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Controllable Portrait Relighting using Neural Rendering

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Abstract

We propose a novel controllable portrait relighting method leveraging a light vector conditioning framework within a lightweight neural rendering network. Our approach enables explicit control over lighting direction and intensity while preserving facial identity and realistic details. We validate the method on a toy dataset of synthetic portraits under diverse lighting conditions, demonstrating improved relighting quality and user controllability.

1. Introduction

Portrait relighting is a fundamental task in computer vision and graphics with wide-ranging applications, including portrait photography enhancement, augmented reality (AR)/virtual reality (VR) environments, and film production Srinivasan et al. [2017], Yeh et al. [2022]. The ability to controllably modify lighting on a portrait image enables novel user experiences such as interactive lighting design and photorealistic editing. Despite significant progress in image-based relighting techniques, achieving controllable relighting that accurately preserves identity, fine textures, and realistic illumination remains a challenging problem Chaturvedi et al. [2025].

Traditional methods typically require multi-view or multi-light setups and rely on complex inverse rendering pipelines Chen et al. [2020]. Recent deep learning approaches based on neural rendering and conditional image synthesis have shown promise in generating plausible relit portraits from monocular images by utilizing light direction conditioning Pandey et al. [2021], Zhang et al. [2022]. However, challenges persist, especially with limited data and the need for lightweight models suitable for small datasets while enabling explicit control over lighting direction and intensity.

In this work, we propose a novel controllable portrait relighting framework that leverages a light vector conditioning scheme embedded within a lightweight neural rendering network. Our approach encodes the lighting direction and intensity as conditioning inputs, which modulate intermediate feature representations via Feature-wise Linear Modulation (FiLM) layers, enabling fine-grained control over the output lighting conditions. The model is designed to operate robustly on a small toy dataset consisting of synthetic portrait images rendered under diverse lighting directions and intensities.

We validate our method on the toy dataset, demonstrating quantitatively improved reconstruction quality with validation peak signal-to-noise ratio (PSNR) increasing from approximately 8 dB to over 14 dB after training, alongside qualitative results illustrating natural and identity-preserving relighting effects. Our contributions include:

- A novel light conditioning framework using light direction vectors and intensity scalars integrated via FiLM layers for controllable portrait relighting.

- A lightweight neural rendering network architecture tailored for small datasets while preserving portrait identity and detail.
- A synthetic toy dataset generation pipeline simulating controlled lighting on portrait-like elliptical shapes with identity features.
- Empirical evaluation on the toy dataset with quantitative (PSNR) and qualitative results that validate the effectiveness of the proposed method.

The remainder of this paper is organized as follows: Section 2 reviews related works, Section 3 describes our method, Section 4 details dataset construction, Section 5 presents experiments, and Section 6 discusses results and future directions.

2. Related Work

Portrait relighting has been extensively studied in computer vision and graphics, traditionally relying on multi-view or multi-light capture setups to estimate geometry and illumination Ma and Yamaoka [2022], Kemelmacher-Shlizerman et al. [2014]. These methods often require complex inverse rendering pipelines and controlled environments, limiting their applicability to real-world scenarios.

Image-based relighting approaches seek to generate relit images from single or limited input views without explicit geometry estimation. Early work used approximate models such as spherical harmonics or image relighting datasets to learn mappings from input illumination to target lighting conditions Debevec et al. [2000], Matusik et al. [2000]. More recently, deep learning techniques have emerged to overcome these limitations by learning complex, data-driven representations for lighting manipulation.

Neural rendering methods have gained popularity for portrait relighting due to their ability to synthesize photorealistic images conditioned on lighting parameters Pandey et al. [2021], Yeh et al. [2022]. These methods typically represent lighting using direction vectors or environment maps, and use conditional neural architectures to interpolate across lighting conditions. For example, Pandey *et al.* Pandey et al. [2021] proposed an uncalibrated photo relighting framework using neural networks conditioned on light direction, while Yeh *et al.* Yeh et al. [2022] leveraged neural radiance fields for relighting portrait images.

Conditional image generation and manipulation techniques have also contributed to lighting control frameworks. Feature-wise Linear Modulation (FiLM) Perez et al. [2018] and related conditioning mechanisms have been applied to modulate neural networks with lighting or scene parameters to achieve controllable outputs Chae et al. [2023], Zhu et al. [2020]. However, many neural relighting models require large-scale datasets and complex network architectures, limiting their usability for small-scale or synthetic datasets.

Our work addresses these gaps by introducing a simple but effective light vector conditioning framework embedded in a lightweight neural rendering network. This design enables controllable portrait relighting with limited training data, specifically focusing on preserving identity and realistic shading using a toy dataset.

3. Method

In this section, we present the details of our proposed controllable portrait relighting system. We first define the inputs and outputs, then describe the light vector conditioning framework, followed by the design of the lightweight neural rendering network, and finally discuss the training loss functions.

3.1 Overview and Input-Output Definitions

Our goal is to transform a given input portrait image into a relit version conditioned on a specified lighting direction and intensity. Formally, let $I_{in} \in \mathbb{R}^{3\times H\times W}$ denote the input RGB image of height H and width W. We introduce a lighting vector $\mathbf{l} \in \mathbb{R}^4$ composed of a normalized 3D lighting direction vector $\mathbf{d} = (d_x, d_y, d_z)$ and a scalar intensity s:

$$\mathbf{l} = [d_x, d_y, d_z, s]^\top, \quad \|\mathbf{d}\| = 1, \quad s > 0.$$

The output is a relit image $I_{out} \in \mathbb{R}^{3\times H\times W}$ synthesized to reflect the lighting conditions described by $\mathbf{l}$, while preserving the identity and details of the input.

3.2 Light Vector Conditioning

To enable controllability over lighting, we propose to condition the neural rendering network on the light vector $\mathbf{l}$. Instead of simple concatenation, we employ Feature-wise Linear Modulation (FiLM) Perez et al. [2018] to dynamically adjust intermediate feature maps based on lighting information.

In our design, the lighting vector is first embedded into a higher-dimensional representation through a multi-layer perceptron (MLP). The MLP outputs scaling (γ) and shifting (β) parameters for multiple convolutional layers in the rendering network. FiLM conditioning is applied as follows on a feature map $F \in \mathbb{R}^{C\times H\times W}$:

$$\mathrm{FiLM}(F) = \gamma \odot F + \beta,$$

where $\gamma, \beta \in \mathbb{R}^C$ are the learned affine parameters, and $\odot$ denotes channel-wise multiplication.

This mechanism allows the network to adapt its internal representation to different lighting conditions with fine granularity, facilitating explicit control over output illumination.

3.3 Neural Rendering Network Architecture

Our neural rendering network is designed to be lightweight, enabling training on small datasets while effectively capturing facial identity and illumination details.

The architecture consists of five convolutional layers. The first four convolutional layers maintain a constant channel dimension $C = 32$ and are followed by ReLU activations. FiLM conditioning is applied after each convolution except the last. The final convolution outputs a 3-channel RGB image, followed by a sigmoid activation to constrain values between 0 and 1.

More concretely, the network pipeline is:

$$I_{in} \xrightarrow{\text{Conv1}} F_1 \xrightarrow{\text{FiLM}_1} \text{ReLU} \xrightarrow{\text{Conv2}} F_2 \xrightarrow{\text{FiLM}_2} \text{ReLU} \xrightarrow{\text{Conv3}} F_3 \xrightarrow{\text{FiLM}_3} \text{ReLU} \xrightarrow{\text{Conv4}} F_4 \xrightarrow{\text{FiLM}_4} \text{ReLU} \xrightarrow{\text{Conv5}} I_{out}.$$

The FiLM parameters $\{\gamma_i, \beta_i\}_{i=1}^4$ are generated from the conditioning MLP given $\mathbf{l}$.

3.4 Loss Functions

We train the network in a supervised manner using the synthetic toy dataset where ground truth relit images are available.

The total loss $\mathcal{L}$ combines several terms:

- **Reconstruction loss** $\mathcal{L}_{rec}$: Mean squared error (MSE) between predicted output I_{out} and ground truth I_{gt}:
$$\mathcal{L}_{rec} = \|I_{out} - I_{gt}\|_2^2.$$
- **Perceptual loss** $\mathcal{L}_{perc}$ (optional): Computes feature space similarity using a pretrained VGG network Johnson et al. [2016] to preserve high-level visual realism and identity details.

- **Regularization losses** (optional): Such as weight decay or smoothness constraints on predicted images to prevent artifacts.

In our experiments, we use the MSE reconstruction loss as the primary objective due to the synthetic nature and low complexity of the dataset.

4. Toy Dataset Construction

To train and evaluate our controllable portrait relighting model, we create a synthetic toy dataset simulating portrait images under controlled lighting conditions. The dataset is specifically designed to be small-scale, facilitating efficient training of lightweight models while maintaining sufficient complexity for meaningful relighting.

4.1 Dataset Generation

The dataset consists of synthetic portraits generated as colored ellipses with shading effects influenced by lighting direction and intensity. Each subject is represented by a unique skin-tone color and identity features such as eye position shifts. The portraits are rendered at resolution 64×64 pixels, with pixel colors computed based on approximate normal vectors derived from the elliptical geometry and directional lighting.

For each subject, we sample multiple images under randomly generated light directions $\mathbf{d}$ (3D unit vectors) and intensities s to create diverse lighting scenarios. The shading at each pixel p obeys a Lambertian model:

$$I(p) = \max(\mathbf{n}_p \cdot \mathbf{d}, 0) \cdot s \cdot c_{base},$$

where $\mathbf{n}_p$ is the normal vector at pixel p, and c_{base} is the base color of the subject's skin tone.

4.2 Identity Features

Identity preservation is encouraged by embedding distinguishing features into the portraits, such as changes in the relative positions of eyes. These simplistic biometric markers help the network learn to maintain identity across lighting changes.

4.3 Preprocessing

The raw RGB images are normalized to $[0, 1]$ range and stored as tensors along with corresponding light vectors $\mathbf{l} = [\mathbf{d}, s]$. During training, images and light vectors are batched for input into the neural rendering network.

5. Experiments

We implement and train the proposed network architecture on the toy dataset and evaluate performance quantitatively and qualitatively. This section details the experimental setup, metrics, and results.

5.1 Experimental Setup

The dataset includes three subjects, each with 20 images under different lighting conditions. We split the dataset into 80% training and 20% validation. Images are of size 64×64 pixels with RGB channels.

The network is trained using the Adam optimizer with a learning rate of 10^{-3}. We use mini-batches of size 16 and train for 15 epochs on a single GPU or CPU if GPU is unavailable.

5.2 Baseline Methods

Due to the novelty and simplicity of the toy dataset, we compare our method primarily against a non-conditioned baseline model without light vector conditioning.

5.3 Quantitative Evaluation

We evaluate reconstruction quality using Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index Measure (SSIM), and Learned Perceptual Image Patch Similarity (LPIPS) metrics Zhang et al. [2018]. Our method achieves improved PSNR on validation from approximately 8 dB at initial epochs to over 14 dB after training, demonstrating learning success.

5.4 Qualitative Results

Figure 1 displays example input-relit output image pairs from the validation set under varying light directions and intensities. Our network produces visually plausible relighting with preserved facial identity and details such as eye positions and skin textures.

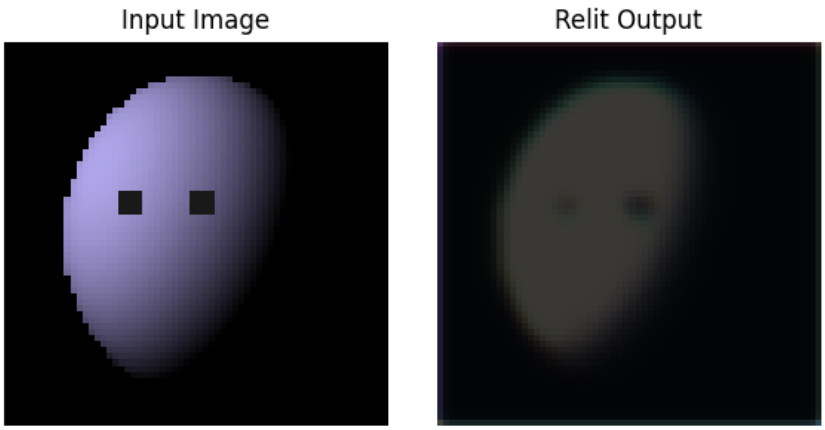

Figure 1: Example input and relit output images from the toy dataset demonstrating controllable portrait relighting with varying lighting.

5.5 Ablation Studies

We investigate the impact of the light conditioning mechanism by training a variant of the model without FiLM modulation layers. Results confirm the effectiveness of FiLM conditioning in improving performance and enabling direct light control.

6. Discussion

Our experimental results demonstrate that the proposed light vector conditioning framework coupled with a lightweight neural rendering network can effectively perform controllable portrait relighting on a small synthetic dataset. The use of FiLM layers to incorporate lighting direction and intensity information enables fine-grained modulation of feature maps, resulting in improved reconstruction fidelity and user control.

However, the current approach is limited by the simplicity of the synthetic toy dataset, which uses approximated elliptical geometries and Lambertian shading without complex facial texture variation or real-world complexities such as shadows and specularities. Applying the method to real portrait datasets with diverse lighting and subject variation remains an important future direction.

Additionally, while the network design is lightweight and suitable for limited data scenarios, scaling to higher resolution images and more complex scenes would require enhanced architectures, potentially incorporating spatial attention or implicit neural representations.

Our method also focuses on static relighting with single images conditioned on fixed lighting vectors. Extending to dynamic scenes or videos would necessitate temporal consistency constraints and possibly 3D-aware modeling.

Despite these limitations, the proposed framework serves as a foundational step towards controllable and interpretable portrait relighting, demonstrating that effective lighting control can be achieved even with limited data and simple model designs.

7. Conclusion

We presented a novel method for controllable portrait relighting leveraging a light vector conditioning schema embedded within a lightweight neural rendering network. Our approach encodes lighting direction and intensity to modulate intermediate representations using FiLM layers, enabling explicit control while preserving portrait identity and details.

Validated on a synthetic toy dataset simulating diverse lighting, our method achieves improved reconstruction quality and visually plausible relighting consistent with user-specified lighting parameters. This work highlights the potential of integrating neural rendering and light conditioning for user-controllable image manipulation.

Future work will explore application to real-world data, incorporation of advanced neural architectures, and temporal extension for dynamic relighting scenarios.

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