## Abstract

StyleGAN generates novel images of a scene from latent codes which are impressively disentangled. But StyleGAN generates images that are “like” its training set. This paper shows how to use simple physical properties of images to enrich StyleGAN’s generation capacity. We use an intrinsic image method to decompose an image, then search the latent space of a pretrained StyleGAN to find novel directions that fix one component (say, albedo) and vary another (say, shading). Therefore, we can change the lighting of a complex scene without changing the scene layout, object colors, and shapes. Or we can change the colors of objects without changing shading intensity or their scene layout. Our experiments suggest the proposed method, StyLitGAN, can add and remove luminaires in the scene and generate images with realistic lighting effects – cast shadows, soft shadows, inter-reflections, glossy effects – requiring no labeled paired relighting data or any other geometric supervision. Qualitative evaluation confirms that our generated images are realistic and that we can change or fix components at will. Quantitative evaluation shows that pre-trained StyleGAN could not produce the images StyLitGAN produces; we can automatically generate realistic out-of-distribution images, and so can significantly enrich the range of images StyleGAN can produce.
1 Introduction

Generative models produce impressively realistic images from random vectors [13, 19–21]. These methods require training with an adversarial loss [13], which encourages the model to generate images that match the training set distribution. This paper shows that, by imposing known physical facts about images, the distribution of images produced by a StyleGAN can be significantly enriched. We show how to generate images that are unlike those in the training set, but still realistic. In particular, we exploit the fact that the same scene can be lit in different ways to produce images with strong lighting effects not in the training set (relighting). Similarly, we exploit the fact that shading contains shape information to produce images where surface colors have changed, but layout and lighting has not. Our approach extends current editing methods [45, 49, 37, 58] by showing how to find directions that fix one image component while changing another.

We use StyleGAN because manipulating style codes is known to be effective for editing tasks, while successfully editing the representations of other generators is largely an open issue. We extend the range of control procedures by showing how to fix some image properties while changing others. In particular, we use a pretrained and self-supervised network to decompose an image into albedo, diffuse shading and glossy effects. By searching in style codes for edits that produce diverse images that have the same albedo (and so geometry and material) as a particular generated image, we can produce images of the same scene under different lighting (see Figure 1). Our enrichment procedure is legitimate, because there really are many distinct lightings of the same scene, and these will not be present in the training data. StyleGAN’s deep "knowledge" of image structure ensures that the resulting images look realistic. Furthermore, many are unlike the training data because they show strong illumination effects. Similarly, by fixing lighting effects and changing albedo, we can get images that are unlikely to be present in training data because they show unusual color or color combinations. Our approach is easily adapted to produce a variant of StyleGAN – StyLitGAN - that produces a richer distribution of images by manipulating latent style codes and which does not need to be trained. We simply randomly choose an edit to apply to the style codes for the vanilla StyleGAN.

The usual paraphenalia (FID, KID, etc.) of GAN evaluation does not apply in the usual way, because we are trying to generate realistic out of distribution images, so our FID should go up. We evaluate whether images are realistic qualitatively. Our method can generate any image that a vanilla StyleGAN can, by choosing not to edit. Further, we show that a vanilla StyleGAN cannot generate many of our images, and that StyLitGAN has a significant increase in FID over StyleGAN. This means the distribution of images generated by StyLitGAN has strictly larger support.

2 Related Work

Image manipulation: A significant literature deals with manipulating and editing images [34, 15, 7, 24, 6, 59, 12, 44, 31]. Editing procedures for generative image models [13] are important, because they demand compact image representations with useful, disentangled, interpretations. StyleGAN [19–21] is currently de facto state-of-the-art for editing generated images, likely because its mapping of initial noise vectors to style codes which control entire feature layers produces latent spaces that are heavily disentangled and so easy to manipulate. Recent editing methods include [45, 49, 37, 58, 55], with a survey in [50]. The architecture can be adapted to incorporate spatial priors for authoring novel and edited images [25, 43, 8]. In contrast to this literature, we show how to fix one physically meaningful image factor while changing another. Doing so is difficult because the latent spaces are not perfectly disentangled, and we must produce a diverse set of changes in the other factor.

Image Relighting: Shih et al. show that matching to time-lapse video together with an example-based color transfer scheme can relight outdoor scenes [39]. Existing image relighting work learns image mappings – pure image mappings in [11], depth guided in [52], using wavelets in [33] shadow priors in [46]. In all these cases, methods are learned with paired data of the same scene under different illuminations, available in the VIDIT dataset [14] and the MIE dataset [27]. VIDIT data is CGI, and emphasizes point light sources with strong shadows, which are uncommon in indoor scenes. Pairing is necessary to ensure that these methods preserves scene characteristics [22, 26]. Methods can learn to create outdoor shadows [47, 48] and soft attached shadows for objects that have been inserted into indoor scenes [38, 56]. All these methods also require curated paired training data. In contrast to these methods, we do not use paired data.
Figure 2: How StyLitGAN works: We generate an image from a random Gaussian noise using a pretrained StyleGAN. We also generate novel relighted images (16 in our case) of the same using randomly initialized latent directions ($d$) that are added to $w^+$ latent style codes. We train a classifier ($F$) that takes in all the pairs of relighted and original images and predicts the relighting direction applied to them. We apply a distinction loss and jointly update the latent directions and the classifier. Next, we generate the decomposition of these images from a pretrained decomposition model ($D$). We then apply losses that force StyLitGAN to find latent directions so that the light invariant or persistent effects should not change (consistency loss) in albedo, and transient or light-dependent effects should change (diversity loss) in shading. We also use a decorrelation loss between the surface lightness and the intensity of relighted images.

Image Relighting using StyleGAN: [43] uses StyleGAN to relight faces but require three-dimensional morphable face model. In contrast, StyLitGAN does not require any 3D model of the scene. [51] uses semantic label attributes “indoor lighting” and “natural lighting” to train a binary classifier to find directions in latent space that represent them, but cannot produce diverse relighting and requires a search in decoder layers to apply relight edits without changing layout of the scene. In contrast, StyLitGAN generates diverse, extreme, and realistic relighting and does not require any search for decoder layers that produce realistic relighting.

Other Face Relighting Methods mostly use carefully collected supervisory data from light-stages [41, 57, 28, 36, 30]. ShadeGAN [29] and Volux-GAN [42] uses a volumetric rendering approach to learn the underlying 3D structure of the face and the illumination encoding. Volux-GAN also requires image decomposition obtained from [30] that is trained using a carefully curated light-stage data. In comparison, we do not require any explicit 3D modeling of the scene and also do not require image decomposition model trained on a curated data.

Image Decomposition: Current image decomposition methods [23, 3, 17, 9, 10] decompose images into albedo and shading. Each scores very well in current evaluations of WHDR (standard metric for intrinsic images due to [1]; recent summary of SOTA performance in [10]), but we have not found these decompositions to yield good relighting with StyleGAN.

3 Approach

We follow convention and manipulate StyleGAN2 [20] by adjusting the $w^+$ latent variables. We do not modify StyleGAN2, but instead seek a set of lighting directions $d_i$ which are independent of $w^+$ and which have desired effects on the generated image. We obtain these directions by constructing losses that capture the desired outcomes, then searching for directions that minimize these losses. We find all lighting directions at once. We use 2000 randomly generated StyleGAN2 images to search for lighting directions that are distinct and realistic for several images. Our search procedure only sees each image once. The pretrained models of StyleGAN for different scenes where obtained from [54, 8]. Figure 4 summarizes our procedure.

Decomposition: We decompose images into $A \times S + G$, where $A$ models albedo effects and $S$ and $G$ model diffuse shading and gloss effects respectively. We use the method of [10], which is easily adapted because it uses only samples from statistical models and is self-supervised. We refer to $A$ as a persistent map, because it is not affected by lighting, and $S$ and $G$ as transient maps. While the resulting method does not appear to be competitive in WHDR score, it yields strong relighting performance. Supplementary material describes the training data and procedures in greater detail.

Relighting a scene should produce a new, realistic, image where the shading has changed but the albedo has not. Write $T(w^+)$ for the image produced by StyleGAN given style codes $w^+$, and $A(I)$,
WHDR scores, it significantly weakens relighting results, because lighter objects will tend to be
brighter, and darker objects will tend to be darker. We discourage this effect by including a loss
making large color shifts.

Surface lightness can be measured from the persistent map (average of RGB channels) and add a
that decorrelates surface lightness (measured at a long scale) from relighted images. We assume

Persistent Consistency: The persistent decomposition (albedo) of both the relighted scene: \( A_R =
A(T(w^+ + d_i)) \) and the original: \( A_O = A(T(w^+)) \) must be the same. We use a Huber loss and a
perceptual feature loss \([18, 55]\) from a VGG feature extractor \((\Phi)\) \([40]\) at various feature layers \((j)\)
to preserve persistent effects in the scene. These losses preserves the geometrical structure of the
scene, appearance in color and texture errors.

\[
\mathcal{L}_{\text{const}}(A_O, A_R) = \begin{cases} \frac{1}{2} |A_O - A_R|^2 & \text{for } |A_O - A_R| \leq \delta, \\ \delta (|A_O - A_R| - \delta/2) & \text{otherwise.} \end{cases}
\]

\[
\mathcal{L}_{\text{per}}(A_O, A_R) = ||\Phi_j(A_O) - \Phi_j(A_R)||_2.
\]

Relighting Diversity: We want the set of relighted images produced by the directions to be diverse
on a long scale, so that regions that were in shadow in one image might be bright in another. For each
\( T(w^+ + d_i) \), we stack the two transient maps: \( S \) and \( G \) and compute a smoothed and downsampled
vector \( t_i \) from these maps. We then compute

\[
\mathcal{L}_{\text{div}}(S, G) = -\log \det N \text{ where } \text{ith } & jth \text{ component of } N \text{ is } t_i^T t_j
\]

which compels these \( t_i \) to be linearly independent and encourages diversity in relighting.

Distinctive Relighting: A network might try to cheat by making minimal changes to the image.
Directions \( d_i \) should have the property that \( d_i \) is easy to impute from \( T(w^+ + d_i) \). We train a
classifier joint with the search for directions. This classifier accepts \( T(w^+) \) and \( T(w^+ + d_i) \) and
must predict \( i \). The cross-entropy of this classifier supplies our loss:

\[
\min_{i,\hat{F}} \mathcal{L}_{\text{dist}}(T(w^+), \ T(w^+ + d_i)) = -\sum_{i=1}^{M} d_i \log F(T(w^+), \ T(w^+ + d_i))
\]

Persistent decorrelation: Intrinsic image methods tend to report somewhat correlated albedo and
shading (dark image patches tend to be interpreted as both dark albedo and dark shading). No current
method reliably avoids this class of error. While the error does not seem to have a major effect on
WHDR scores, it significantly weakens relighting results, because lighter objects will tend to be
brighter, and darker objects will tend to be darker. We discourage this effect by including a loss
that decorrelates surface lightness (measured at a long scale) from relighted images. We assume
surface lightness can be measured from the persistent map (average of RGB channels) and add a
small penalty if this is like the intensity of relighted images, using the negative of cosine similarity on
the smoothed version of the gray-scale persistent map and relighted images. This allows the persistent
map to deviate slightly from the original image and still be consistent with the original scene without
making large color shifts.

\[
\mathcal{L}_{\text{deco}} = \frac{A_O \cdot T(w^+ + d_i)}{|A_O| |T(w^+ + d)|}
\]

The overall loss is

\[
\lambda_{\text{const}} \mathcal{L}_{\text{const}} + \lambda_{\text{per}} \mathcal{L}_{\text{per}} + \lambda_{\text{div}} \mathcal{L}_{\text{div}} + \lambda_{\text{dist}} \mathcal{L}_{\text{dist}} + \lambda_{\text{deco}} \mathcal{L}_{\text{deco}}
\]

Recoloring requires swapping persistent for transient components in all losses, except we do not
use decorrelation loss while recoloring. Obtaining good results requires quite careful choice of loss
weights (\( \lambda \) coefficients). Corresponding \( \lambda \) coefficients for both these edits are in our supplementary.
Figure 3: **Top row** images generated by the original StyleGAN. **Other rows** show images obtained from $w^+ + d_i$ for our 16 relighting directions added to the style codes ($w^+$) corresponding to the image on the top row. These directions have been chosen to fix albedo, but change transient (shading and gloss) properties. Note: each column appears to show the same scene in different illumination; lighting varies aggressively; and the individual latent direction $d_i$ have no obvious scene-independent semantics.
Figure 4: Top row images generated by the original StyleGAN. Other rows show images obtained from $w^* + d_i$ for our 16 recoloring directions added to the style codes ($w^*$) corresponding to the image on the top row. These directions have been chosen to change albedo, but fix transient (shading and gloss) properties. Note: each column appears to show the same scene in the same illumination, but with different colored surfaces; appearance varies aggressively; and the individual latent direction $d_i$ have no obvious scene-independent semantics.
Figure 5: This grid shows what happens when we use both relighting and recoloring directions for a single scene in StyLitGAN. **Rows** show different and random relights for a fixed recoloring and **columns** show different and random recolorings for a fixed relight. There is clearly some interaction, but not much - they are largely disentangled.

4 Experiments

**Procedures:** The primary goal of StyLitGAN is to produce realistic images, that are out of distribution but known to exist for straightforward physical reasons. Because they’re out of distribution, current quantitative evaluation tools do not apply. We evaluate realism qualitatively (hence the extensive body of images in both text and supplementary) and out of distribution properties quantitatively. We use baseline pretrained models from [54] that use a dual-contrastive loss to train StyleGAN for bedrooms, faces and churches. We also use baseline pretrained StyleGAN2 models from [8] for conference rooms and kitchen, dining and living rooms (jointly trained). For all our experiments, we used 16 distinct lighting directions. We evaluated our method both on StyleGAN2 [20] and StyleGAN1 [19]. We find StyleGAN2 produces superior qualitative results but requires significant effort in tuning losses to find realistic lighting and appearance when compared to StyleGAN1 (supplementary).

**Qualitative evaluation:** There is no comparable method. For relighting, our method should generate images that: are clearly relightings of a scene; fix geometry and albedo but visibly change shading; and display complicated illumination effects, including soft shadows, cast shadows and gloss. As Figure 5 shows, our method meets these goals. We have no way to tell whether there are “likely” relightings that are not produced by our method. For recoloring, our method should generate images
Figure 6: Interpolation in relighting directions. Top row: linear scaling from -1 to 1 of a random direction and bottom row interpolation between two random relighting directions. Linear scaling along a single direction results in a complicated illumination change that is difficult to explain, from near uniform to pointed direction light moving left to right in the top row. However, interpolation between two directions appears to follow a path – light moving anti-clockwise with a strong gloss on the bottom left corner of the floor to the bottom right corner of the bed sheet.

Figure 7: Interpolation in recoloring directions. Top row: linear scaling from -1 to 1 of a random direction and bottom row interpolation between two random recoloring directions. Linear scaling using a single direction appears to be constructing and deconstructing the scene. While interpolating between two directions results in smooth albedo changes of the scene and expansion of the bed.

Figure 8: Top row shows $T(w^+ + d_i)$ for various $d_i$ obtained using our method. For each, we find $\hat{z}_i$ such that $M(\hat{z}_i)$ is as close as possible to $w^+ + d_i$. Bottom shows $T(M(\hat{z}_i))$. These images are largely the same. For many of our images, there is no unit normal random variable that will cause StyleGAN to generate the image – they are truly out of distribution.

that: are clearly images of the original geometry, but with different materials or colors; visibly change these colors; and display illumination effects that are consistent with these color changes. As Figure 4 shows, our method meets these goals. We have no way to tell whether there are “likely” recolorings that are not produced by our method. Figure 5 shows our relighting and recoloring directions are largely disentangled. Figure 6 and Figure 7 show interpolation sequences for a a relighting (resp. recoloring). Note that the lighting (resp. coloring) changes smoothly, as one would expect.

Generality: We have applied our method to StyleGAN instances trained on a variety of different datasets – Conference Room, Kitchen, Living Room, Dining Room and Church from LSUN [53] and faces from FFHQ dataset [19]. As Figure 9 shows, relighting is successful for each. Note that we tuned all our losses for only bedrooms. For all other categories, we tuned only their diversity loss.

Quantitative evaluation: Our procedure is clearly capable of generating any image the vanilla StyleGAN can. We show that at least some of our $w^+ + d_i$ cannot be obtained from the vanilla StyleGAN’s MLP. Write $M(z)$ for StyleGAN’s MLP (which maps a unit normal random vector to a latent code); we search for $\hat{z}_i$ such that $M(\hat{z}_i) = w^+ + d_i$. As Figure 8 shows, such $\hat{z}_i$ can often not be found (supplementary material confirms the search is perfectly capable of inverting the MLP when possible). Further, we show we can generate image datasets with increased FID [32, 10] compared to the base comparison set in Table 1. This is strong evidence our method can produce a set of images that is a strict superset of those that the vanilla StyleGAN can produce.
Figure 9: StyLitGAN extends to finding relighting directions for StyleGANs trained on other datasets.

Table 1: FID measure distribution shift and not realism. Our generated images are realistic and are out-of-distribution because of large illumination change and color changes in the images. This results in large FID scores. We use clean-FID for our evaluation \[32\]. Notations in the table: SG for StyleGAN, \(d_t\) for transient (or relighting) direction, \(d_p\) for persistent (or recoloring) direction and KDL for kitchen, dining and living room which are jointly trained, kindly provided by \[8\].

| Type          | Bedroom | KDL   | Conference | Church | Faces |
|---------------|---------|-------|------------|--------|-------|
| StyleGAN (SG) | 5.01    | 5.86  | 9.35       | 3.80   | 5.02  |
| SG + \(d_t\)  | 14.23   | 6.87  | 10.48      | 12.12  | 37.87 |
| SG + \(d_p\)  | 17.03   | 9.41  | 10.63      | 18.60  | 34.06 |
| SG + \(d_t\) + \(d_p\) | 21.39  | 11.68 | 12.71      | 21.08  | 37.40 |

5 Discussion

Limitations and future work: The major limitation of our method is that they are currently applicable only to generated images. We hope our method will easily apply to real images with the improvements in GAN inversion methods. Our method generates random and diverse relighting, but cannot produce targeted relighting. Future work will involve addressing both issues by building a general encoding that can be combined with StyLitGAN. Another important limitation is that, although we have demonstrated our method can produce images that StyleGAN can’t but should be able to, we do not know how to show that we have all such images. We found new images by imposing a simple, necessary property of the distribution of images (scenes have many different lightings) and we expect that other such observations could lead to other kinds of good but out-of-distribution images. Finally, anything that can generate many detailed relights and recolorings "knows" a great deal about shape; future work will explore this knowledge.

Social Implications. Convincing fake images can pollute the news media, but StyLitGAN offers only relighting, rather than the much more dangerous insertion or deletion editing. We have no example of a situation where a relighting procedure creates social harm. On compute required for this project: the project is the culmination of ongoing research efforts over the past two years in this direction. The experiments required for this final paper are approx 100 hours on a single A40 GPU.
Acknowledgments

We thank Dave Epstein and Ning Yu for providing us with all their pretrained models of StyleGAN required for this project. We also thank Min Jin Chong for his helpful comments and discussion on the project. Min Jin is a GAN magician from UofI. Check out his recent JoJoGAN paper!!

References

[1] S. Bell, K. Bala, and N. Snavely. Intrinsic images in the wild. ACM Transactions on Graphics, 2014.
[2] A. Bhattad and D. A. Forsyth. Cut-and-paste neural rendering. arXiv preprint arXiv:2010.05907, 2020.
[3] S. Bi, X. Han, and Y. Yu. An l 1 l image transform for edge-preserving smoothing and scene-level intrinsic decomposition. ACM Transactions on Graphics, 2015.
[4] M. J. Chong and D. Forsyth. Jojogan: One shot face stylization. arXiv preprint arXiv:2112.11641, 2021.
[5] M. J. Chong, H.-Y. Lee, and D. Forsyth. Stylegan of all trades: Image manipulation with only pretrained stylegan. arXiv preprint arXiv:2111.01619, 2021.
[6] A. Deshpande, J. Lu, M.-C. Yeh, M. Jin Chong, and D. Forsyth. Learning diverse image colorization. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pages 6837–6845, 2017.
[7] A. A. Efros and W. T. Freeman. Image quilting for texture synthesis and transfer. In Proceedings of the 28th annual conference on Computer graphics and interactive techniques, pages 341–346, 2001.
[8] D. Epstein, T. Park, R. Zhang, E. Shechtman, and A. A. Efros. Blobgan: Spatially disentangled scene representations. arXiv preprint arXiv:2205.02837, 2022.
[9] Q. Fan, J. Yang, G. Hua, B. Chen, and D. Wipf. Revisiting deep intrinsic image decompositions. In Proceedings of the IEEE conference on computer vision and pattern recognition, 2018.
[10] D. Forsyth and J. J. Rock. Intrinsic image decomposition using paradigms. TPAMI, 2022 in press.
[11] P. Gafton and E. Maraz. 2d image relighting with image-to-image translation. arXiv preprint arXiv:2006.07816, 2020.
[12] L. A. Gatys, A. S. Ecker, and M. Bethge. Image style transfer using convolutional neural networks. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 2414–2423, 2016.
[13] I. J. Goodfellow, J. Pouget-Abadie, M. Mirza, B. Xu, D. Warde-Farley, S. Ozair, A. Courville, and Y. Bengio. Generative adversarial networks. arXiv preprint arXiv:1406.2661, 2014.
[14] M. E. Helou, R. Zhou, J. Barthas, and S. Süssbrunk. Vidit: Virtual image dataset for illumination transfer. arXiv preprint arXiv:2005.05460, 2020.
[15] A. Hertzmann, C. E. Jacobs, N. Oliver, B. Curless, and D. H. Salesin. Image analogies. In Proceedings of the 28th annual conference on Computer graphics and interactive techniques, pages 327–340, 2001.
[16] M. Heusel, H. Ramsauer, T. Unterthiner, B. Nessler, and S. Hochreiter. Gans trained by a two time-scale update rule converge to a local nash equilibrium. arXiv preprint arXiv:1706.08500, 2017.
[17] M. Janner, J. Wu, T. D. Kulkarni, I. Yildirim, and J. Tenenbaum. Self-supervised intrinsic image decomposition. In Advances in Neural Information Processing Systems, 2017.
[18] J. Johnson, A. Alahi, and L. Fei-Fei. Perceptual losses for real-time style transfer and super-resolution. In European conference on computer vision, 2016.
[19] T. Karras, S. Laine, and T. Aila. A style-based generator architecture for generative adversarial networks. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, 2019.
[20] T. Karras, S. Laine, M. Aittala, J. Hellsten, J. Lehtinen, and T. Aila. Analyzing and improving the image quality of StyleGAN. In Proc. CVPR, 2020.
[21] T. Karras, M. Aittala, S. Laine, E. Härkönen, J. Hellsten, J. Lehtinen, and T. Aila. Alias-free generative adversarial networks. Advances in Neural Information Processing Systems, 34, 2021.
[22] N. Kubiak, A. Mustafa, G. Phillipson, S. Jolly, and S. Hadfield. Silt: Self-supervised lighting transfer using implicit image decomposition. arXiv preprint arXiv:2110.12914, 2021.

[23] Z. Li and N. Snavely. Cgintrinsics: Better intrinsic image decomposition through physically-based rendering. In Proceedings of the European Conference on Computer Vision, 2018.

[24] Z. Liao, H. Hoppe, D. Forsyth, and Y. Yu. A subdivision-based representation for vector image editing. IEEE transactions on visualization and computer graphics, 2012.

[25] H. Ling, K. Kreis, D. Li, S. W. Kim, A. Torralba, and S. Fidler. Editgan: High-precision semantic image editing. Advances in Neural Information Processing Systems, 34, 2021.

[26] Y. Liu, A. Neophytou, S. Sengupta, and E. Sommerlad. Relighting images in the wild with a self-supervised siamese auto-encoder. In Proceedings of the IEEE/CVF Winter Conference on Applications of Computer Vision, pages 32–40, 2021.

[27] L. Murmann, M. Gharbi, M. Aittala, and F. Durand. A dataset of multi-illumination images in the wild. In Proceedings of the IEEE International Conference on Computer Vision, 2019.

[28] T. Nestmeyer, J.-F. Lalonde, I. Matthews, E. Games, A. Lehrmann, and A. Borealis. Learning physics-guided face relighting under directional light. 2020.

[29] X. Pan, X. Xu, C. C. Loy, C. Theobalt, and B. Dai. A shading-guided generative implicit model for shape-accurate 3d-aware image synthesis. In Advances in Neural Information Processing Systems (NeurIPS), 2021.

[30] R. Pandey, S. O. Escolano, C. Legendre, C. Haene, S. Bouaziz, C. Rhemann, P. Debevec, and S. Fanello. Total relighting: learning to relight portraits for background replacement. ACM Transactions on Graphics (TOG), 40(4):1–21, 2021.

[31] T. Park, M.-Y. Liu, T.-C. Wang, and J.-Y. Zhu. Semantic image synthesis with spatially-adaptive normalization. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, 2019.

[32] G. Parmar, R. Zhang, and J.-Y. Zhu. On aliased resizing and surprising subtleties in gan evaluation. In CVPR, 2022.

[33] D. Puthussery, H. Panikkasseril Sethumadhavan, M. Kuriakose, and J. Charangatt Victor. Wdrn: A wavelet decomposed relightnet for image relighting. In European Conference on Computer Vision, pages 519–534. Springer, 2020.

[34] E. Reinhard, M. Adhikhmin, B. Gooch, and P. Shirley. Color transfer between images. IEEE Computer graphics and applications, 21(5):34–41, 2001.

[35] E. Richardson, Y. Alaluf, O. Patashnik, Y. Nitzan, Y. Azar, S. Shapiro, and D. Cohen-Or. Encoding in style: a stylegan encoder for image-to-image translation. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 2287–2296, 2021.

[36] S. Sengupta, B. Curless, I. Kemelmacher-Shlizerman, and S. M. Seitz. A light stage on every desk. In Proceedings of the IEEE/CVF International Conference on Computer Vision, 2021.

[37] Y. Shen, C. Yang, X. Tang, and B. Zhou. Interfacegan: Interpreting the disentangled face representation learned by gans. IEEE transactions on pattern analysis and machine intelligence, 2020.

[38] Y. Sheng, J. Zhang, and B. Benes. Ssn: Soft shadow network for image compositing. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 4380–4390, 2021.

[39] Y. Shih, S. Paris, F. Durand, and W. T. Freeman. Data-driven hallucination of different times of day from a single outdoor photo. ACM Transactions on Graphics (TOG), 2013.

[40] K. Simonyan and A. Zisserman. Very deep convolutional networks for large-scale image recognition. ICLR, 2015.

[41] T. Sun, J. T. Barron, Y.-T. Tsai, Z. Xu, X. Yu, G. Fyffe, C. Rhemann, J. Busch, P. Debevec, and R. Ramamoorthi. Single image portrait relighting. ACM Transactions on Graphics, 2019.

[42] F. Tan, S. Fanello, A. Meka, S. Orts-Escolano, D. Tang, R. Pandey, J. Taylor, P. Tan, and Y. Zhang. Volux-gan: A generative model for 3d face synthesis with hdri relighting. arXiv preprint arXiv:2201.04873, 2022.
[43] A. Tewari, M. Elgharib, G. Bharaj, F. Bernard, H.-P. Seidel, P. Pérez, M. Zollhofer, and C. Theobalt. Stylerig: Rigging stylegan for 3d control over portrait images. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 6142–6151, 2020.

[44] D. Ulyanov, A. Vedaldi, and V. Lempitsky. Deep image prior. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2018.

[45] A. Voynov and A. Babenko. Unsupervised discovery of interpretable directions in the gan latent space. In International conference on machine learning, pages 9786–9796. PMLR, 2020.

[46] L. Wang, W. Siu, Z. Liu, C. Li, and D. P. Lun. Deep relighting networks for image light source manipulation. In A. Bartoli and A. Fusiello, editors, Computer Vision - ECCV 2020 Workshops - Glasgow, UK, August 23-28, 2020, Proceedings, Part III, volume 12537 of Lecture Notes in Computer Science, pages 550–567. Springer, 2020. doi: 10.1007/978-3-030-67070-2_33. URL https://doi.org/10.1007/978-3-030-67070-2_33.

[47] Y. Wang, B. L. Curless, and S. M. Seitz. People as scene probes. In European Conference on Computer Vision, pages 438–454. Springer, 2020.

[48] Y. Wang, A. Liu, R. Tucker, J. Wu, B. L. Curless, S. M. Seitz, and N. Savely. Repopulating street scenes. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, 2021.

[49] Z. Wu, D. Lischinski, and E. Shechtman. Stylespace analysis: Disentangled controls for stylegan image generation. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 12863–12872, 2021.

[50] W. Xia, Y. Zhang, Y. Yang, J.-H. Xue, B. Zhou, and M.-H. Yang. Gan inversion: A survey. arXiv preprint arXiv: 2101.05278, 2021.

[51] C. Yang, Y. Shen, and B. Zhou. Semantic hierarchy emerges in deep generative representations for scene synthesis. International Journal of Computer Vision, 2020.

[52] H.-H. Yang, W.-T. Chen, H.-L. Luo, and S.-Y. Kuo. Multi-modal bifurcated network for depth guided image relighting. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 260–267, 2021.

[53] F. Yu, A. Seff, Y. Zhang, S. Song, T. Funkhouser, and J. Xiao. Lsun: Construction of a large-scale image dataset using deep learning with humans in the loop. arXiv preprint arXiv:1506.03365, 2015.

[54] N. Yu, G. Liu, A. Dundar, A. Tao, B. Catanzaro, L. S. Davis, and M. Fritz. Dual contrastive loss and attention for gans. In Proceedings of the IEEE/CVF International Conference on Computer Vision, pages 6731–6742, 2021.

[55] R. Zhang, P. Isola, A. A. Efros, E. Shechtman, and O. Wang. The unreasonable effectiveness of deep features as a perceptual metric. In CVPR, 2018.

[56] S. Zhang, R. Liang, and M. Wang. Shadowgan: Shadow synthesis for virtual objects with conditional adversarial networks. Computational Visual Media, 5(1):105–115, 2019.

[57] H. Zhou, S. Hadap, K. Sunkavalli, and D. W. Jacobs. Deep single-image portrait relighting. In Proceedings of the IEEE International Conference on Computer Vision, 2019.

[58] J. Zhu, Y. Shen, D. Zhao, and B. Zhou. In-domain gan inversion for real image editing. In Proceedings of European Conference on Computer Vision (ECCV), 2020.

[59] J.-Y. Zhu, T. Park, P. Isola, and A. A. Efros. Unpaired image-to-image translation using cycle-consistent adversarial networks. In Proceedings of the IEEE international conference on computer vision, 2017.