed method automatically classifies fine art design images with significant improvements in classification accuracy and efficiency. Experimental tests are conducted and the results show that the beautification of night images using this technique has good fine art presentation capabilities, improves the aesthetic and visual sensory expressive performance of the images, and has good fine art application value.

1. Introduction

Fine art and design have played a very important role in the history of world civilization [1, 2]. Of course, fine art is also a true portrayal of a period or era by the painter, through which the social scene and ideology of the time can be found [3]. The aesthetic nature of art design determines that it has a very important role to play in the beautification of people’s lives and minds [4]. Through aesthetic activities in art work, people can enhance their aesthetic ability towards life, sublimate human and social emotions, and develop their own temperament. Thus, art and design can help the general public improve their self-cultivation and fully express the social culture and ideology of human beings at different times.

In everyday production and communication, the public consciously or unconsciously uses art and design to enhance group consciousness and social identity. This sense of group consciousness and social identity is reflected in the social attributes of human beings, specifically as the commonality or appeal of human emotions [5]. Through the interaction of human emotional commonalities or evocations in social groups, people can better understand each other in order to promote social prosperity. As the Swiss psychologist Junge says, “Only in fine art design do people understand a rhythm that allows all people to communicate their emotions, thus binding them into a whole.” Fine art painting, therefore, plays a very, very important role in promoting good relations between people and people and between people and society.

It is thus clear that art and design have made a great contribution to the building of human civilization, especially to the building of human spiritual civilization. This has led to a large number of artworks that are digitally collected and exchanged in various forums, social welfare organizations, and museums on the Internet [6]. But also to thoroughly understand the aesthetics of fine art paintings in everyday life [7]. Therefore, in order to cope with the promotion of fine art painting to the general public and the widespread need for analysis of fine art paintings by the general public, the distribution and processing of fine art paintings by computers instead of humans manually will greatly improve in terms of efficiency.

There are many tasks that need to be refined in the automated processing and analysis of fine art and design images, such as forgery detection [8], object retrieval [9], and...
archiving and retrieval of fine art and design works [10]. However, all of these tasks are derived from the classification task of art and design images. The task of classifying art and design images is therefore the most fundamental and most fundamentally solved motivation for automated processing and analysis.

Little attention has been paid to the automatic classification and discrimination of fine art images in existing work. This paper will therefore investigate the task of classifying styles, genres, and fine artists in fine art design images based on a deep learning approach. The method proposed in this paper can automatically classify fine art painting images with significant improvements in accuracy and efficiency.

2. Related Work

Most of the work in image processing has been slowly extended from natural images to specialized areas such as remote sensing images, infrared imaging, and fine art design. This is because natural images are simpler to collect and their content is easier to understand than other types of images [11].

For the classification task of natural images, many local or global features and machine learning methods are widely used. Among them, local features used include GIST, scale-invariant feature transform (SIFT) [12], etc. Classifiers for machine learning methods include support vector machines (SVM), k-nearest neighbor (KNN), improved Fisher encodings [13], and so on. Among the many machine learning methods, the main process for natural image classification is to first extract the image features and use a low-dimensional column vector to represent the features, and then input them into the classifier to obtain the classification results. In the process of classifying natural images based on machine learning methods, most of the effort is spent on feature extraction. Therefore, a good representation of the image features has a multiplier effect on the final classification result of the classifier.

For example, a typical approach for natural image classification tasks based on machine learning methods is the bag-of-words (BoW) model [14]. Typically, the bag of words model framework consists of three main processes: underlying feature extraction, feature encoding, and classifier design. Among them, the most critical step is feature extraction, and the process is time-consuming and laborious [15].

With the great success of machine learning-based methods for natural image classification [16], there has been some work that attempts to draw on classification methods on natural images to solve classification tasks related to fine art paintings. Jasinievicius et al. [17] proposed an improved Fisher encoding method which achieved better classification results for fine art painting images with less training data. [18] proposed a local feature called classemes based on natural images and experimentally verified that classemes local features can better represent the content of natural images than local features such as SIFT. For the classification task of fine art painting images, [19] used a machine learning approach based on classemes local features and experimentally demonstrated that classemes features showed superior performance compared to other local features. [20] K-nearest neighbor and support vector machine classification methods were compared on the classification task of fine art painting images, and it was shown that the K-nearest neighbor classifier outperformed the support vector machine classifier.

The size of the dataset they used was very limited and the model was constructed for only two types of classification problems (van Gogh vs. non-van Gogh). Pitcher et al. [21] used a grey-scale co-occurrence matrix as a feature to assess the authenticity of fine art paintings, which was effective for fine art painting images. Inspired by previous work, Grossberg [22] considered the factorization of the grey-scale co-occurrence matrix in four directions as a feature for classifying fine art painting images. In a study by Vanclay [23], four statistics of the grey-scale co-occurrence matrix: correlation, contrast, energy, and homogeneity, were calculated as deep-level features of fine art painting images.

A large body of work has shown that the success of deep learning methods relies on the availability of large-scale datasets with labels [24, 25]. However, for the classification task of fine art design images, the classification performance achieved directly using deep learning-based methods is poor, although these methods have achieved good classification performance on natural image classification tasks. One important reason is that there is a publicly available dataset of fine art paintings, but it only has 4266 fine art design images. [26] investigated the impact of the relationship between different features.

An in-depth study of residual networks in fine art painting images was conducted by Bharadwaj et al. [27] to address the task of detecting which style a fine art painting belongs to. These neural networks were initially pretrained on different classification tasks and showed how their performance improved when these networks were fine-tuned by layering a number of improved CNN structures to form a crosslayer CNN [28]. In the crosslayer CNN structure, each modified CNN structure is identical to Alex Net except that some convolutional layers are removed.

3. Image Acquisition Pixel Feature Representation

In order to achieve the beautification of the image, it is necessary to first decompose and express the pixel characteristics of the captured image. The image was captured using a Nikon D7100 digital imaging device with an autofocus lens, a set sensitivity of ISO 100, and an exposure time of 60 s. The output of the captured image was

\[ I(x) = f(x) + A(1 - t(x)). \]  

(1)

Under the effect of multiscale light supplementation, the color subspace and luminance of the night image are calculated, and the digital graphic image processing method is used to perform adaptive feature weighting on the captured image and edge contour feature extraction, and the constrained optimization solution vector of the image is defined as
\[
\begin{align*}
\min f(\vec{x}), & \quad \vec{x} = (x_1, x_2, \ldots, x_n) \in \mathbb{R}^n, \\
\text{s.t.} & \quad g_j(\vec{x}) \leq 0, \quad j = 1, 2, \ldots, l, \\
& \quad h_j(\vec{x}) = 0, \quad j = l + 1, l + 2, \ldots, p,
\end{align*}
\]  

(2)

where \(x \in \Omega\) denotes the feasible domain for uniform pixel traversal of the night image. Under dark lighting conditions, the output mathematical model of the captured image is set up and the image’s grey-scale pixel feature vector is constructed to obtain the output pixel expression of the night image capture as

\[
L = I(w, e) - \sum_{i=1}^{N} a_i \{w^T \varphi(x_i) + b + e_i - y_i\}. 
\]

(3)

The fusion process of the image is carried out using the constraint-optimized evolutionary method, and the scale decomposition and steady image processing are performed in the wavelet domain for the acquired night image. In order to improve the beautification capability of the image, the expression for analyzing the acquired pixel features of the right image in the pixel template \(m \times n\) is obtained by template matching as

\[
I(\vec{x}, y) = G(x, y, a_\beta) \sum L \cdot I(x) - f(\vec{x}) \vec{x}, \\
S(\vec{x}, y) = G(x, y, a_\beta) \sqrt{g_j(\vec{x}) \cdot h_j(\vec{x})}. 
\]

(4)

On the basis of the image pixel feature expression, the image noise reduction process is carried out in order to improve the beautification performance of the image. Under lighting background conditions with insufficient exposure intensity, the collected fine art image usually has noise, and the set of noise points of the image is

\[
W = \{m_i | i = 1, 2, \ldots, n\}. 
\]

(5)

Noise reduction process using wavelet noise reduction technique to give the mother wavelet function is as follows:

\[
\text{fitness}(\vec{x}) = \begin{cases} 
f(x), & \text{feasible}, \\
1 + rG(\vec{x}), & \text{otherwise}.
\end{cases}
\]

(6)

Within the continuously distributed feature space of the continuous image, the time-frequency decomposition is performed using the wavelet ridge transform to obtain a family of time-frequency composite weighting functions of the image \(\Psi_{ab}\) is obtained from \(\varphi(t)\) by the wavelet ridge transform, denoted as

\[
\Psi_{ab}(t) = [U(a, b)\varphi(t)] = \frac{1}{\sqrt{|a|}} \varphi(t - b/a),
\]

(7)

where \(U(a, b)\) is the Euclidean distance; the factor \(1/\sqrt{|a|}\) ensures the amplitude normalization of the ridge transform. In a complex illuminated background, let \(t(x) = e^{-\beta d(x)}\), where \(0 < t(x) < 1\) and \(t(x)\) denotes the neighborhood of feature point \(i\) of the image, be obtained by wavelet noise reduction, and the image grey-scale pixel features are

\[
c = \sum_{j=1}^{m} P(z(k)\varphi_{jk}^{k-1})P(z(k)\varphi_{jk}^{k-1}) = \sum_{j=1}^{m} A_j(k)\xi_j. 
\]

(8)

The blurred image obtained by wavelet noise reduction on a multisource chromatic illumination background is

\[
M = \min_{c \in C} \sqrt{\text{fitness}(\vec{x})} + \max_{P_2, \varphi_{ab}} P_2(\varphi_{ab}(t)), 
\]

(9)

where \(P_1\) and \(P_2\) are the time domain and frequency of the pixels in the neighborhood, respectively. Through the above processing, the image noise reduction preprocessing is achieved and the foundation for image beautification is laid.

4. Image Beautification

Process Implementation

This paper analyzes the application of computer graphics image processing technology in the fine arts and carries out image beautification processing on the basis of image noise reduction preprocessing. This paper proposes a beautification processing technique for night scene images based on multiple chromatic aberration compensation of illumination and adopts the light adaptive equalization technique for white balance optimization of night scene images, searches for thresholds based on the edge contour information of the image, and defines the neighborhood of the feature point \(i\) of the image noise distribution in terms of \(N_i\) as

\[
N_i = \{i' \in S | \text{dist}(i, i') \leq r, i \neq i'\}. 
\]

(10)

In the white balance processing of the night image, the white balance optimization of the night image is carried out using the light adaptive equalization technique. The distance of the pixels in the neighborhood of the right image to be beautified is described by \(\text{dist}(i, i')\) and \(r\) is a constant to obtain the multiple chromatic aberration kernel of the night image to be beautified

\[
R_i = \frac{1}{\sum_{j=1}^{N} g_j d(\|i - j\|_2)} \sum_{j=1}^{N} g_j d(\|i - j\|_2). 
\]

(11)

A morphological segmentation method is used to fully blindly deconvolute the image, and the adaptive equilibrium constraint function for the image color difference is obtained from the prior knowledge of the fuzzy kernel in the sparse prior regularization distribution space as

\[
\min kp = \lambda g_i + \beta g_j, 
\]

(12)

where \(\lambda\) and \(\beta\) are the regularization parameters. Based on the mathematical expression of the fuzzy kernel, the results of the white balance optimization of the night image are obtained as

\[
\text{LRT} = \min kp |R_i, N_i|^t. 
\]

(13)

The shadow region and luminance region segmentation curves are obtained by multithreshold segmentation of the image, which is described as
\[
G_{\text{nor}}(\vec{x}_i) = \frac{\sum_{j=1}^{p} G_j(\vec{x}_j) / G_{\text{max}}^j}{p},
\]

where \( i \in \{1, 2, \ldots, N\} \) is the sequence value. In the measurement of the whole image, the time overhead of the regular term of the blurred image is measured, and the blurring kernel of the high-frequency image \( y \) is obtained as

\[
\Omega = \{ \vec{x} \in s g_j(\vec{x}) \leq 0, j = 1, 2, \ldots, l; h_j(\vec{x}) \\
= 0, j = l + 1, l + 2, \ldots, p \}.
\]

The unconstrained iterative reweighted least-squares (IRLS) algorithm is used to update the fuzzy kernel, denoted as

\[
\min \vec{y} = f(\vec{x}) = (f_1(\vec{x}), f_2(\vec{x}), \ldots, f_m(\vec{x})),
\]

where \( \vec{x} = (x_1, x_2, \ldots, x_n) \notin X \subset \mathbb{R}^n \) is the initial value vector of each feature point of the beautified night scene image, \( X \) is the decision space for optimal evolution, \( \vec{y} \in Y \subset \mathbb{R}^m \) is the single-scale feature quantity of the shadow region of the night scene image to be beautified, and \( Y \) is the target space for optimal evolution. The image contour shadow deviation compensation achieves the low-frequency information superposition of the image, and the image contour shadow deviation compensation objective function is obtained as

\[
G(\vec{x}, \vec{y}) = \min \vec{y} \sum_{j=1}^{l} G_{\text{nor}}(\vec{x}_j) + \Omega^3.
\]

Through the light color difference of the shadow region and luminance region segmentation method, the contour shadow deviation compensation, improve the beautification effect of the night scene image, get the image contour shadow deviation compensation beautification process is shown in Figure 1.

5. Analysis of Simulation Experiments

Computer graphics image technology is used for image beautification and is applied in image art design. The simulation experiment of image processing is established in MATLAB 7 experimental platform. In the image acquisition, the original image is a 600 × 400 JPEG image. The threshold of light intensity of the image is set at \( \varepsilon = 1.0 \) and the high-frequency feature covariance of the 8 × 8 pixel grid direction in 9 directional blocks is used for image beautification to obtain the original acquired night image as shown in Figure 2.

As can be seen from Figure 2, the original image is not good due to underexposure and other reasons, so it is necessary to carry out image beautification processing, using the night scene image shown in Figure 2 as a test sample, using the wavelet noise reduction method for image noise reduction processing, through wavelet noise reduction to achieve information enhancement, to obtain the image processing effect as shown in Figure 3.

On the basis of the image effect processed in Figure 3, the light adaptive equalization technique is used to optimize the white balance of the image to improve the beautification effect of the night scene image, and the final output result after image beautification is obtained as shown in Figure 4.
The comparison between Figure 4 and the original image in Figure 2 shows that the beautification of the night scene image using this technique has better artistic presentation, improves the aesthetic and visual sensory expression performance of the image, and has better image beautification processing capability [29, 30].

The superiority of the FPTD proposed in this paper for the task of classifying fine art painting images is demonstrated. In these three sections, the classification performance is evaluated from a macro perspective by examining the overall top-1 error rate on the 3 subsets of style, genre, and artist. In this section, we delve into the impact of the classification performance of each of the categories included in the 3 subsets under different models.

For each of the three subsets, style, genre, and artist, we count the results of the classification experiments for all categories included in each subset under the two-channel model. The detailed classification results for all categories in each subset under the two-channel model can be found in Table 1 and 2. The 50-layer ResNet in Tables 1 and 2 also uses a two-channel architecture, unlike FPTD, where the DPN is displaced by the ResNet. That is, they differ only in the choice of network, while the two-channel architecture is identical.

The improvement in performance of FPTD for classifying style subsets is overall and not specific to individual style categories. The improvement in the classification performance of the genre subset by FPTD is overall and not specific to individual genre categories. Looking at the experimental results in Table 2, we see that there is a large difference in the classification performance of each category in the genre subset. For example, the still life category has a top-1
classification error rate of about 10% in the two-channel model, while the genre painting category has a top-1 classification error rate of about 50%. This shows that the classification performance of different categories in the genre subset varies greatly. Comparing the classification performances of the different two-channel models to that of the ResNet 50-layer two-channel model, we found that FPTD did not improve the classification performance of each class. On the contrary, the classification performance of FPTD in some classes is worse than that of the ResNet 50-layer two-channel model. Thus, we can also see that FPTD improves the overall classification performance, but not for all classes. We show some examples of paintings from the WikiArt dataset and the Gallerix dataset in Figure 5.

Thus, although images from both the WikiArt and Gallerix datasets are fine art painting images, they are still very different between classes, at least from visual observation. Therefore, this places a high demand on the generalization performance of the FPTD model proposed in this paper, and the learning model needs to be generalized from WikiArt to Gallerix to judge its robustness.

### Table 2: Subcategory names in the genre subset of the WikiArt dataset.

| Subcategory/top-1 error rate (%) | Two-channel deep learning model | 131 layer ResNet | 50 layer ResNet | FPTD |
|----------------------------------|---------------------------------|-----------------|----------------|------|
| Abstract                         | 1.17                            | 2.70            | 2.61           |
| Cityscape                        | 2.96                            | 2.55            | 2.56           |
| Genre painting                   | 5.48                            | 4.99            | 4.87           |
| Illustration                     | 3.21                            | 4.14            | 3.21           |
| Landscape                        | 2.56                            | 2.61            | 2.56           |
| Nude painting                    | 2.35                            | 2.56            | 2.35           |
| Portrait                         | 1.10                            | 2.78            | 1.10           |
| Religious painting               | 2.15                            | 3.96            | 2.15           |
| Sketch and study                 | 2.80                            | 2.26            | 2.80           |
| Still life                       | 5.23                            | 1.57            | 5.23           |

### 6. Conclusions

This paper analyzes the application problem of visual sensing technology in fine art under a deep learning model and proposes an image beautification processing technology based on multiple chromatic aberration compensation of light. The experimental analysis results show that the beautification processing of night scene images using the technology in this paper has better art presentation ability, improves the aesthetic and visual sensory expression performance of images, has better art application value, and demonstrates superior application performance.

### Data Availability

The data underlying the results presented in the study are available within the manuscript.

### Conflicts of Interest

The authors declare that there are no conflicts of interest with this journal, and that all authors have seen the manuscript and agreed to submit this journal for publication.

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