Local Relighting of Real Scenes

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Figure 1. Can we use deep generative models to edit real scenes “in the wild”? We propose using a pretrained generator model to generate an unbounded dataset of paired images to train an image-to-image translation model to relight visible light sources in real scenes. In the examples above, the original photo is highlighted with a red border. We show that our unsupervised method is able to turn on light sources present in the training domain (i.e. lamps) in (a). Additionally, our method can detect and adjust prelit light sources that are way outside its training domain, such as fire fans (b), traffic lights (c), and road signs (d).

Abstract

We introduce the task of local relighting, which changes a photograph of a scene by switching on and off the light sources that are visible within the image. This new task differs from the traditional image relighting problem, as it introduces the challenge of detecting light sources and inferring the pattern of light that emanates from them. We propose an approach for local relighting that trains a model without supervision of any novel image dataset by using synthetically generated image pairs from another model. Concretely, we collect paired training images from a stylespace-manipulated GAN; then we use these images to train a conditional image-to-image model. To benchmark local relighting, we introduce Lonoff, a collection of 306 precisely aligned images taken in indoor spaces with different combinations of lights switched on. We show that our method significantly outperforms baseline methods based on GAN inversion. Finally, we demonstrate extensions of our method that control different light sources separately. We invite the community to tackle this new task of local relighting.

*Shahin Mahdizadehaghdam and Rohit Kumar were at Signify when this work was done.
1. Introduction

The desire to turn on or off the lights in a photograph is a longstanding challenge in computer vision: changing lighting is widely useful, but it is also difficult because the physics of light transport make no distinction between a photon that arrives due to a bright intrinsic color, a well-aligned surface normal, or a strong light source. The problem of altering a 2d scene to change the direction of distant “global light” that illuminates the objects in a scene is a topic of ongoing research [3]. However, the task of altering what we call local relighting, in which the light source to be changed is itself within the scene, has not yet been characterized.

Our paper poses the following questions: Is it possible to relight a 2d image where the light source is visible in the scene? If so, how can it be done, and how can success be measured?

The first significant problem is the absence of any existing dataset that establishes a ground truth that shows exactly how a scene would appear if local lights are changed. Therefore, we introduce a new dataset of ground-truth images of identical scenes under different local lighting conditions. The dataset contains 306 images of 9 scene categories in which a set of photographs is precisely aligned, in which the only change is the the lighting condition. Figure 2 illustrates some examples of this curated dataset. The cost of collecting such a dataset is high, so the scale of the dataset is useful for benchmarking, but not training a large model.

The second significant problem is that presence of the light source in a scene introduces the challenge of recognizing the light source as well as the illumination attributed to it. Classic computer graphics techniques are insufficient, so we turn to deep learning. Typically deep learning methods require a wealth of labeled training data in order to solve a problem, but in this case we have only a small number of paired images. We shall demonstrate that nevertheless, it is possible to design a nearly fully unsupervised training procedure that creates a model that can relight many local light sources in real scenes. The training relies only on unpaired images; it can be done without image labels nor collection of a large dedicated lighting dataset. As part of our contribution, we show how to use a pretrained image synthesis model to generate paired training images, giving us an unbounded number of training samples. This data source is used to train an image-to-image translation model to apply the relighting technique to real images “in the wild” as illustrated in Fig. 1.

Furthermore, we demonstrate that by exploiting a widely-available object segmentation model, we can extend the training method to provide fine-grained control that allows a user to select which light to turn on or off.

In this paper we make the following contributions:

- We introduce a carefully curated dataset of scenes under varied lighting conditions as a ground truth for benchmarking the local relighting challenge.
- We introduce an unsupervised method for tackling local relighting by using a pretrained model to generate an unbounded number of paired data as the only data source to train another model to relight real scenes.
- We introduce a “user selective” method that allows users to control which lights are to be turned on and off. Our method exploits segmentation information during the training process. Our code can be accessed here. Our benchmark dataset will be made available upon publication.

2. Related Work

Image Relighting. Image relighting is the problem of rendering a scene under different and novel lighting conditions. Traditional methods addressed this problem by modelling the light transportation function, i.e., the function that maps the incident illumination from a specific direction to the radiance at each pixel of the image. This modelling was done by gathering a large number of images from the same scene in order to interpolate new lighting conditions [13,17,18,20]. In contrast to the need of having large collections of images of the same space to model the light transportation function, Xu et al. [27] presented a deep learning approach based that only requires 5 images of a scene to reproduce scene appearance under any directional light lying in the visible hemisphere. They accomplish this training a deep convolutional neural network for relighting using a large synthetic dataset. More recently, El Helou et al. [9] introduced the VIDIT dataset, a collection of images showing versions of the same scene under varying global lighting conditions, with the light source being out of frame, facilitating the training of deep learning models. Later, El Helou et al. [3] has posed the task of reconstructing a given scene with new global lighting settings of an input image, given the scene’s depth map. The depth map enables approaches that construct a physical understanding of the scene, such as using features for texture and structure [28], for albedo and shading [29], or disentangling intrinsic structure from lighting [24]. Using VIDIT, [4] trained a conditional image to image translation model to relight images in the 8 cardinal directions. For the problem of local relighting, there is no existing dataset depicting the scenes under varying local lighting that is large enough to reliably train a complex model.

Semantic image editing. StyleGAN2 [15] [16], a state of the art image synthesis model, maps a latent $z$ into another latent space $w$ to create a representation disentangled
for meaningful image attributes. Realistic semantic image edits can be made by steering latents in optimized directions [7, 12, 19], or by finding and activating neurons that encode semantic concepts [2]. Bau et al. [1] used a user specified mask to decouple $w$ latents, enabling region specific edits while preserving the content of unmasked areas. Wu et al. [25] discovered that the channel-wise style latent space (StyleSpace) of StyleGAN is significantly more disentangled than other latent spaces. Thus, manipulation of StyleSpace enables fine control of specific image attributes.

GAN inversion methods. The semantic editing methods described above can only be directly applied onto generated images. In order to apply such semantic edits to real images, the image must be inverted into a GAN latent space representation first, which is a nontrivial challenge. Existing GAN inversion methods include [6, 14, 21, 33]. Our method works around the difficult GAN inversion problem by using image-to-image translation methods instead to preserve the structure of original image, similar to [22]. However, while [22] requires a classifier pretrained with facial attribute labels to train their image-to-image translation model, our training method does not require supervision.

3. Lonoff Dataset

The 'Lights on/off' Dataset (Lonoff) is a collection of images taken in indoor spaces under different illumination conditions. Concretely, in each space we collected several different pictures, including different combinations of light sources switched on. In general, when the switches allow to switch on each light separately, all the possible light combinations are included for each scene. For example, if a space contains three light sources or lamps, denoted by $l_1, l_2, l_3$, the dataset contains a total of 7 images of this space: 3 images with just one light switched on, $\binom{3}{1}$ images with two lights switched on ($\{l_1, l_2\}, \{l_1, l_3\}, \{l_2, l_3\}$), and 1 image with all the three lights switched on. The images are taken using a tripod so that the location of the camera is the same for all the images collected in the same space. Fig.2 shows all the images of two of the spaces included in the Lonoff dataset: a dining room (a) and a kitchen (b). Notice that in the example of the kitchen, the light sources include lamps as well as a window. In particular, the last image of the kitchen space shows the kitchen illuminated just with the light that comes through the widow, with all the lamps switched off.

The Lonoff dataset contains images of 9 place categories: bathroom, bedroom, corridor, dining room, entrance, kitchen, living room, storage room, and studio. Fig.3.a shows the number of spaces per place category and Fig.3.b shows the number of images per space histogram. We observe there is just one space that contains 15 different pictures, with is the living room shown in Fig.2.a.

The dataset also includes the following manual annotations: segmentation of all the light sources, light source category (ceiling recessed light, floor lamp, fluorescent tube, flush mount light, light troffer, pendant lamp, sconce, spotlight, table lamp, or window), segmentation of the light source parts (e.g. column, shade, arm, aperture, backplate), and the on/off attribute per light source, indicating whether the light source is switched on or not.

The intent of the Lonoff dataset is to provide a detailed and curated dataset for testing indoor illumination understanding models.
4. Methods

In this section, we formalize our objectives on how to train a generative model by learning from another generative model as the source of data, how to relight scenes without supervision, and how to selectively edit light sources.

4.1. Using a GAN to generate training data

How do we train a model to relight a visible light source without a large training dataset? An ideal training dataset would supply a large number of paired examples of scenes in which the only difference between the pair of images is a change in lighting. However, collecting such a large-scale dataset is prohibitive.

Instead, we propose using a pretrained generative model as a source of training data. It has been observed that state-of-the-art GANs such as StyleGAN2 disentangle meaningful factors of variation in their latent channels [25]. For example, by altering a single channel, StyleGAN2 can change a single image attribute, such as a person’s hairstyle, or a car’s wheel angle. We have observed that StyleGAN2 will alter a single channel, StyleGAN2 can change a single image attribute, such as a person’s hairstyle, or a car’s wheel angle. We have observed that StyleGAN2 will...
though pix2pix does not disentangle a latent for lighting, we can teach it to edit lighting by training it to translate images from.

Our first task is to relight a scene in an unsupervised manner. Because there is no user input on which specific light source should be relit, this task assumes that all visible light sources should be altered.

In order to control the intensity of lighting in the relit scene, we introduce modulation to the ResNet blocks [8] in the bottleneck of $G_c$. Our modulation method is inspired by that of StyleGAN: we apply a trainable affine transform $A$ onto the scalar $m$ to obtain a style vector $A(m)$.

Let $r$ be the input to each ResNet block, and $F$ be the ResNet block mapping function. Our modulated ResNet block can be represented as:

$$r = r + F(r \odot (1 + A(m)))$$

where $\odot$ denotes the Hadamard product. We add 1 to $A(m)$ to avoid annihilating $r$ if $A(m)$ is close to 0. We implement $F$ as a 2 layer convolution block. The bottleneck of our $G_c$ uses 9 ResNet blocks, the same number as pix2pixHD.

We keep the discriminator $D_c$ unaltered from pix2pixHD, which calculates the following loss:

$$L = L_{GAN} + \lambda L_{FM}$$

We pass the following inputs to the GAN loss $L_{GAN}(G_c, D_c)$:

$$E_{(x,x')}[\log D_c(x, x')] + E_{x}[\log(1 - D_c(x, G_c(x)))]$$

and perceptual loss $L_{FM}(G_c, D_c)$:

$$E_{(x,x')} \sum_{i=1}^{T} \frac{1}{N_i} |||D_c^{(i)}(x, x') - D_c^{(i)}(x, G_c(x))|||_1$$

for each layer $i$ in a $T$ layer discriminator with $N_i$ elements in that layer, used by the importance controller $\lambda$.

We notice that while $G_c$ brightens lights realistically when $m$ is positive, it often creates an unrealistic dark patch over the light source when we set $s_L$ to a negative $m$. Because the quality of $G_c$’s relighting results depends on the quality of data it is trained on, we propose using reversed training samples as shown in Fig. 5 to teach $G_c$ how to turn off lights realistically. In that training procedure, we choose a random positive $m$, so that $x'$ is a brightened version (to varying intensities) of $x$. For half of the training samples, we follow the method illustrated by Fig. 4. The other half is “reversed”: we pass the brightened $x'$ as the input to $G_c$, modulate ResNet blocks with $-m$, and use $x$ as the target image to calculate discriminative losses $L_{GAN}$ and $L_{FM}$:

$$E_{(x',x')}[\log D_c(x', x')] + E_{x'}[\log(1 - D_c(x', G_c(x')))]$$

Fig. 6 shows the effect: using reversed training samples allows lamps to be turned off more realistically.

During inference, $G_c$ takes as input a real photo and a scalar $m$ (which can be either positive or negative), and outputs the photo relit to an intensity $m$. Fig. 7 shows examples of relighting the same photo to varying intensities.

4.3. User selective edits

Would it be possible to control light sources in the same scene separately? We propose a second task of allowing a user to select which light source to relight.

As demonstrated in Fig. 8, we define a light location
Figure 8. (a) shows an overview of our regional editing method. We keep the overall framework of using $G_s$ to synthesize paired training data to train $G_c$. After we generate $x = G_s(z)$, we create a mask $M$ centered at the centroid of the largest lamp present in $G_s$, which we locate using a segmenter. We modify $G_s'$ to only change the lighting channel $s_L$ to a scalar $m$ under the masked region $M$. $G_s$ now takes both $x$ and $M$ as input to generate $G_c(x, M)$. Additionally, $M$ is also conditioned on to calculate discriminative losses. In (b), we show that the masked $S$ successfully brightens just the left lamp without altering the right lamp, whereas the non masked $S$ (approach we take in the unsupervised method) also alters the right lamp.

![Diagram](image)

Table 1. We compare our method to other candidate relighting methods. We evaluate relighting accuracy using several image similarity metrics against the "ground truth" image from our Lonoff dataset. We also evaluate realism using the Fréchet inception distance (FID) against 50k images from the LSUN Bedrooms dataset. *For FID on the inverter provided by StyleGANADA [14], we only evaluate on 2.5k samples due to time limitations. ADA inverts via an optimization loop, which takes significantly longer than a forward pass through an encoder.

| Method                  | LPIPS | MSE | RMSE | FID 50k |
|-------------------------|-------|-----|------|---------|
| Ours                    | 0.205 | 0.084 | 7.54 | 1.842   |
| No modulation           | 0.207 | 0.103 | 8.48 | 1.982   |
| e4e inversion [21]      | 0.498 | 0.115 | 14.35| 25.79   |
| ADA inversion [14]      | 0.471 | 0.153 | 13.86| 19.73*  |

$s_L = m$. To train $G_c$, we concatenate $G_s(x)$ and the mask $M$ as the input. We keep our modulated ResNet method and also employ reversed training samples for teaching $G_c$ how to turn off lights. Our inputs for discriminative loss terms remains the same as described in Sec. 4.2.

Figure 7. Examples are from our unsupervised method. We show that modulating the resnet bottleneck in $G_c$ allows for fine control over relighting intensities in real scenes. This allows us to both brighten and dim light sources to varying degrees.

![Image](image)

5. Results

5.1. Comparison of methods on Lonoff

We use Lonoff to quantitatively evaluate our method against other approaches for local relighting. We focus on the unsupervised task of turning all visible light sources on.

During inference, the user paints over the a photo to create a mask, which is then Gaussian blurred. $G_c$ takes the photo, the mask, and $m$ as input to output a version of that photo with only masked light sources relit to an intensity $m$. Images depicting the

\[ S = S_m \circ M + S_0 \circ (1 - M) \] (9)

where $S_0$ denotes the original style vector expanded into a tensor, and $S_m$ is the expanded style tensor containing

\[ s_L = m. \]
same scene with a different combination of lights turned on/off would therefore be paired with the same ground truth image. This gives us 206 pairs for evaluation. For consistency, we rescale all images to $256 \times 256$ using bilinear interpolation.

To measure accuracy of relighting in comparison to a ground truth, we use the following quantitative metrics. Mean Squared Error (MSE) measures for pixelwise image similarity, which can be limiting because a small distortion can cause a large pixelwise fluctuation. Grosse et al. [5] propose a more forgiving metric, Local Mean Squared Error (LMSE), which sums the MSE over several windows. We choose for the windows to be $20 \times 20$ spaced 10 pixels apart. Lastly, Learned Perceptual Image Patch Similarity (LPIPS) [30] measures for image perceptual similarity, which is how similar two images are based on human visual perception. For all methods, we translate each input image into three variations of increasing lighting intensity. For the inversion baselines e4e [21] and ADA [14], we use their method to invert the image into StyleGAN’s latent space, identify the style channel that visually best controls for lighting, and activate the channel to three increasing intensities. We use the best out of three relit scenes to calculate each image similarity metric.

We do not quantitatively evaluate the task of turning lights off because the Lonoff dataset was created such that if all lights were turned off, the scene would be pitch black.

To evaluate realism, we use the Frechét Inception Distance [10] on $50K$ samples from LSUN Bedrooms against $50K$ relit scenes generated by each method taking randomly sampled LSUN bedrooms as input. We allow each method to relight bedrooms at a randomly chosen intensity (i.e. we choose $m$ randomly out of a range of both positive and negative values). This generates samples of scenes both with lights turned on and off.

In Tab. 1, we see that we outperform other methods for all metrics. It is expected that our main method beats the ablation of not modulating the ResNet blocks. Modulation
Figure 10. We qualitatively examine the capabilities and limitations of our methods on diverse real images containing visible light sources. Images with a red border are the original photos. We discuss each case in Section 5.2.

allows for increased control over lighting intensity. This would generate more diverse lighting conditions that aligns closer with the distribution of real images and more likely relights an image that aligns with the ground truth. Visually, we see in Fig. 9 that inversion methods result in highly distorted reconstructions that often removes visible light sources from the input. This corroborates with the significantly worse metrics of inversion methods.

We note that in instances like (d) in Fig. 9, the unsupervised method fails to detect unlit light sources, especially when they deviate from the style of lamps that the pretrained StyleGAN2 generates. In these cases, a user can successfully turn them on using the selective method.

5.2. Unsupervised and region specific edits on out of domain images

In in Fig. 1 and Fig. 10 we demonstrate our relighting methods on a diverse set of real images that go far beyond the narrow domain of bedrooms that $G_c$ is trained on. While $G_c$ only sees examples of relit lamps, it can adjust the lighting of fire, road signs, and strip lighting.

In Fig. 10, (a) and (b) demonstrate our unsupervised method for turning light sources brighter and dimmer, respectively. While (b) successfully turns the flashlight off, it does not remove the reflected light on the table. (c) and (d) show our selective editing method, allowing control over a subset of visible light sources. (c) depicts an artistic painting, showing that our method can work on stylized light sources. (d) masks both a light and a non-light source (a spot on the wall). This is a successful case of controlling a masked light source and accurately preserving the underlying original image under a masked non-light source. (e) demonstrates an interesting failure case of our unsupervised method when a non-light source (the cat) is incorrectly detected. (f) shows that this can be corrected with a user drawn mask on the actual light source. However, (g) shows the cat lighting up after it is masked.

6. Discussion

We have introduced the task of local relighting: relighting a scene in which a local light source is visible. By exploiting the ability of a GAN to disentangle factors of variation corresponding to lighting, we have been able to train a model on the challenging task of local relighting without a special training set and without supervision of labels. We have used the synthesis model to generate an unbounded training set of relit image pairs, which are used to train a pix2pix generative image model. To facilitate benchmarking of this new task, we have introduced the Lonoff dataset, a new dataset of precisely aligned scene photographs with local lighting changes. We have found that our method outperforms baseline methods based on GAN inversion, and that our method can be also applied to diverse, out of domain images.
7. Ethical Considerations

While manipulating lighting in an image is an application mainly of interest in artistic and aesthetic applications, we acknowledge that our work could be potentially misused, for example to create realistic manipulated images that misrepresent the state of traffic lights in an evidence photo, or lights in other images relied upon to be realistic. By releasing our code, we hope to enable the community to reproduce our methods and continue to develop countermeasures against misinformation.

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Appendices

A. Identification of the lighting channel $s_L$

Our method for identifying the lighting channel $s_L$ introduces a new approach to controlling a large image generation network through one annotated example. Our work is inspired by [25], which used a pretrained classifier or between 10-30 example images to identify StyleSpace channels for controlling specific scene attributes, and by [31], which used between 16-40 manually segmented images to train a small decoder to segment any image generated by a GAN. Unlike [25] and [31], we observe that using just a single manually annotated image can be sufficient.

We begin by generating 12 StyleGAN bedroom scenes and manually selecting a single generated image $x = G_s(z)$ that depicts a lamp casting light that is reflected on a wall. On $x$, we manually select the region occupied by the reflected light as the target control area $T$. We are interested in the network’s ability to model the propagation of light throughout the scene, rather than to merely mimic the shape of the light fixture itself. We then iterate through the 5120 StyleSpace channels $s$ that control feature maps in this version of StyleGAN. For each $s$, we set $s = 0$ to generate a modified image $x' = G'_s(z)$. Each $s$ is ranked by $\sum |x - x'| \circ T$, which is the pixelwise sum of the absolute difference that lands in the target control area. $s_L$ is selected as the single highest ranking channel.

![Diagram](image)

Figure 11. (a) We iterate through and zero out each channel $s$ in StyleSpace to generate modified images $x'$. (b) Each $s$ is then ranked based on the difference in the manually chosen target control area. (c) Shows the highest ranking channels. Notice the five highest ranking channels control for slightly different characteristics of lighting, such as reflections, lampshade size, color temperature, and light angle. The single highest ranking channel modifies lighting in the way that best suits our objective of predicting light propagation in a scene, so we select it as $s_L$. 

1. Task lighting + reflections
2. Lampshade size
3. Reflections only
4. Color temperature
5. Cast light angle
B. Modulation of Multiple Channels

Here we show that our work extends the idea of channel modulation beyond the StyleSpace channel for lamp lighting. We apply the technique described in Appendix A for finding a channel that controls window light intensity. By modifying the two channels for lamps and windows respectively, we can generate a dataset of paired samples containing variations in both lamp and window lighting.

We can then use the dataset to train a pix2pix with its ResNet bottleneck modulated by two scalars instead of just a single value. We find that pix2pix learns to control both disentangled scalars, allowing us to control lamps and windows separately. Some qualitative results are illustrated in Fig. 12.

Figure 12. Lamp and window modulation example on a real image. The original image is boxed in red. We show that during inference, lamp and window lighting can be controlled separately by inputting different modulation scalars. No further supervision is required to separately control different light source types.
C. Additional Qualitative Examples

Additional qualitative examples of our unsupervised relighting method are shown in Fig. 13. Note these images are quite outside of the distribution of the bedroom dataset that we generated from StyleGAN2 for training pix2pixHD.

Figure 14 illustrates more examples of our “user selective” editing, where the user can choose which light(s) to edit. For ease of visualization and comparison, we show the edits on the same bedroom image.

Figure 13. More examples of our unsupervised method on diverse images. In each panel, the red box shows the original image, and lower and/or higher light intensities are illustrated in its left and right images, respectively. The example in the middle row of the right column shows an originally unlit pink desk lamp (boxed in blue) being turned on by our method.
Figure 14. Demonstrations of our user selective method. Examples on the left demonstrate different combinations of lights being turned off, and examples on the right demonstrate different lights being turned on.
D. Lonoff Dataset Samples

Figure 15 illustrates a snapshot of the organization of Lonoff along with some examples. Each image’s filename contains its light information. For instance, in the “kitchen” category, the “place110” directory contains images of a kitchen with 4 light sources. The subsequent letter “e” corresponds to “external light,” and the subsequent numbers (ex. 23) correspond to the indices of light sources, scanning from left to right.

Figure 15. A snapshot of our dataset “Lonoff” with samples in three categories.