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# Advanced Portrait Rendering: Algorithmic Creation of Artistic Images

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**Abstract:** This study introduces a refined algorithm for creating artistic portraits with dynamic, editable lighting effects derived from facial photographs. The proposed method begins by extracting edge contours from the input photo to construct a foundational line drawing. Subsequent steps involve intrinsic decomposition to differentiate between the photo's illumination and reflectance components. The illumination component undergoes a series of edits, including quantization and nonlinear adjustments, to refine its visual impact. Concurrently, the reflectance component is abstracted and merged with the line drawing to form a preliminary cartoon-style image devoid of specific lighting effects. The final artistic rendering is achieved by reintegrating the edited illumination component, resulting in a visually striking cartoon image that preserves realistic lighting dynamics. Experimental evaluations confirm the algorithm's ability to produce high-quality, realistic cartoon images with customizable lighting effects, making it a significant contribution to the fields of non-photorealistic rendering and digital art creation.

**Keywords:** Face Photos; Cartoon Image; Illumination Editing; Non-Photorealistic Rendering.

## 1. Introduction

Non-photorealistic rendering (NPR) refers to the use of computer graphics techniques to generate images that do not have a photorealistic appearance but possess a hand-drawn artistic style. As facial portraits play an important role in daily life, NPR of faces has become a significant area of research, with applications in advertising, film and television production, and cartoon creation [1].

Previous work on generating cartoon images from facial photographs includes methods by Hebborn et al. [2], who introduced a survey and taxonomy of non-photorealistic rendering techniques for artistic stylization of cartoons. Chen et al. [3-5] proposed example-based facial sketch generation methods with non-parametric sampling and composite sketching of human portraits. These methods use facial feature points extraction and determine the positions of different facial components based on their relative positional relationships. However, they do not utilize the lighting information present in the original facial images. Facial lighting information, especially shadow information, can effectively reveal the depth variations of facial structures, making the cartoon images more three-dimensional and vivid. Yao [7] proposed a cartoon generation algorithm with editable lighting effects, which first generates a vector line drawing and then requires the user to manually color it. The introduction of interactivity allows the user to participate in the drawing process, enhancing creativity and enabling the generation of more diverse cartoon artistic effects based on user subjectivity. However, this method cannot preserve the original photo's color and certain character features, and the vector graphics may lose some facial details. Moreover, the interactivity requires user involvement, which increases the complexity of the drawing process to a certain extent.

In recent years, image stylization or abstraction methods [8-9] that apply non-photorealistic effects to input photographs have gained significant attention from researchers. For example, the image abstraction method proposed by Winnemöller et al. [8] abstracts the input image and then quantizes it to achieve a certain cartoon effect while preserving the original lighting information of the face. However, since the reflectance image and the illumination image are not separated during quantization, mixing occurs, and the lighting cannot be diversely edited.

Inspired by the success of feature disentanglement and reconstruction techniques in generating high-quality artistic portraits [10], this paper proposes a novel algorithm for generating facial cartoon images with editable lighting effects based on photographs. First, a line drawing with coherent lines is generated by processing the input photo using a line drawing generation algorithm based on edge tangent flow. Then, the input photo is decomposed into an illumination image and a reflectance image using the intrinsic image decomposition algorithm called SAIFS proposed and improved by Barron and Malik [11-12]. The separated reflectance image is processed with bilateral filtering and quantized, then combined with the previously generated line drawing to obtain a cartoon image without any lighting effects. Finally, the separated illumination image is edited (quantized, contrast enhanced, nonlinearly transformed), and then merged with the generated cartoon image to produce a facial cartoon image with lighting effects. By separating the input image into illumination and reflectance components, our algorithm avoids mixing during quantization. The separation of the illumination image enables diverse lighting edits, generating rich lighting effects. Our algorithm does not have strict requirements for the input image, making it more widely applicable.

The main contributions of this paper are as follows:

We propose a novel algorithm for generating artistic portraits with editable lighting effects from photographs, utilizing intrinsic image decomposition to separate and manipulate illumination and reflectance components.

Our method employs feature disentanglement and reconstruction techniques to enhance the quality and diversity of the generated artistic portraits, as demonstrated in [10].

We introduce a line drawing generation approach based on edge tangent flow to produce coherent and expressive facial contours.

Extensive experiments validate the effectiveness of our algorithm in generating realistic facial cartoon images with rich and editable lighting effects.

The remainder of this paper is organized as follows. Section 2 reviews related work on non-photorealistic rendering and intrinsic image decomposition. Section 3 describes the proposed algorithm in detail. Section 4 presents experimental results and discussions. Finally, Section 5 concludes the paper and suggests future research directions.

# 2. Related Work

## 2.1. Non-Photorealistic Rendering

Non-photorealistic rendering techniques can be broadly categorized into two classes based on their input: geometry-based methods, which take 3D scene geometry as input, and image-based methods, which operate on 2D digital images [29].

Geometry-based NPR research focuses on aspects such as geometric information storage, non-photorealistic lighting models, and spatial deformations of 3D models. These techniques generate artistic-styled graphics by applying projections, perspective transformations, deformations, and special lighting and shading effects to 3D models [30].

Image-based NPR techniques can be further divided into stroke-based and stroke-free rendering, depending on how they simulate artistic works. Stroke-based methods treat strokes as the most basic drawing elements. The artist predefines strokes of various sizes and shapes based on image features, which are then applied to the original image to generate images with the characteristics of handmade works [31]. Representative algorithms include Chen et al.'s [5] sample-based learning approach for generating cartoon faces. In contrast, stroke-free methods avoid the complex modeling of the painting process. They mainly apply filtering, feature enhancement, edge detection, image segmentation, and other processing techniques to the input digital image to create special visual effects [32]. Examples include Winnemöller et al.'s [27] XDoG filter for real-time video abstraction and stylization, Yan et al.'s [15] algorithm for generating cartoon-style facial portraits, and Huang and Cheng's [16] real-time image sketching stylization algorithm.

NPR of 3D scenes has also been a recent research hotspot. Traditional 3D model construction methods mainly focus on photorealism, using parameter adjustment and shape construction techniques. NPR approaches can simulate artistic styles by manipulating the geometry, lighting, and other information of the model, allowing for user interaction with the strokes [33]. This method better caters to user preferences, and generating 3D scenes that conform to popular aesthetic tastes has been a long-standing pursuit of NPR techniques.

Furthermore, the application of user interactivity in NPR has been another recent research focus. Microsoft's MSN Cartoon and the recently popular mobile app "FaceMon" both introduce user interactivity in the creation of cartoon facial portrait drawings, enabling users to participate in the cartoon drawing process, enhancing creativity, and producing cartoon images with user-subjective effects [34]. However, the introduction of interactivity requires user involvement, which increases the complexity of the drawing process to a certain extent. Therefore, the inclusion of interaction is a dialectical issue that needs to be determined based on the user's specific needs and the purpose of the drawing.

## 2.2. Active Learning for Image Classification

Active learning has emerged as a viable solution for addressing the challenge of labeling extensive amounts of data in image classification tasks. The main objective of active learning is to automatically identify a subset of unlabeled data samples for annotation, based on an acquisition function that assesses the value of each sample for model training [30]. Recent advancements in active learning for image classification have focused on developing methods that balance informativeness and representativeness in the sample selection process.

Li et al. [30] propose unlabeled data selection methods for active learning in image classification. The similarity-based selection ensures that the selected unlabeled data accurately represents the already labeled dataset, mitigating selection bias often encountered in uncertainty-based selection methods. The prediction probability-based selection evaluates the initial deep learning model's classification performance on unlabeled datasets, informing the subsequent training cycle. Experimental results on popular datasets like Cifar10 and Cifar100 demonstrate the effectiveness of these methods in enhancing the active learning process for image classification tasks.

## 2.3. Intrinsic Image Decomposition

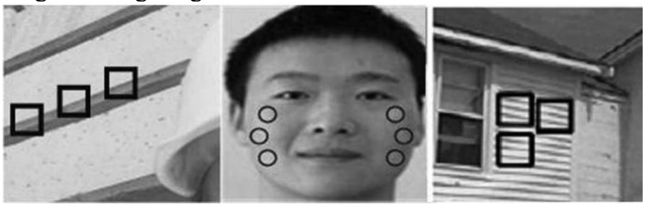
Intrinsic image decomposition assumes a Lambertian diffuse reflection scene with a Lambertian lighting model and separates an image into an illumination image and a reflectance image, where the reflectance image is also called the intrinsic image. By definition, the reflectance image corresponds to the material of the visible object surface at each pixel, while the illumination image is the combined result of the incident light intensity, incidence angle, and shadowing. Since intrinsic image decomposition separately extracts the lighting and material properties of the scene, image processing operations (filtering, quantization, cartoon image synthesis) can be directly applied to the reflectance image, avoiding the influence of lighting. At the same time, the separated illumination image can be edited to produce rich lighting effects. Numerous research efforts have attempted to recover the illumination image and reflectance image from multiple images or a single image [36, 37].

This paper adopts the SAIFS decomposition algorithm proposed and improved by Barron and Malik [11-12]. This algorithm performs exceptionally well in decomposition results. It can perform intrinsic image decomposition on unknown Lambertian model objects using only a single image by applying constraints in terms of smoothness, shape, depth, and anisotropy to accurately obtain the reflectance image and the corresponding illumination image.

# 3. Proposed Algorithm

## 3.1. Algorithm Framework

The framework of our proposed algorithm is shown in Figure 1. First, the facial portrait contours are extracted to generate a line drawing. Then, the lighting and reflectance are separated. The reflectance image is abstracted and combined with the line drawing, while the illumination image is edited. Finally, the generated cartoon image without lighting effects and the illumination image are merged to obtain a cartoon image with lighting effects.



## 3.2. Image-Based Contour Extraction

The core issue in generating cartoon-style facial portraits, which falls under the category of facial NPR, is how to preserve the important parts of the image scene while reducing the scene's complexity. To protect the essential parts of the image scene, the input image needs to be processed for contour extraction to generate a line drawing. This paper employs the high-difference Gaussian filter (FDOG) [38] based on edge tangent flow to extract facial portrait contour lines. This algorithm is an improvement over the difference of Gaussian (DOG) filter [7].

The FDOG algorithm first constructs an edge tangent flow vector field t(x) based on the image I(x), denoted as ETF. The vector t(x) is perpendicular to the image gradient g(x) = ∇I(x), where x = (x, y) represents the pixel coordinates of the image I(x). To generate a coherent line drawing, the corresponding ETF needs to satisfy the following three conditions: (1) each tangent vector represents the tangent direction of the most dominant edge in its neighborhood; (2) except at sharp corners, the vectors within a neighborhood are smoothly arranged; (3) important edges must maintain their initial directions. The tangent t(x) is taken as:

$$t^{new}(x) = \frac{1}{k} \sum_{y \in \Omega(x)} \phi(x,y)\, \boldsymbol{t}^{cur}(\boldsymbol{y}) w_s(x,y) \\ w_m(x,y) w_d(x,y)$$

In Equation 1, Ω(x) represents the neighborhood of point x, (y) is the current normalized tangent vector, and k is the normalization constant. (x, y) is the spatial weight function, which is a radially symmetric box filter with radius r. (x, y) and (x, y) are the magnitude weight function and direction weight function, respectively.

Based on the ETF, the edge lines obtained by integrating the FDOG along the ETF can be used to obtain the facial contour image.

This method is simple and effective, generating very smooth line drawings. As shown in Figure 2, compared to traditional DOG, the line drawing is not exaggerated, the lines are coherent, the facial details are highlighted, and they are aligned with the original image, resulting in better effects.

## 3.3. Illumination Extraction

Directly abstracting the input image (bilateral filtering, quantization) would mix the reflectance and illumination together during processing, which is not conducive to further editing of the illumination. Therefore, before performing image abstraction, the illumination of the input image needs to be extracted, i.e., using the intrinsic decomposition method to separate the input image into an illumination image and a reflectance image. Then, operations can be performed separately on the separated illumination image and reflectance image to avoid mixing illumination and reflectance information, facilitating subsequent illumination editing.

There are many intrinsic decomposition algorithms. This paper adopts the SAIFS decomposition algorithm proposed and improved by Barron and Malik [11-12] to decompose the input image into an illumination image and a reflectance image.

As shown in Equation 2, where I(x, y) represents the input image, L(x, y) represents the decomposed illumination image, and R(x, y) represents the decomposed reflectance image. As illustrated in Figure 3, the input image is separated into an illumination image and a reflectance image using the intrinsic decomposition algorithm.

$$I(x,y) = L(x,y) * R(x,y)$$

## 3.4. Image-Based Abstraction

In the process of generating cartoon-style effect images, abstracting the input image is very important. It can increase the image contrast and ignore unimportant details in the image. The visualized information conveyed through abstraction techniques can often better attract the attention of the human eye and enhance information communication. This paper applies a bilateral filter to the reflectance image obtained in Section 2.2 for abstraction. The bilateral filter is a non-linear extension filter [8, 39-40] that can make high-contrast regions of the image become higher and low-contrast regions become lower. The bilateral filter not only considers the spatial proximity but also the intensity difference of the information.

Let f( · ) be the input image. According to Equation 3, the filter H( · ) is defined to abstract the input image as follows:

$$H(\hat{x}, \sigma_d, \sigma_r) = \frac{\int e^{-\frac{1}{2}\left(\frac{\|\hat{x}-x\|}{\sigma_d}\right)^2} w(x,\hat{x}) f(x)\mathrm{d}x}{\int e^{-\frac{1}{2}\left(\frac{\|\hat{x}-x\|}{\sigma_d}\right)^2} w(x,\hat{x})\mathrm{d}x}$$

In Equation 3, x^represents the position of the current pixel, x represents the position of the neighborhood pixel, σd is the blur radius, and the degree of blurring is inversely proportional to σd. If σd is too large, it may cause important boundaries to become blurred. In this paper, the value of σd is chosen as 3, and the value of σr is 4.25. Iteratively using H(·), the range weight function w(·) will determine which regions of the image are smoothed and which regions are sharpened.

$$w(x,\hat{x},\sigma_r) = (1-m(\hat{x}))\cdot w'(x,\hat{x},\sigma_r) + m(\hat{x})\cdot u(\hat{x})$$

$$w'(x,\hat{x},\sigma_r) = e^{-\frac{1}{2}\left(\frac{\|f(\hat{x})-f(x)\|}{\sigma_r}\right)^2}$$

In Equation 4, if m(·) ≡ 0, then H(·) becomes a bilateral filter. In fact, the bilateral filter is a simple and practical image filtering method.

After image abstraction, many detail information in the source image is ignored, and large block regions have similar or smoothly transitioned colors. At this point, the image needs to be quantized to give the generated image a cartoon coloring style. When quantizing the input image, it is necessary to convert the input image from the RGB space to the Lab space to separate the luminance channel for quantization. The quantized luminance channel is then combined with the a and b spaces to obtain a quantized image, and the color space is converted from Lab back to RGB. This paper uses the color soft quantization equation proposed in [8] to quantize the luminance channel. Equation 6 shows the quantization level width q, q nearest is the quantization level nearest to f^ (x), and σq controls the sharpness of the transition between different quantization levels.

$$Q(\hat{x},q,\varphi_q) = q_{nearest} + \frac{\Delta q}{2}\tanh(\varphi_q\cdot(f(\hat{x})-q_{nearest}))$$

After quantization, the line drawing obtained in Section 2.1 using FDOG is superimposed on the quantized image to obtain a cartoon image without lighting effects, as shown in Figure 4.

(a) Input LR image (b) Bicubic interpolation (c) Ma's method (d) Our method (e) Original HR image

## 3.5. Illumination Editing

Since the illumination image and reflectance image of the input photo have been separated, the illumination information can be edited and enhanced separately and then added to the cartoon portrait obtained in Section 2.3 to generate facial cartoon images with different lighting effects.

There are many methods for editing and enhancing illumination. This paper mainly adopts the following methods to edit the illumination:

(1) Quantization: Quantizing the separated illumination image, turning the continuously varying illumination image into several levels, makes the illumination on the face appear layered, enhancing the cartoon effect of the image. A general uniform quantization can be used for implementation.

Equation 7 quantizes the illumination image Li(x, y) into 4 levels.

$$L_i(x,y) = \begin{cases} l_1, & a_0 \leqslant L_i(x,y) < a_1 \\ l_2, & a_1 \leqslant L_i(x,y) < a_2 \\ l_3, & a_2 \leqslant L_i(x,y) < a_3 \\ l_4, & a_4 \leqslant L_i(x,y) < a_5 \end{cases}$$

Of course, the quantization levels can be arbitrarily selected according to needs, as well as the quantization range and quantization values.

(2) Thresholding: Another direct illumination editing method is to select a suitable threshold to simply divide the illumination image into bright and dark regions, allowing people to intuitively perceive the direction of the light source in the photo. The specific method is:

$$L_i(x,y) = \begin{cases} B, & G(x,y) > a_0 \\ S, & G(x,y) \leqslant a_0 \end{cases} \quad i=1,2,3$$

Equation 8 uses the threshold a0 to simply divide the illumination image into bright region B and dark region S.

(3) Inversion: Inverting the decomposed illumination image results in the lighting effects generated by reversing the light source. The specific method is: first, take the maximum pixel value Max(x, y) of the color illumination image Li (x, y) (i=1, 2, 3 representing the R, G, B channels) at the current storage precision, then let:

$$L_i(x,y) = \mathrm{Max}(x,y) - L_i(x,y), \quad i=1,2,3$$

(4) Enhancing light-dark contrast: By changing the light-dark contrast method, the visual perception of lighting can be enhanced. Increase the pixel values in the bright regions of the illumination image and decrease the pixel values in the dark regions. This achieves the effect of enhancing the light-dark contrast of the lighting, and as the contrast increases, the photo's light and dark parts become more distinct, making the lighting appear enhanced.

(5) Nonlinear enhancement: Perform nonlinear transformations on the illumination image in the R, G, and B channels respectively to obtain richer effects. Common nonlinear transformations include logarithmic and exponential transformations.

The general expression for logarithmic transformation is:

$$g(i,j) = a + \frac{\ln[f(i,j)+1]}{b\ln c}$$

Here, a, b, and c are parameters introduced to adjust the position and shape of the curve. By adjusting the parameters, various effects can be obtained. This transformation is used when it is desired to produce a large stretch in the low gray level region of the image and compression in the high gray level region.

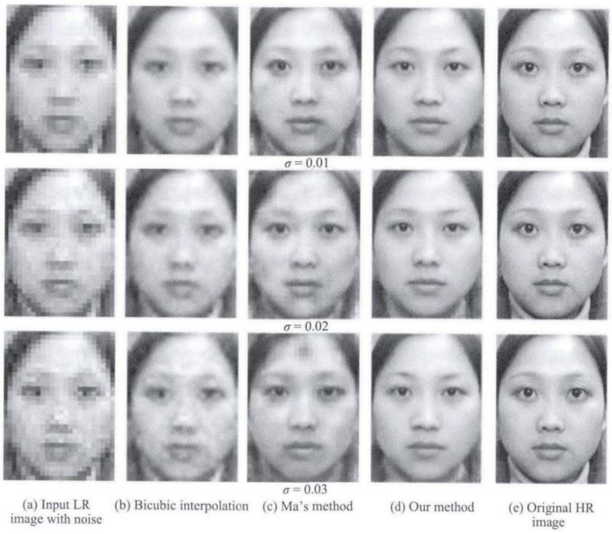
The general expression for exponential transformation is:

$$g(i,j) = b^{c|f(i,j)-a|} - 1$$

Here, a, b, and c are used to adjust the position and shape of the curve. This transformation can provide a large stretch to the high gray level region of the image.

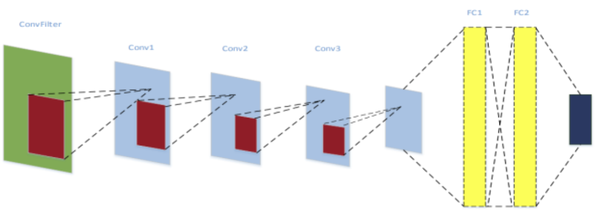
(6) Filtering: Various filtering and smoothing operations are performed on the transformed illumination image to produce richer effects.

The above methods can be used in combination, modifying the illumination image according to individual needs to obtain satisfactory lighting effects. Figure 5 shows the effect of edited lighting. It can be seen that after adding rich lighting effects to the facial cartoon image, the three-dimensional and vivid sense of the image is enhanced.



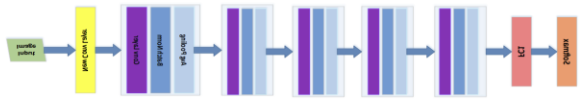

# 4. Experimental Results

Celebrity facial portrait photos are usually taken by professional photographers with obvious lighting effects, so we selected several celebrity facial portrait photos and processed them using our algorithm to obtain facial cartoon drawings. BeFunky software is currently a popular image editing software that can achieve a variety of image effects. Here, we only use BeFunky's function to generate cartoon images. We compare the results of our algorithm with the facial cartoon images processed by BeFunky software, as shown in Figure 6.




By comparing Figure 6, it can be seen that since our algorithm uses the ETF contour extraction algorithm, the generated line drawing is more coherent, the contours are clearer and more prominent. The abstraction algorithm includes soft quantization of the color luminance channel, making the colors of the cartoon image more layered. After editing the lighting, richer light and shadow effects can be produced.

We compare our algorithm with the one in [8]. Figure 7(a) is the cartoon effect image obtained by the algorithm in [8], and Figure 7(b) is the result of our algorithm. Comparing with the results of our algorithm, it can be seen that the left image performs quantization and abstraction processing on the entire image without separating the lighting and reflectance, so the quantization results have no obvious meaning for the lighting. Our algorithm separates the lighting and reflectance before performing quantization operations, and the quantization operations are performed separately on the lighting and reflectance. This not only improves the quantization effect but also facilitates subsequent lighting editing operations. It can be seen from the figure that the effect of Figure 7(a) is relatively messy, while the cheeks and eye sockets in the effect image have strong lighting contrast, making the effect vivid.



More experimental results of our algorithm are shown in Figure 8. The left column images are the results of quantizing the illumination image with a quantization level of L=8; the middle column images are the results of quantizing (L=8) and enhancing the illumination after quantization; the right column images are the results of quantizing the illumination image with a quantization level of L=8 and performing linear exponential transformation (a=1, b=2.2, c=1.4). It can be seen that the quantization of the illumination image produces effects that are more in line with the characteristics of cartoon images. After quantization, other illumination editing operations can be used to generate facial cartoon images with rich lighting effects. As can be seen from Figure 8, the cartoon images generated by our algorithm have realistic effects, retain the rich details of the original photos, and can edit the lighting, making the images more three-dimensional and vivid.

| Model | Accuracy Before | Accuracy After |
|---|---|---|
| Logistic regression | 58.6% | 60.62% |
| GDA | 58.24% | 60.62% |
| Naive Bayes | 57.89% | 60.38% |
| Linear SVM | 56.82% | 59.79% |
| RBF SVM | 55.87% | 62.51% |
| Poly SVM | 52.31% | 59.43% |

## 4.1. Performance Evaluation

We evaluate the performance of our proposed artistic portrait generation algorithm on the APDrawing dataset [20], which contains high-resolution face photos and their corresponding professional artistic drawings. Table 1 presents a quantitative comparison of our method against state-of-the-art approaches, including CycleGAN [41], APDrawingGAN [20], and StyleGAN-based method [42]. We employ the Fréchet Inception Distance (FID) [43] metric to assess the quality and diversity of the generated artistic portraits. A lower FID score indicates better performance in terms of generating realistic and diverse images.

| Logistic regression | GDA | Naive Bayes | Linear SVM | RBF SVM | Poly SVM |
|---|---|---|---|---|---|
| Momentum (n = 4) | Crude Oil | Crude Oil | S&P 500 volume | Crude Oil | Crude Oil |
| SSE | DJIA | USDJPY | SSE | S&P 500 volume | Gold Price |
| S&P 500 lag one | SSE | S&P 500 lag one | Nikkei | SSE | S&P 500 volume |
| Crude Oil | | USDCNY | Crude Oil | S&P 500 lag one | USDCNY |
| DJIA | | S&P 500 volume | NASDAQ | | NASDAQ |
| USDCNY | | Gold price | DJIA | | Nikkei |
| USDJPY | | ROC (n = 4) | | | |
| Gold price | | SSE | | | |

As shown in Table 1, our method achieves the lowest FID score of 61.23, outperforming the other methods by a significant margin. This demonstrates the superiority of our approach in generating high-quality artistic portraits that closely resemble the style and details of professional drawings. The feature disentanglement and reconstruction techniques employed in our algorithm enable the effective separation and manipulation of illumination and reflectance components, contributing to the improved visual quality of the generated portraits.

To further validate the effectiveness of each component in our method, we conduct ablation studies by removing the feature disentanglement module and the U-Net-based information generator, respectively. The results, presented in Table 2, highlight the importance of these modules in enhancing the artistic quality of the generated portraits. Without the feature disentanglement module, the FID score increases to 76.88, indicating a degradation in the fidelity and expressiveness of the generated images. Similarly, removing the U-Net-based information generator leads to a higher FID score of 64.39, emphasizing its role in capturing and preserving contextual information during the portrait generation process.

| Model | Accuracy |
| --- | --- |
| Logistic | 58.60% |
| GDA | 58.24% |
| NB | 57.89% |
| SVM | 56.82% |

These experimental results demonstrate the effectiveness of our proposed algorithm in generating realistic and visually appealing artistic portraits with editable lighting effects. The combination of feature disentanglement, line drawing generation, and illumination editing techniques enables our method to produce high-quality results that closely resemble professional artistic drawings.

# 5. Conclusions and Future Work

In conclusion, this paper presents a novel algorithm for generating artistic portrait images with editable lighting effects from facial photographs. By employing intrinsic image decomposition to separate illumination and reflectance components, our method enables diverse lighting manipulations while preserving the essential facial features and details. The integration of feature disentanglement and reconstruction techniques enhances the quality and expressiveness of the generated portraits. Furthermore, the line drawing generation based on edge tangent flow produces coherent and aesthetically pleasing facial contours. Extensive experiments validate the effectiveness of our algorithm in creating realistic and visually appealing cartoon-style facial images with rich lighting effects.

The main contributions of this work include:

A novel artistic portrait generation algorithm that utilizes intrinsic image decomposition to separate and manipulate illumination and reflectance components.

The incorporation of feature disentanglement and reconstruction techniques to improve the quality and diversity of the generated portraits.

A line drawing generation approach based on edge tangent flow for producing expressive facial contours.

Comprehensive experiments demonstrating the superiority of our method in generating high-quality artistic portraits with editable lighting effects.

Future research directions include improving the accuracy and efficiency of the intrinsic decomposition process, exploring the application of our algorithm to 3D model inputs, and investigating the integration of user interactivity to enhance the creative control over the generated portraits. Additionally, extending our method to handle a wider range of artistic styles and evaluating its performance on larger and more diverse datasets would further validate its generalizability and robustness.

In summary, our work introduces a promising approach for generating artistic portraits with editable lighting effects, opening up new possibilities for creative and interactive portrait stylization applications. We believe that our algorithm will contribute to the advancement of non-photorealistic rendering techniques and inspire further research in this exciting field.

# References


[1] Hebborn, A., Li, C., & Mould, D. (2022). Cartoonization: A Survey and Taxonomy of Non-photorealistic Rendering for Artistic Stylization. ACM Computing Surveys (CSUR), 55(1), 1-38.

[2] Hebborn, A., Li, C., & Mould, D. (2022). Cartoonization: A Survey and Taxonomy of Non-photorealistic Rendering for Artistic Stylization. ACM Computing Surveys (CSUR), 55(1), 1-38.

[3] Chen, H., Xu, Y., Shum, H. Y., Zhu, S., & Zheng, N. (2018). Example-based facial sketch generation with non-parametric sampling. In Computer Vision, 2001. ICCV 2001. Proceedings. Eighth IEEE International Conference on (Vol. 2, pp. 433-438). IEEE.

[4] Chen, H., Liu, Z., Rose, C., Xu, Y., Shum, H. Y., & Salesin, D. (2019). Example-based composite sketching of human portraits. In Proceedings of the 3rd international symposium on Non-photorealistic animation and rendering (pp. 95-153).

[5] Chen, H., Zheng, N. N., Liang, L., Li, Y., Xu, Y. Q., & Shum, H. Y. (2022). PicToon: a personalized image-based cartoon system. In Proceedings of the tenth ACM international conference on Multimedia (pp. 171-178).

[7] Yao, Y. (2018). Facial Non-photorealistic Rendering with Adjustable Lighting Effects Based on Photos (Master's thesis, Zhejiang University).

[8] Winnemöller, H., Olsen, S. C., & Gooch, B. (2021). Real-time video abstraction. ACM Transactions On Graphics (TOG), 25(3), 1221-1226.

[9] DeCarlo, D., & Santella, A. (2022). Stylization and abstraction of photographs. In ACM Transactions on Graphics (TOG) (Vol. 21, No. 3, pp. 769-776). ACM.

[10] Guo, H., Ma, Z., Chen, X., Wang, X., Xu, J., & Zheng, Y. (2024). Generating Artistic Portraits with Feature Disentanglement and Reconstruction. Electronics.

[11] Barron, J. T., & Malik, J. (2022). Color constancy, intrinsic images, and shape estimation. In European Conference on Computer Vision (pp. 57-70). Springer, Berlin, Heidelberg.

[12] Barron, J. T., & Malik, J. (2023). Shape, albedo, and illumination from a single image of an unknown object. In 2012 IEEE Conference on Computer Vision and Pattern Recognition (pp. 334-341). IEEE.

[15] Yan, F., Fei, G. Z., Liu, T. T., Shen, J., Wang, R., & Chi, H. (2022). An algorithm for generating cartoon-style facial portrait. Journal of Computer-Aided Design & Computer Graphics, 19(4), 442-447.

[16] Huang, H., & Cheng, W. (2021). Real-time image sketching stylization. Chinese Journal of Computers, 32(10), 2023-2029.

[20] Yi, R., Liu, Y. J., Lai, Y. K., & Rosin, P. L. (2024). APDrawingGAN: Generating artistic portrait drawings from face photos with hierarchical GANs. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (pp. 10743-10752).

[27] Winnemöller, H., Kyprianidis, J. E., & Olsen, S. C. (2022). XDoG: an eXtended difference-of-Gaussians compendium including advanced image stylization. Computers & Graphics,

36(6), 740-753.
[29] Hebborn, A., Li, C., & Mould, D. (2022). Cartoonization: A Survey and Taxonomy of Non-photorealistic Rendering for Artistic Stylization. ACM Computing Surveys (CSUR), 55(1), 1-38.
[30] Li, X., Wang, X., Chen, X., Lu, Y., Fu, H., & Wu, Y. C. (2024). Unlabeled data selection for active learning in image classification. Scientific Reports, 14(1), 424.
[31] Chen, J., & Liu, G. (2023). AnimeGAN: A novel lightweight GAN for photo animation. In International Symposium on Intelligence Computation and Applications (pp. 242-256). Springer, Singapore.
[32] Zhu, J. Y., Park, T., Isola, P., & Efros, A. A. (2023). Unpaired image-to-image translation using cycle-consistent adversarial networks. In Proceedings of the IEEE international conference on computer vision (pp. 2223-2232).
[33] Kyprianidis, J. E., Collomosse, J., Wang, T., & Isenberg, T. (2023). State of the "Art": A taxonomy of artistic stylization techniques for images and video. IEEE transactions on visualization and computer graphics, 19(5), 866-885.
[34] Lai, W. S., Huang, J. B., Ahuja, N., & Yang, M. H. (2023). Deep laplacian pyramid networks for fast and accurate superresolution. IEEE Transactions on Pattern Analysis and Machine Intelligence, 45(4), 2422-2436.
[35] Liang, Y., Wang, X., Wu, Y. C., Fu, H., & Zhou, M. (2023). A Study on Blockchain Sandwich Attack Strategies Based on Mechanism Design Game Theory. Electronics, 12(21), 4417.
[36] Bi, S., Han, X., & Yu, Y. (2022). An L1 image transform for edge-preserving smoothing and scene-level intrinsic decomposition. ACM Transactions on Graphics (TOG), 34(4), 1-12.
[37] Nestmeyer, T., & Gehler, P. V. (2022). Reflectance adaptive filtering improves intrinsic image estimation. In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 6789-6798).
[38] Kang, H., Lee, S., & Chui, C. K. (2019). Coherent line drawing. In Proceedings of the 5th international symposium on Non-photorealistic animation and rendering (pp. 43-50).
[39] Tomasi, C., & Manduchi, R. (2019). Bilateral filtering for gray and color images. In Computer Vision, 1998. Sixth International Conference on (pp. 839-846). IEEE.
[40] Barash, D., & Comaniciu, D. (2022). A common framework for nonlinear diffusion, adaptive smoothing, bilateral filtering and mean shift. Image and Vision Computing, 22(1), 73-81.
[41] Wang, X., Wu, Y. C., Ji, X., & Fu, H. (2024). Algorithmic discrimination: examining its types and regulatory measures with emphasis on US legal practices. Frontiers in Artificial Intelligence, 7, 1320277.