Improving Illumination Estimation using Shading Residue

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Abstract

SfSNet[1] is a framework for producing a decomposition of an unconstrained human face image into shape, reflectance and illuminance. SfSNet is uses face normal and spherical harmonics to generate shading which is based on intrinsic decomposition assumption. In this work, we introduce new representation to capture more flexible and comprehensive illumination effect that is not modeled by shading layer in SfSNet. This new representation modifies the shading generated from SfSNet model, we have introduced simpler representation which captures the difference of shading missed in older representation and can be directly added into SfSNet generated shading. In SfSNet, due to lack of shading loss, residue it pushed down into albedo. We start from this point and work on new representation and albedo to improve overall reconstruction and capture details. We fix Normal and Spherical Harmonics and learn new representation. Due to lack of ground truth dataset and availability of noisy ground truth collected using pretrained SfSNet model, we also introduce use of generative adversarial networks[2] to eliminate residue from albedo and generate albedo in synthetic domain space using Cycle-GAN training paradigm[3]. We evaluate both supervised and gan based method for albedo generation.

1 Introduction

Learning face decomposition such as albedo, normal and spherical harmonics is useful for face editing application. Different approaches have been tried out for the same. Deforming Auto-encoders[4], SfSNet, LDAN[5] are some of the successful attempts. SfSNet have achieved highest results but faces issues with Albedo generation. Due to lack of shading loss, reconstruction loss pushes shading residual into albedo which leads to not so accurate albedo.

We started off with implementing SfSNet in PyTorch and Skip-Connection based network to generate CelebA data for pseudo-supervision. Then we built our experiments on top of the base model by adding network to generate shading residue and different approach to compute shading using latent lighting representation instead of Spherical Harmonics.

Later, we moved towards using pre-trained model provided of SfSNet and build experiments on top of that to remove residue from albedo and add into shading instead using reconstruction loss and optionally with lesser albedo loss. Pre-trained model does not generate albedo accurately and hence, we thought of using generative approach to generate albedo in synthetic albedo space which is known true ground truth. Here, we sample synthetic albedo as real albedo and generated albedo as a fake albedo to ensure accurate albedo generation. We experimented with both no albedo loss and albedo loss with less weight approach. For GAN training, we adopted CycleGAN.

At the end, we compare generated albedo and shading with our methods with each other as well as with the base SfSNet method. Comparison metric is generated albedo being free of the residue and same residue being seen in generated shading. Figure 1 shows difference between SfSNet and our method.

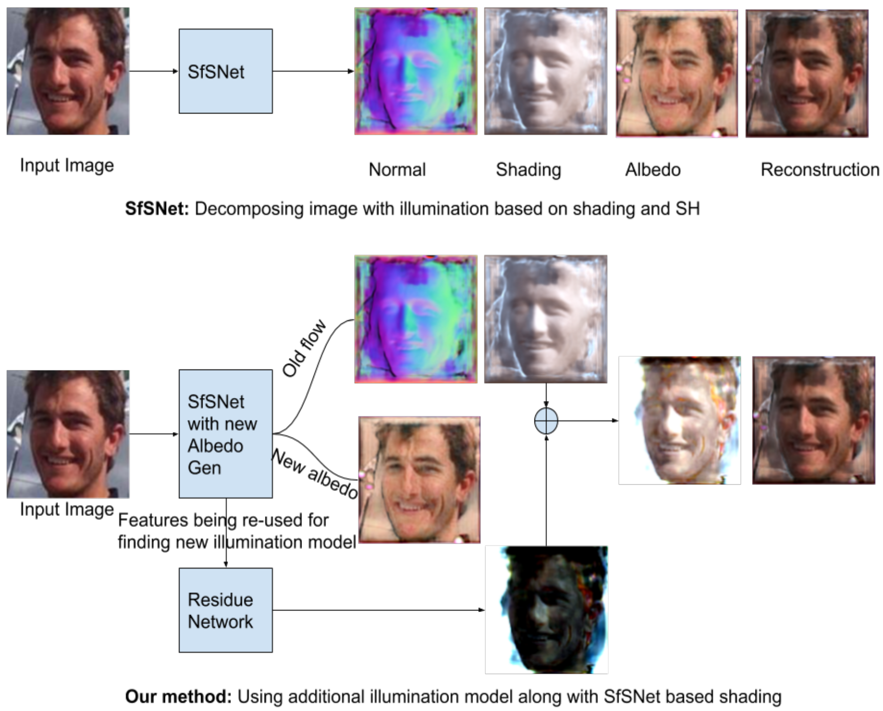

Figure 1: Comparing SfSNet method with ours- High level flow of the system

2 Connection with work from previous semester

In Spring 2018, we worked on Label Denoising Auto-encoder which uses GANs for domain adaptation to map learned real images features into synthetic domain space in order to take advantage of highly tuned network on synthetic dataset with ground truth. In Fall 2018, we worked on an application of Deforming Autoencoder for lighting transfer, where we worked on both latent lighting as well as spherical harmonics.

From our prior work, we understand that using GANs for domain adaptation to map noisy ground truth albedo into synthetic domain space would be promising approach. From our work in second semester, we can experiment with latent lighting representation and assess the impact of latent lighting representation on correcting the shading.

3 Spherical Harmonics

Spherical harmonics(SH)[7] is well studied and commonly used rendering method for generating realistic lighting and shading. Lighting can be represented as a spherical function and used along with face normal to generate shading for the faces [8]. Figure 2 shows face normal and spherical lighting based lighting as discussed in SIRFS[7].

Our work with be evaluate both using spherical harmonics as well as using new lighting representation for generating shading from input image.

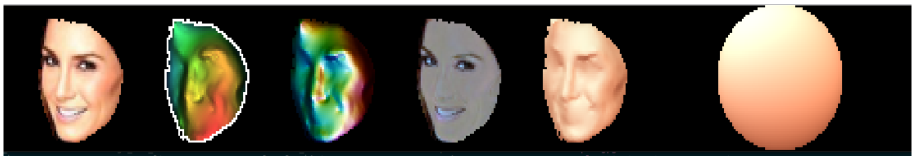

Figure 2: Input image, Shape, Normal, Shading, Reflectance and SH based lighting respectively

4 Baseline

We implemented base SfSNet and Skip connection based model for baseline and ground up for our work. Figure 4 demonstrates SfSNet pipeline and figure 3 demonstrates Skip connection based model.

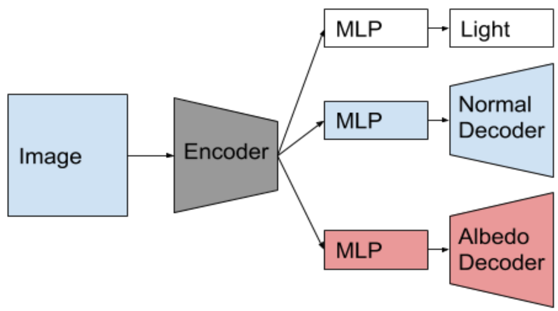

Figure 3: SkipNet

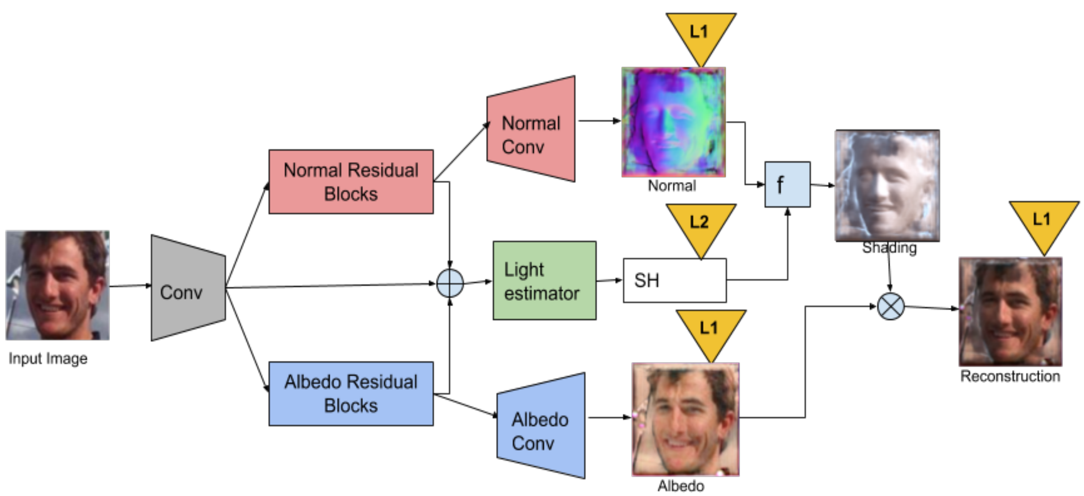

Figure 4: SfSNet Model

Training procedure is as follow:

1. Train Skip-Connection based model on synthetic data
2. Generate Albedo, Normal and SH for CelebA data using trained skip-connection based model
3. Use Synthetic data with true ground truth and generated CelebA data as pseudo-supervision
4. Train SfSNet using dataset described in step 3

4.1 Skip-Connection based dataset

Skip connection network is same as used in SfSNet and Neural face editing[6] We trained Skip-Connection based network for 20 epochs with learning rate of 0.0002 with Adam optimizer and no weight decay.

CelebA generated data is not very good and does have some artifacts. Few experiments with this dataset leads to inaccurate albedo generation and hence, we initialized sfsnet with pretrained weights, fixed all the weights except albedo residual, generation and new residue generation network. Now, task is to learn albedo and shading residue. Now, problem is with pretrained albedo which does have residue and we need to un-learn it. High level idea is to learn residue and remove residue from albedo generation(i.e. albedo residual block and albedo generation net).

You can check results and evaluation of number of experiments we performed here https://app.wandb.ai/bhushan-s-94/SfSNet-CelebA-Baseline-V3-SkipNetBased

4.2 SfSNet

In SfSNet model, we first extract image features using convolution layers, then we use these features and apply residual blocks for normal and albedo separately and then pass output of residual blocks through two separate de-convolution layers to produce Normal and albedo. For generating lighting, we combine Normal, Albedo residual blocks output along with convolution features and pass it through Lighting estimator to generating a vector of size 27 for generating spherical harmonics for RGB image. Residual blocks are useful to extract image features for CelebA and are useful for wild images. Figure 4 shows sfsnet model introduced in SfSNet.

Training procedure uses L1 losses for Normal, Albedo and L2 loss for Spherical Harmonics. L1 reconstruction loss is used for CelebA images as major loss and pseudo-supervision data is being used as ground truth data for celeba dataset for which we lack ground truth, in which case, re-construction loss plays important role.

5 Problem Statement

SfSNet generated shading is generated using Normal and Spherical Harmonics which does not captures the full illumination details. Due to geometric imperfection and spherical harmonics inaccuracy, generated shading is not near to perfect. Later, shading is used along with albedo to reconstruct the image. Figure 5 shows traditional shading model which is based on Normal and Spherical Harmonics.

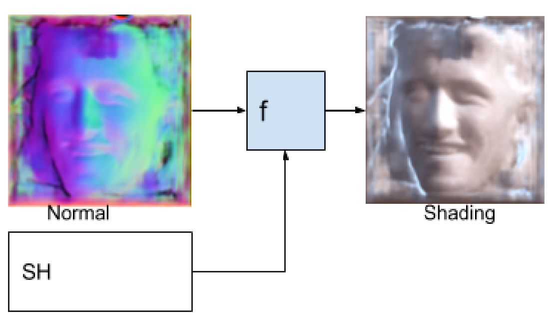

Figure 5: Illumination model based on Normal and Spherical Harmonics

SfSNet uses L1 losses for Normal and Albedo. It does not use any loss for shading is computed using normal and spherical harmonics which are trained using L1 and L2 loss respectively and hence, supervision for shading is not required. For reconstruction of image, we take hamazard product of shading and albedo. Reconstruction loss is added for training real data with pseudo-supervision dataset. Note that, reconstruction loss is pushing information backwards which is received by shading and albedo which is further passed to Normal and SH. Due to imperfect shading capture, difference of illumination captured by reconstruction loss is then pushed to albedo.

Question is, why features are being pushed into albedo and not shading? It is easy to see that shading is not computed using any neural network but using pre-determined non-learning function. This is major reason, gradients for albedo leads to generating noisy or albedo with residue.

6 Our Solution

We propose to introduce new shading layer to capture more flexible and comprehensive illumination effect that is not modelled by 27 dimensional spherical harmonics like SfSNet. We capture this representation directly using image features and residual block being used in SfSNet for albedo and normal. Later, we add this representation into SfSNet based generated shading. This shading layer is residue of illumination missed by SfSNet. Figure 6 shows new illumination model we are proposing.

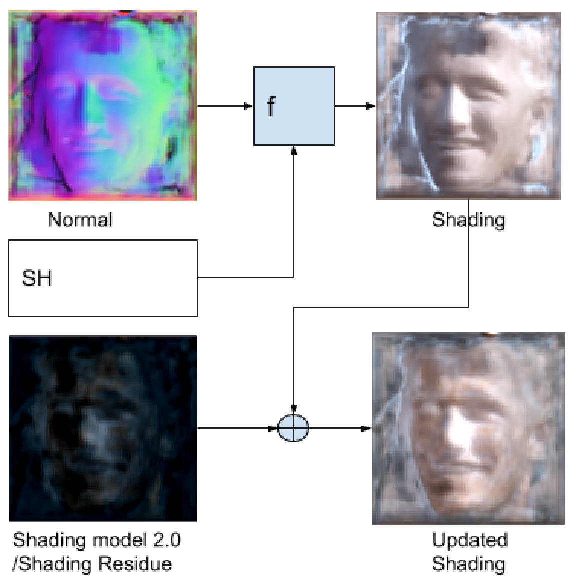

Figure 6: New Illumination model introducing new shading layer on top of traditional based on Normal and Spherical Harmonics

This new representation is not based on normal and spherical hormonics and hence, is hence, able to capture the missing details in the shading. Secondly, this representation can be learned with deep-neural network architecture where we only train the new shading model by keeping sfsnet based shading model fixed. In next, section, we elaborate over extensive experiments we perfomed and go over results.

7 Dataset

We lack ground truth for real images and hence policy is to combine real images and synthetic images during training which helps in capturing both high frequency and low frequency details from real and synthetic images respectively.

We use Synthetic image dataset used in SfSNet which is collected using 3DMM[9] in various viewpoints, reflectance and illumination. 27 dimensional spherical harmonics are estimated from distrubution of 3DMM fitting over real images from CelebA dataset using classifcal methods. Figure 7 shows synthetic dataset that was used throughout the experiment.

We generated pseudo-supervision dataset using skip connection network, dataset is not fined tune and contained few artifacts in albedo. Also, Spherical Harmonics were not accurate enough. Due to which, we decided to use SfSNet's pre-trained model to generate pseudo-supervision dataset as shown in figure 8

Figure 7: Synthetic dataset being used for training SkipNet and SfSNet

8 Experiments

High level idea is to generate shading residue and then add the residue into shading, then we use this updated shading for reconstruction. We hope to capture residue and successfully eliminate residue from albedo by training only for albedo and residue network.

Following are few approaches we experimented with for residue learning.

1. **Shading Correcting Network**- In this approach, we update shading using latent lighting representation. We hypothesize that latent lighting representation (spherical harmonics 2.0) will captures details missed by spherical harmonics and fill in the residue for shading. Here, Shading correcting network is responsible for combine existing shading and residue.
2. **Latent Shading Generation**- In this approach, we generate shading without spherical harmonics and only use normal and latent lighting representation. Here, Shading generation network is responsible for generating correct shading and here we do not rely on residue as neural network is expected to learn the representation accurately.
3. **Shading Residue Network**- In this approach, we simply determine the residue and add into predicted shading. This simplifies overall learning and residue learning task.
4. **Two way Residue Network**- In this approach, we determine the residue similar to approach 3, but we not only add the residue in shading but also subtract the residue from albedo. Here, we have more strong supervision on residue. We can use analogy of take from albedo and

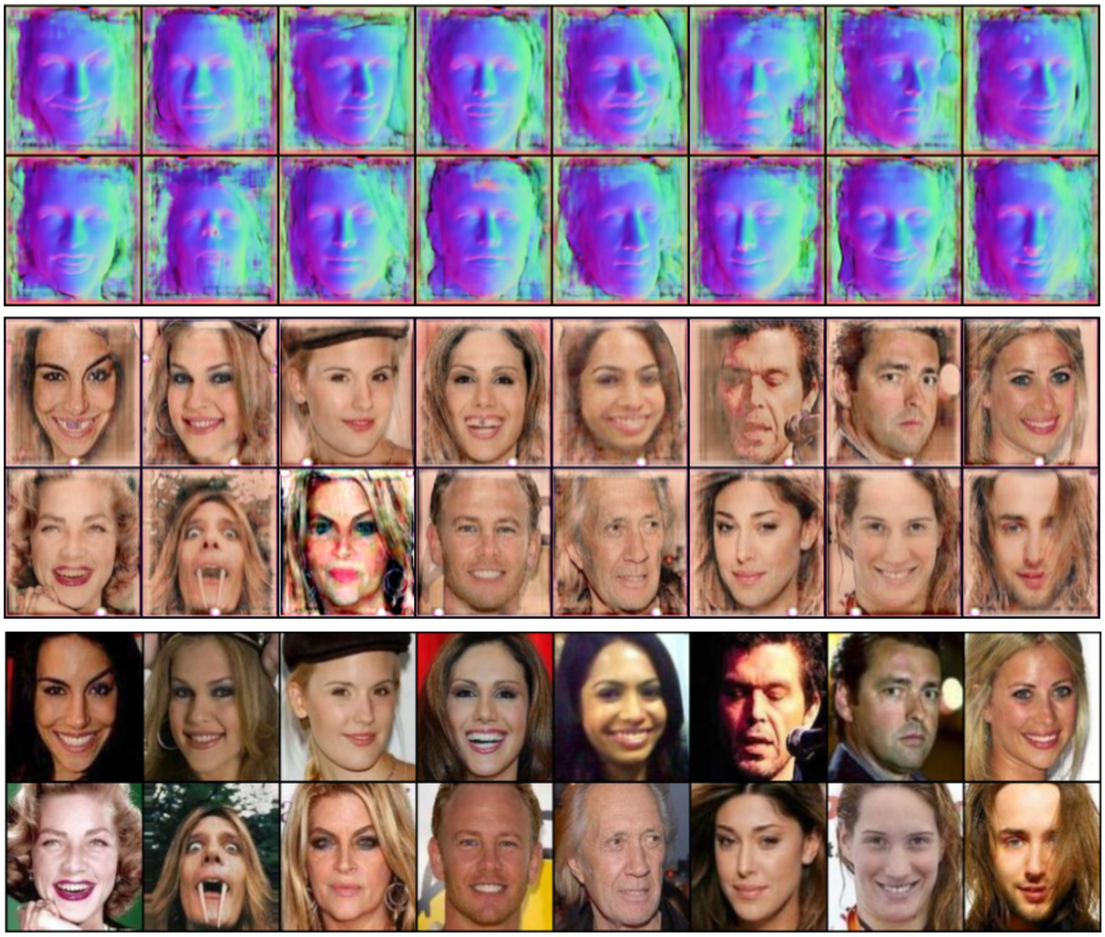

Figure 8: CelebA Pseudo-Supervision dataset generated using Pretrained SfSNet model. This dataset is used along with synthetic dataset7 to learn the decomposition

give it to shading. Here, we fix albedo network as well and add supervision on updated albedo which is 'albedo - residue'.

5. **GAN based approach for Albedo generation for shading residue Network**- In all of the above approaches, we faced issue for generating ground truth albedo (which we only have for synthetic data). Hence, we use GANs to generate albedo in synthetic domain space. We additionally added supervision with very small weight to albedo with Smooth loss.

Below, we will first go over GAN based approach (i.e. approach 5) and then other approaches.

8.1 GAN based approach for Albedo generation for shading residual network

In this approach, we are using pre-trained model and hence fixing weights for normal and spherical harmonics estimation. We make a copy of albedo residual block and use albedo conv as generator in GAN training setting.

Figure 9 demonstrates GAN based model architecture. We keep rest of the flow similar to SfSNet model due to pretrained weights being used to ensure minimal changes and assess learning of residue and albedo.

We use CycleGAN training paradigm for training albedo generation and traing Generator along with full network training. We experimented with and without L1 smoothing loss and observed that L1 smoothing loss with very small weight helps learning albedo generation. With only reconstruction

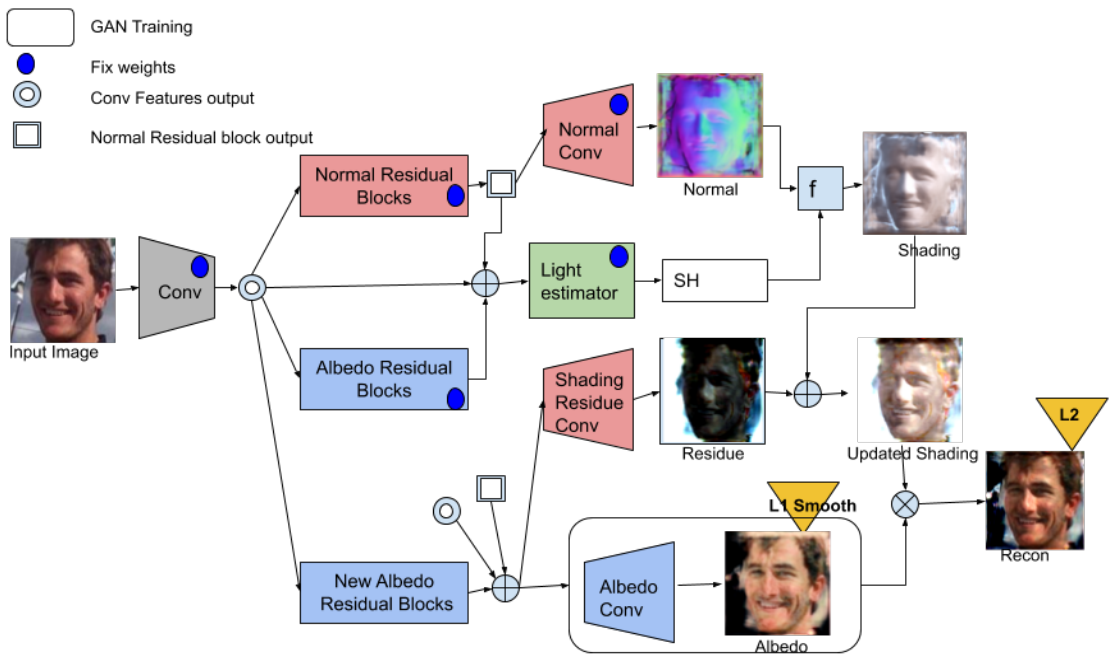

Figure 9: GAN for albedo generation and Shading Residue based model

loss, all the learning is pushed towards shading residue network and albedo generation is not learned properly. Note that, we are using small weights for gan loss and albedo loss (0.01 and 0.2 respectively).

We experimented with very small weight for gan loss i.e. 0.002, but that did not help and lead to incorrect albedo generation. Figure 16 and 17 shows interpolation and comparison for celeba and synthetic image.

Plot 10 shows training loss for gan based model. Plot 11 shows reconstruction and albedo loss for gan based model.

You can go through detailed results and evaluation of our experiments here https://app.wandb.ai/bhushan-s-94/SfSNet-CelebA-GANLoss-Shading-Residual-PreTrained/runs/gouvywws

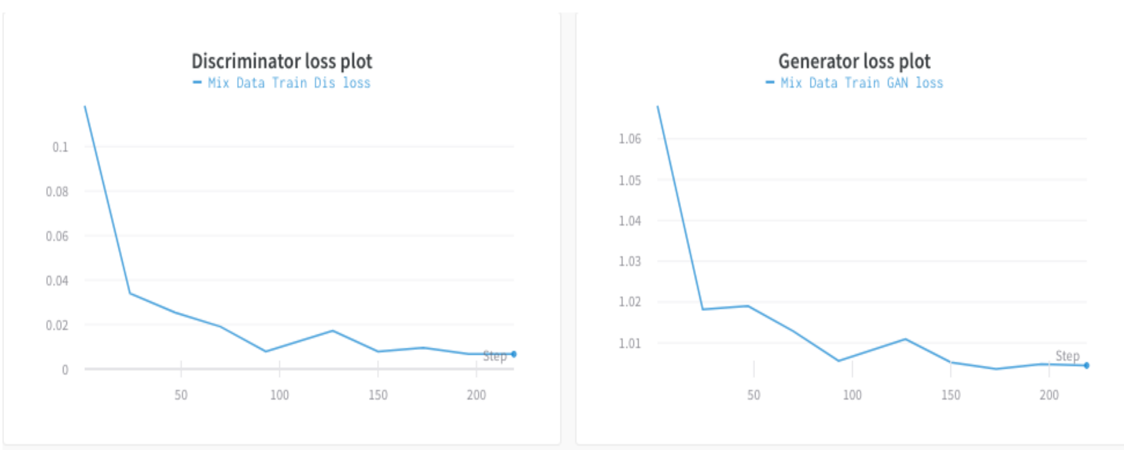

Figure 10: GAN and shading residue model training plots: GAN loss

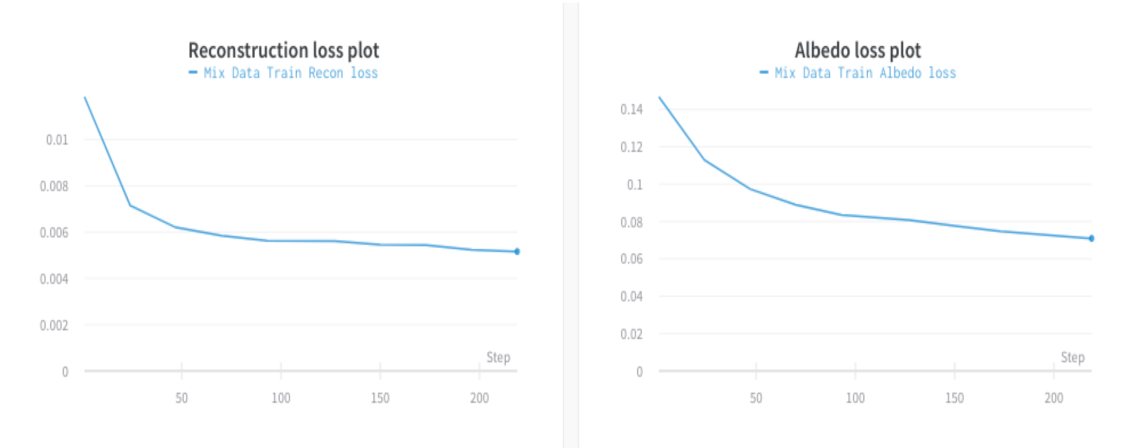

Figure 11: GAN and shading residue model training plots: Reconstruction and albedo loss plot

8.2 Shading Residue Network

Our claim is that, some of the shading residue is pushed down into albedo. Instead of learning normal, spherical harmonics from scratch, we propose to build on top current model by adding residue network.

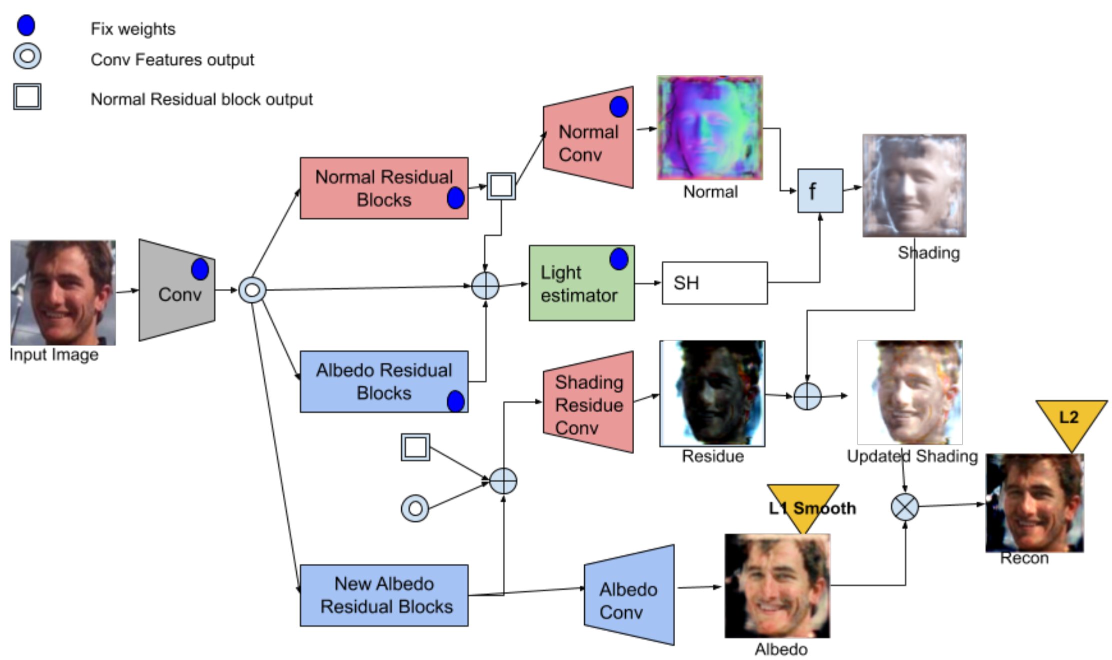

Figure 12: Shading Residue model

Idea is to find the residue pushed down into albedo and add into shading. Network with this setting will be trained primarily with reconstruction loss. Use of shading loss will be more strong supervision and will be useful for finding better residue, but due to lack of ground truth normal, spherical harmonics, we cannot use the shading loss. Hence, we use lower weights for albedo and focus more on reconstruction loss and also don't comprise on albedo much.

Figure 12 explains architecture used for this experiment. First, we compute residue and then simply add it into generated shading. Note that, we are not learning normal and spherical harmonics and hence, we ensure to only update albedo and shading using residue network and reconstruction loss.

You can go through detailed results and evaluation of our experiments here https://app.wandb.ai/bhushan-s-94/SfSNet-CelebA-Shading-Residual-PreTrained/runs/3ik5agcy

8.3 Shading - Albedo Residue Network or Two-Way Residue Network

In Shading residue network, we added computed residue in generated shading and relied on network learning to remove residue from albedo. In this approach, we subtract residue from generated albedo and add same residue into shading.

In this architecture, we don't need to create new albedo generation network as we will not generate albedo from scratch but only update the existing one i.e. fixing and not generating. We can imagine residue network as Robinhood who takes from albedo and gives to shading.

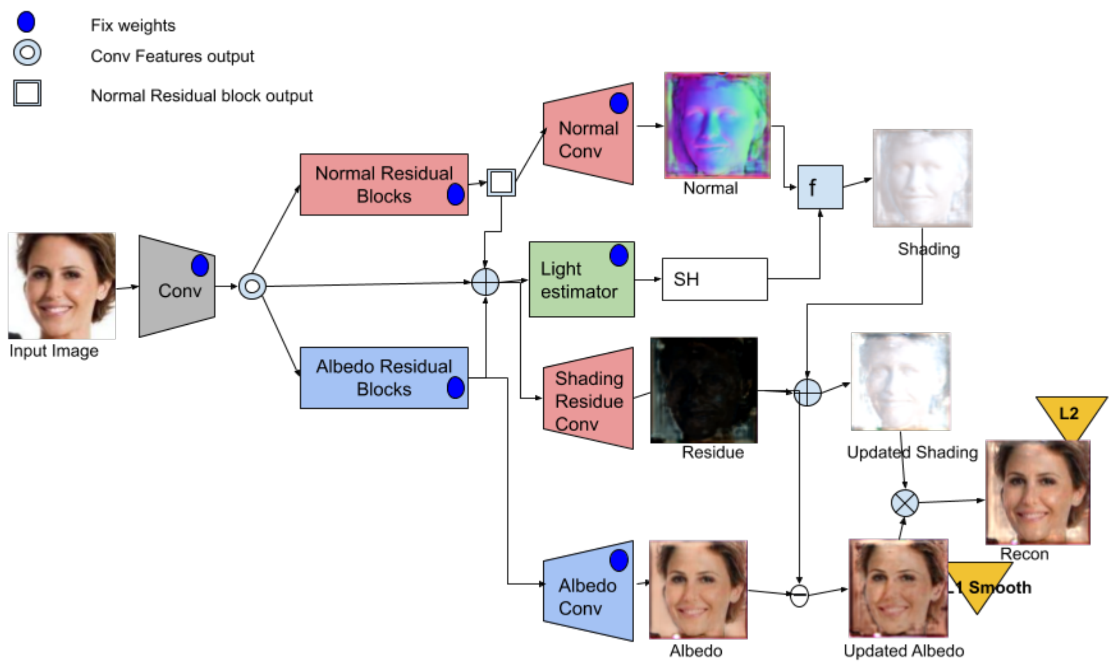

Figure 13: Shading-Albedo Residue model

Figure 13 demonstrates architecture being used. You can go through detailed results and evaluation of our experiments here https://app.wandb.ai/bhushan-s-94/SfSNet-CelebA-Shading-Albedo-Residual-PreTrained/runs/kzepw1e7

Primary issue in this approach is again ground truth albedo for CelebA dataset. Hence, we again use smaller weight for albedo loss to focus on reconstruction loss.

8.4 Shading Correcting Network

This was very first experimented we tried. In this approach, we use latent lighting representation, let's say Spherical Harmnics 2.0 to update or correct the generated shading.

We generate SH 2.0 using similar input as SH i.e. using conv features, normal residual block features and albedo residual block features. Later, we use this generated shading along with SH 2.0 to correct the shading. Shading correcting network uses SH 2.0 and adds missing details in traditional shading.

Proposal is to generate SH 2.0 representation as an add-on on top of the SH which collects and looks after missing lighting representations.

Figure 14 shows the shading correcting model. You can go through detailed results and evaluation of our experiments here https://app.wandb.ai/bhushan-s-94/SfSNet-CelebA-Shading-Correcting-Net-PreTrained/runs/0wq42sko

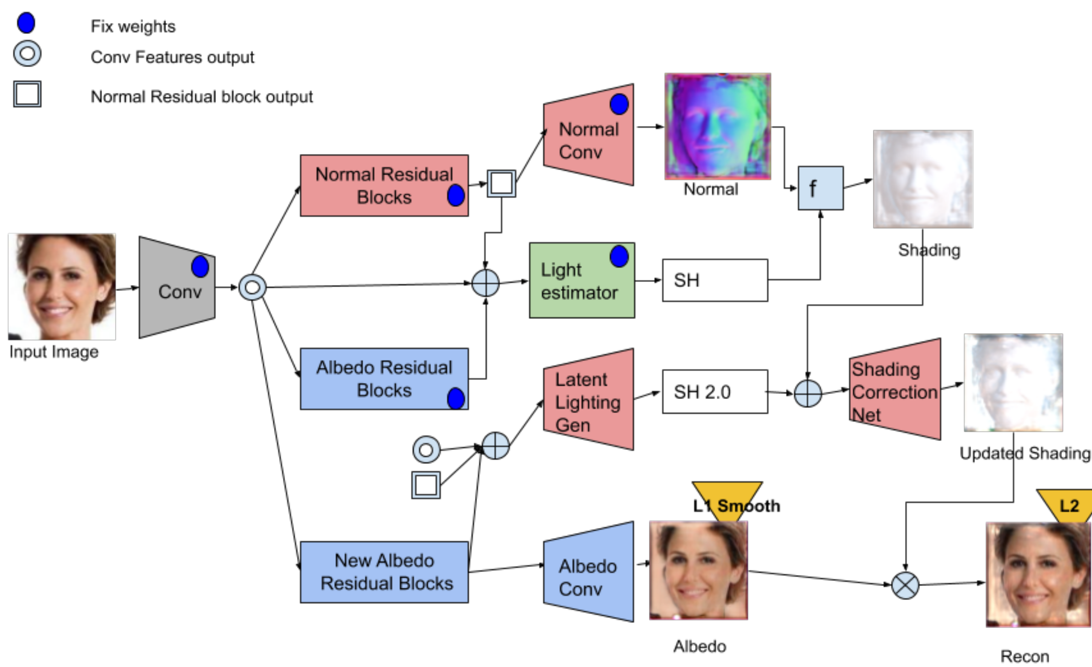

Figure 14: Shading Correcting model

8.5 Shading Generation using SH 2.0

In Shading Correcting approach, we used two lighting representations. In this experiment we assessed need of spherical harmonics and used SH 2.0 along with normal to generate the shading.

Lighting representation is equivalent to image dimensions for each plane. We concatenate lighting representation along with normal and feed into shading generation network to generate shading using these two representation. We are fixing normal and hence, ensuring that latent lighting representation is being valid and representing lighting similar to spherical harmonics. Note that, we are not aware of function it is approximating to and expect it to be some what but not exactly similar to spherical harmonics.

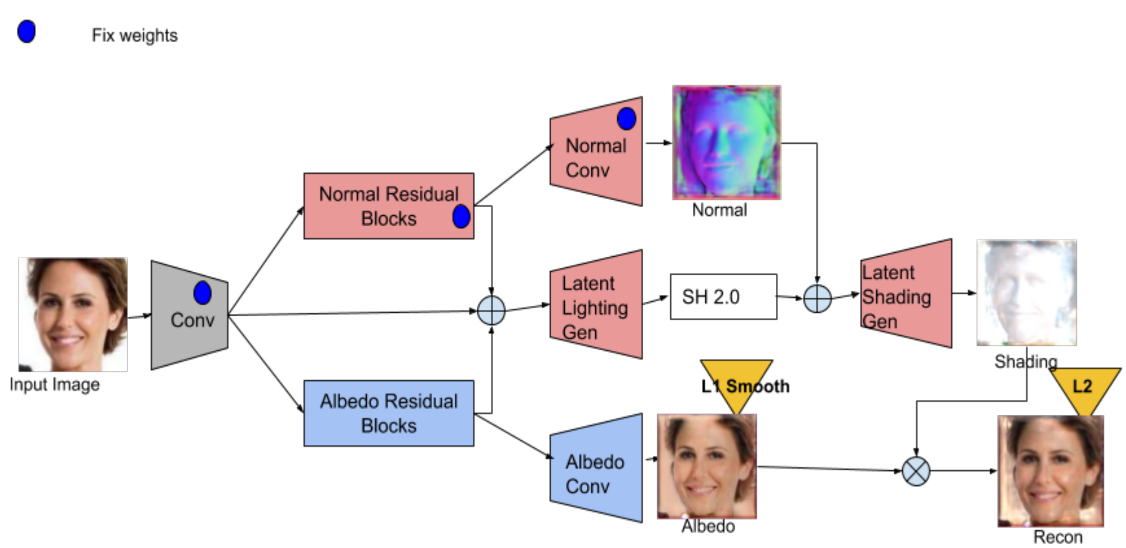

Figure 15: Latent Shading generation using SH 2.0

Figure 15 explains the latent shading generation model. You can go through detailed results and evaluation of our experiments here https://app.wandb.ai/bhushan-s-94/SfSNet-CelebA-Latent-Shading-Gen/runs/altgj0uj

9 Results

We performed extensive experiments with above methods with different weights to albedo loss, adding shading loss and also removing albedo loss.

Albedo loss: No including albedo loss leads to albedo gen network collapse and learning is pushed down into residual networks. Using albedo loss with less weight was viable choice as we indeed want to use albedo loss but give more weight on reconstruction instead of albedo for which ground truth albedo has residue in it.

Shading loss: Addition of shading loss is important as it helps pushing the residue into shading network with valid shading ground truth. Due to lack of which, we added shading loss optionally with small weight. But, no significant benefit was seen with small shading loss due to incorrect ground truth available.

Following are the results of each method.

9.1 GAN based albedo generation in synthetic domain space

GAN based shading residue method performed quite well, keeping balance in albedo and shading generation. lighting representation was well captured in shading. We have analyzed the results in comparison section.

Figure 32 shows predicted albedo, shading, residue, updated shading and reconstruction with this method. Figure 16 and 17 shows results on GAN based method on unseen samples on celeba and synthetic images.

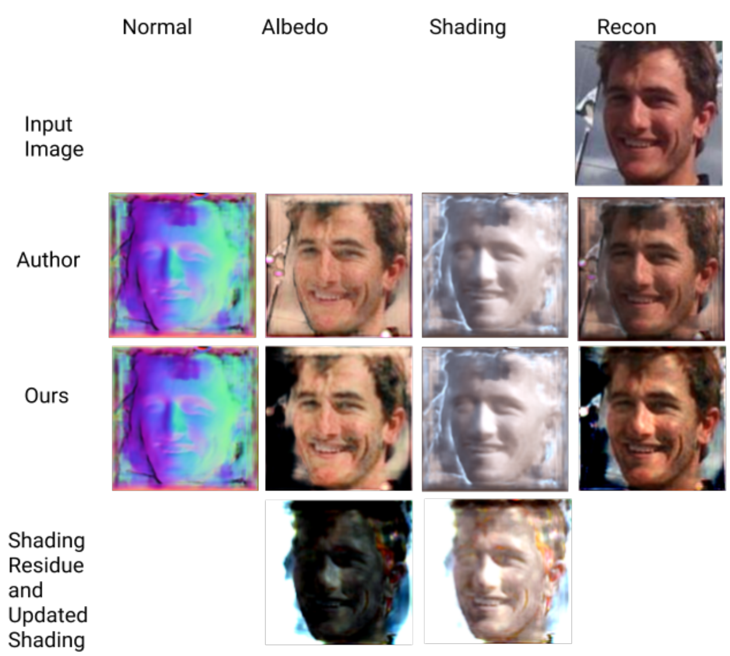

Figure 16: GAN + Shading Residue model sample result for CelebA

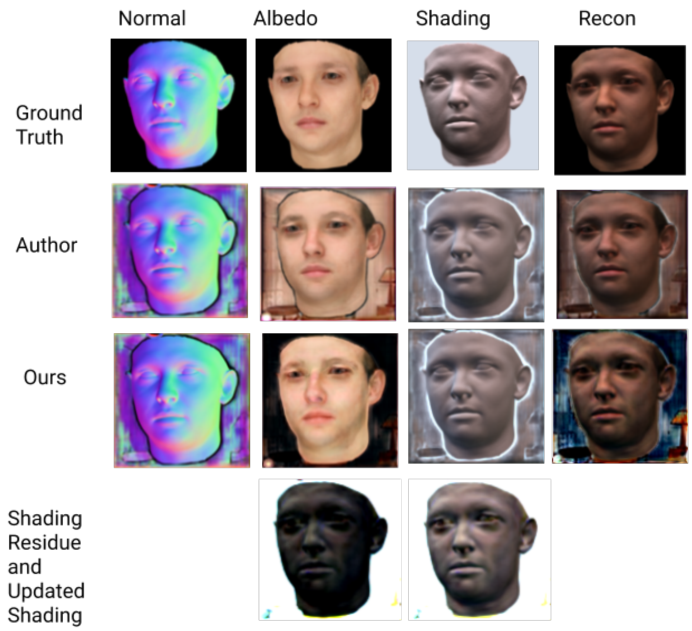

Figure 17: GAN + Shading Residue model sample result for Synthetic dataset

9.2 Shading residue network

Figure 18 and 19 shows output of residual based network. We have added more examples of sample output in appendix.

Shading residue output shows few artifacts in generated albedo and are consistent across the samples. One reason behid the artifacts could be due to distribution difference of synthetic and real dataset. Albedo and residue of CelebA and synthetic data needs to capture different sets of features and with mixture of data, network is not able to capture the details perfectly and leads to consistent artifacts. We have already seen that similar architecture with GAN for albedo generation does not produce artifacts and hence helping bridge the domain gap leading to artifacts.

But, with shading residue method, updated shading captures illumination details better than our baseline.

9.3 Shading-Albedo Residue network

In this approach, we have better control over shading model. But, generated residue to leading to create darker version of albedo which is adjusted in updated shading. This creates moving the details from albedo completely and representing in shading. Figure 20 and 21 shows output of residual based network. We have added more examples of sample output in appendix.

9.4 Shading Correction Network

This approach did not perform well overall. This approach has many downsides-

1. lots of parameters
2. Albedo is not albedo exactly
3. Due to shading correcting network, image features are pushed into updated shading

Shading correction is done by network which only has reconstruction loss as supervision. Due to lack of supervision for shading loss, image features are pushed into shading.

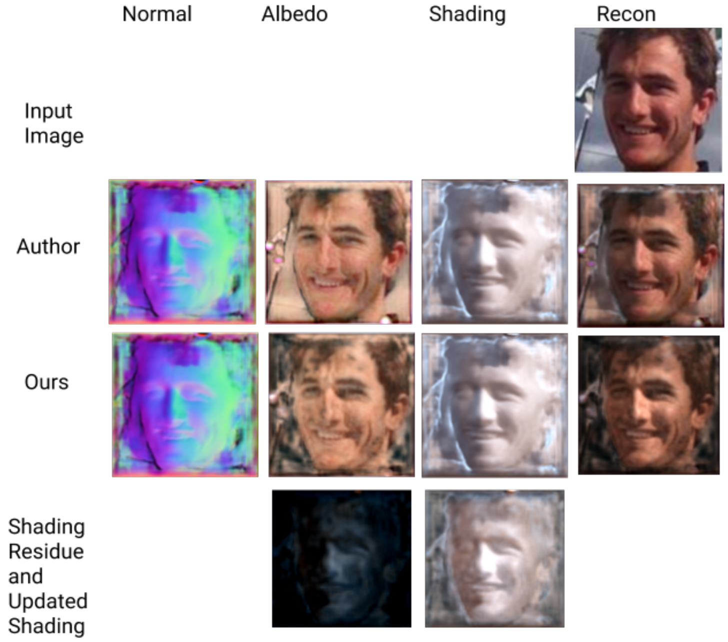

Figure 18: Shading Residue based model result for CelebA

Figure 22 and 23 shows output of shading correcting network on CelebA and synthetic data respectively. We have added more examples of sample output in appendix.

9.5 Shading Generation using SH 2.0

This network is simpler version of shading correction network where we don't depend on spherical harmonics and completely rely on latent lighting representation. Image features are pushed into shading.

Figure 24 and 25 shows output of shading correcting network on celeba and synthetic data respectively. We have added more examples of sample output in appendix.

This approach is simplified version of shading correcting network. This generates shading directly using latent lighting and normal. But faces similar issue of image features being pushed into shading.

10 Analysis and Comparison

In this section, we analyze and compare results above experiments performed.

As captured in figure 27, for synthetic images, GAN based approach outperforms all other methods leading to better shading model 2.0 and resuling into better shading representation and reconstruction. Use f less albedo loss weight was also helpful during training. For Shading residue and shading-albedo residue albedo loss had weight of 0.5 where as GAN based method had albedo loss weight of 0.2. Domain difference in CelebA and synthetc image's albedo lead to few artifacts that were observed in shading residue based method which are further passed into the reconstructed image. Where as, use of generative adversarial network helped bridging the domain gap of generated albedo and help generated more stable albedo than any other method. Use of Smooth L1 Loss helped generate albedo on track to not loss intensity of albedo like we observed in figure 26 with no albedo loss. Shading-Albedo residue based method also performed better for synthetic images. Residue computation is balanced and we can see albedo close to ground truth and better than GAN based method. But, updated shading failed to capture the details for shadow. This could be because of lack of shading loss. Adding shading loss in this method should likely improve the performance in correct shading generation. Lastly, Shading-correcting and Latent shading generation approaches clearly

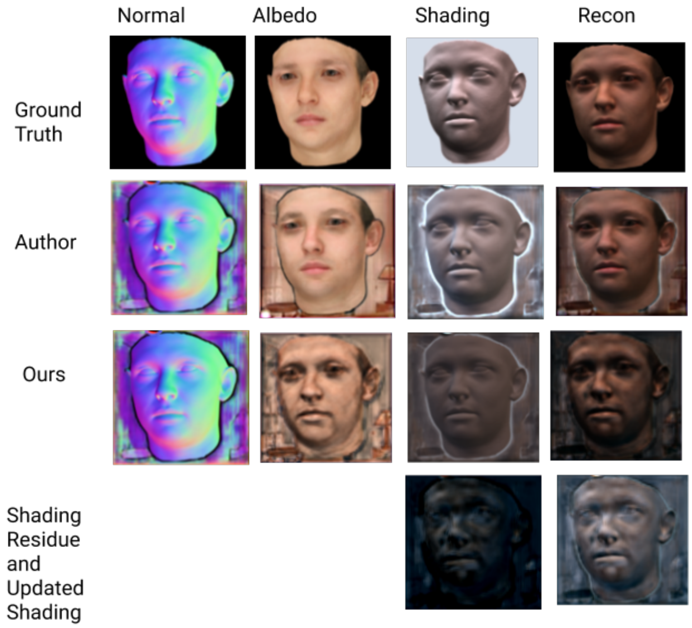

Figure 19: Shading Residue based model result for Synthetic dataset

fails to capture both albedo and shading details. Note that we are indeed using albedo loss for training but due to heavy number of parameters in shading correcting networks and latent representation leads to pushing image features into shading generation in latent shading and shading correction network in case of shading correcting network.

Now, let's analyze performance of each network on CelebA and real world images. From figure 28, 31, 29 and 30, Shading residue network performed best from our experiments. This is acceptable as network is only fine-tuned on albedo and learning residue which is much simpler than heavier network such as shading correcting. We can still observe few artifacts in albedo which are later reflected in reconstruction similar to synthetic images. This is probably due to not fine-tuning issue as this is observed in both the datasets as is consistent in all output. Ignoring this artifact, shading generated by shading residue looks good, capturing the lighting details on original image reflected in reconstruction. On the other hand, shading-correction and latent shading fails again due to image feature being pushed into shading. Shading-albedo residue also performs quite good but note better than shading residue for capturing details in shading but albedo looks darker, possibly due to not learning residue properly due to lack of shading loss and hence, decreasing values of albedo near to zero. GAN based approach seems to capture both Albedo and shading details clearly. GAN based approach is extension of shading residue approach with GAN for albedo and we can clearly see albedo beign improved significantly than shading residue method. In some cases, shading is darker but, lighting details are very well captured. We believe this is due to correct albedo generatin which is leading to correctly pushing residue into shading which is also removing need of shading loss whose lack is bottleneck in shading-albedo residue method.

For confirming need of albedo loss in GAN based approach, we also ran an experiment without albedo loss and using only gan loss and re-construction loss. Figure 26 shows that without albedo loss, brightness of albedo is pushed down into shading residue. Note that, albedo color is not lost only intensity of the albedo is pushed down into residue. This can be resolved with shading loss, as we need supervision where to distribute the intensity. With either shading or albedo loss, we are guarding how much intensity to consume from albedo and shading. This confirms that we indeed need light supervision either in albedo or as form of shading.

Table 1 summarizes hypothesis, verdict and next steps for each of the experiment we have discussed so far.

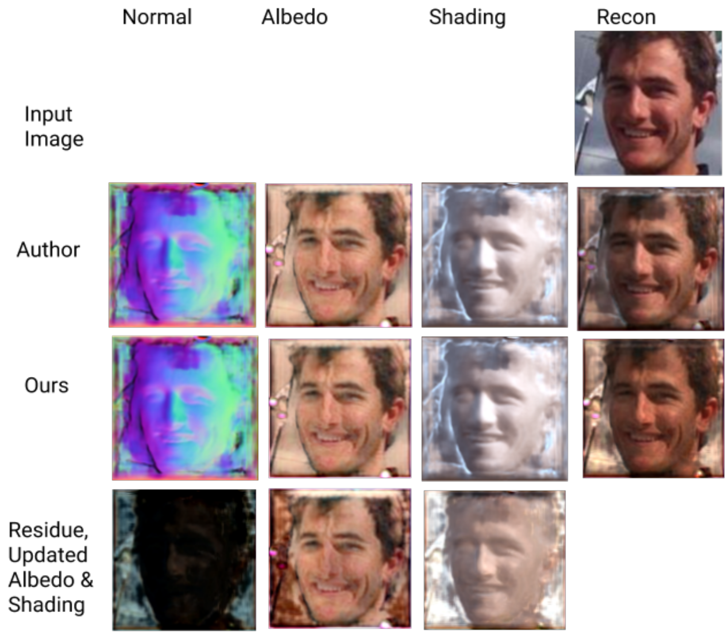

Figure 20: Shading-Albedo Residue based model result for CelebA

11 Conclusion

Latent lighting representations were not useful due to lack of shading loss and more importantly lack of ground truth for pseudo-supervision. Shading correcting and latent shading generation approach are not promising as of now and should be re-visited with better pseudo-supervision data for real dataset along with shading loss.

GAN based approach produced convincing results with use of low weights to albedo and gan loss. This approach shows that we can work with noisy and spurious data with the use of synthetic dataset and generating real image output in synthetic domain space.

Shading Residue network is also promising approach to pursue further. Unlike GAN based approach, it is solely depended on supervision. In this setting, we relied on reconstruction error and rely on noise albedo loss in small proportion. We can investigate this furhter once we generate or get pseudo supervision data without albedo residue.

Shading-Albedo residue network did not performed better than shading-residue network due to lack of shading loss as residue is highly depended reconstruction loss and does pushes the features into shading space.

12 Next Steps

1. GAN based approach: Try different or more stable GAN setting e.g. Wassertian-GAN gradient penalty[8]
2. Fine-tune skip-connection network to generate stable and artifact free, non-distorted pseudo-supervision dataset
3. Once, accurate pseudo-supervision dataset is available
   (a) Adding shading loss in base sfsnet
   (b) Adding shading loss in shading correcting and latent shading gen
   (c) Adding shading loss in residue networks
   (d) Adding L1 smoothing loss with more weight for albedo
   (e) Adding albedo loss with groud truh data for Shading-Albedo Residue network

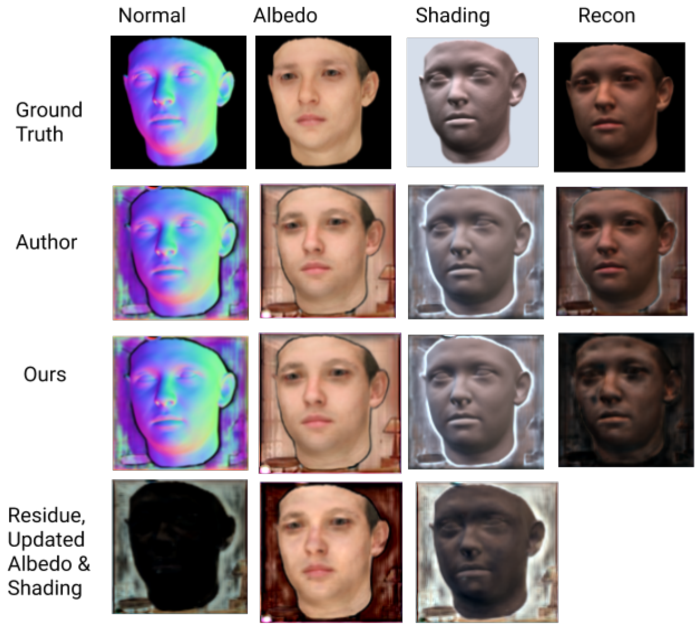

Figure 21: Shading-Albedo Residue based model result for Synthetic dataset

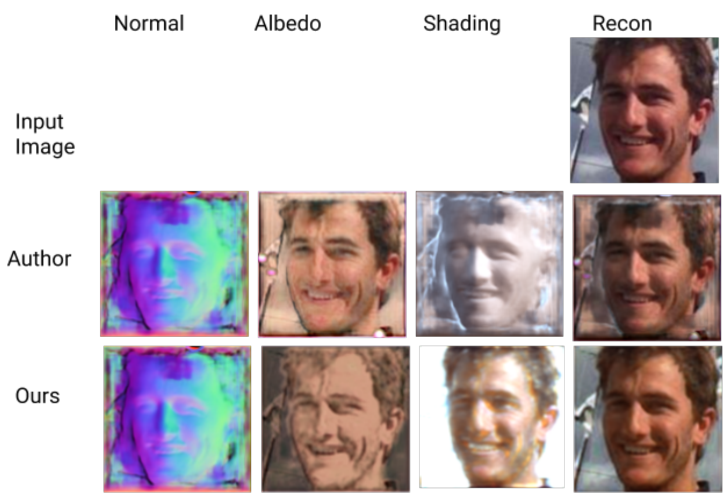

Figure 22: Shading correcting model result for CelebA

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4. Zhixin Shu, Mihir Sahasrabudhe, Alp Guler, Dimitris Samaras, Nikos Paragios, Iasonas Kokkinos. Deforming Autoencoders: Unsupervised Disentangling of Shape and Appearance

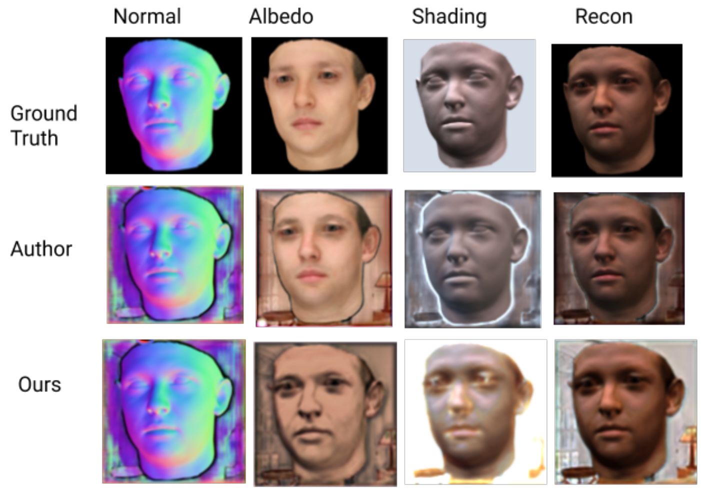

Figure 23: Shading correcting model result for Synthetic dataset

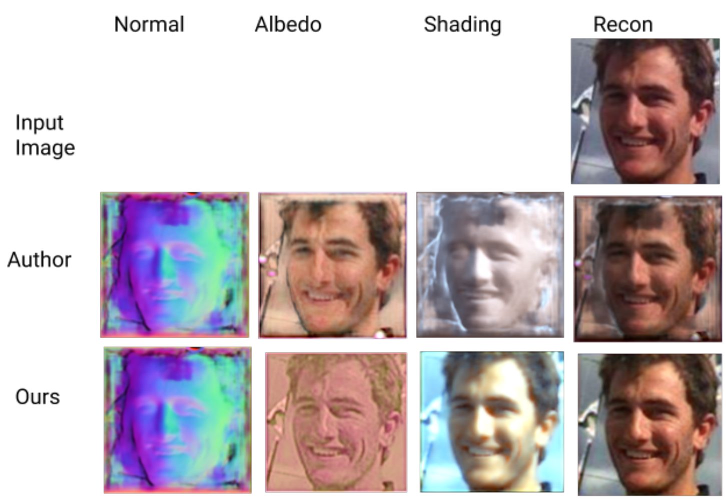

Figure 24: Shading generation using SH 2.0 result for CelebA

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6. Z. Shu, E. Yumer, S. Hadap, K. Sunkavalli, E. Shechtman, and D. Samaras. Neural face editing with intrinsic image disentangling

7. Jonathan T. Barron, Jitendra Malik , SIRFS

8. Ishaan Gulrajani, Faruk Ahmed, Martin Arjovsky , Vincent Dumoulin , Aaron Courville. Improved Training of Wasserstein GANs.

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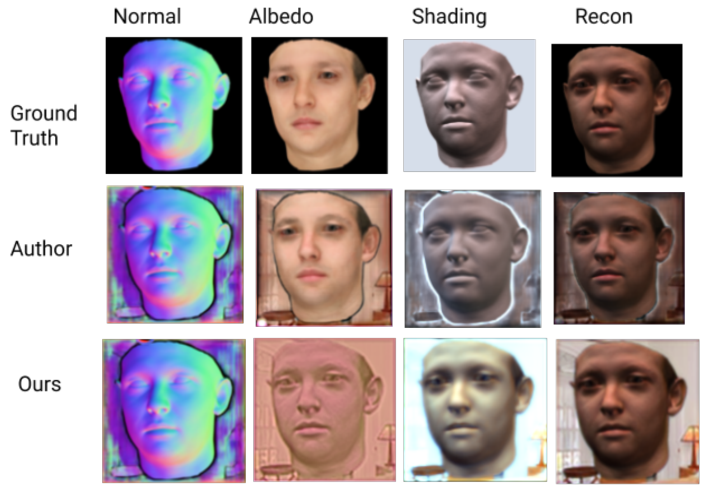

Figure 25: Shading generation using SH 2.0 result for Synthetic dataset

13 Appendix

13.1 More examples of sample output

Following, we go over more sample output of each of the model described above. Figures 33, 34, 35, 36, 32 shows sample output for shading correcting, latent shading generation, shading residue, shading-albedo residue and gan based approach respectively.

13.2 Source code

1. Baseline SFSNet and SkipNet https://github.com/bhushan23/SfSNet-PyTorch
2. All experiments- https://github.com/bhushan23/SC-Net

Method	**Hypothesis**	**Verdict**	**Next steps**
Shading Correcting	1. Latent represention (SH 2.0) will improve shading in latent space 2. Will help capture missing lighting details which can be applied using NN	1. Due to lack of shading loss, image features are pushed into shading. 2. Too heavy network	Try adding shading loss along with ground truth data
Latent shading generation	1. Completly depend on SH 2.0 and discards SH 2. Generate shading using latent space using new lighting representation which should capture details missed by SH and hence improve albedo and shading	1. Similar to approach image features are pushed into shading 2. No supervision for SH 2.0 - don't know what we are learnig	Try adding shading loss
Shading residue network	1. Learn shading residue and add into shading 2. Training with reconstruction loss and albedo loss with less weight should help extract shading residue	1. Shading residue was indeed extracted correctly 2. Few artifact observed in albedo probably due to domain difference 3. Generated shading looks promising	Using less weight to albedo due to noisy albedo, it will be good to see with full albedo loss once ground truth albedo is available
Shading-albedo network	1. Shading-residue is only adding residue into shading. Goal is to pass residue from albedo to shading. 2. Works on Robinhood's principle, i.e. take from albedo and give to shading.	1. Did not perform better than shading-residue network 2. Probably due to more manual interface which depends on shading loss	Try shading loss with ground truth information.
GAN with shading residue	1. Shading residue network failed to generate correct albedo. 2. We have ground truth albedo for synthetic data and noisy for celeba. 3. Using GAN to generate albedo in synthetic space for celeba as well	1. Results are promising 2. Shading is little darker compare to other methods. but light intensity is very well captured 3. Fails with no albedo loss 4. Using small albedo loss weight.	Experiment with true ground truth data i.e. Work on skip-net to generate better albedo and normal.

Table 1: Summary of experiments

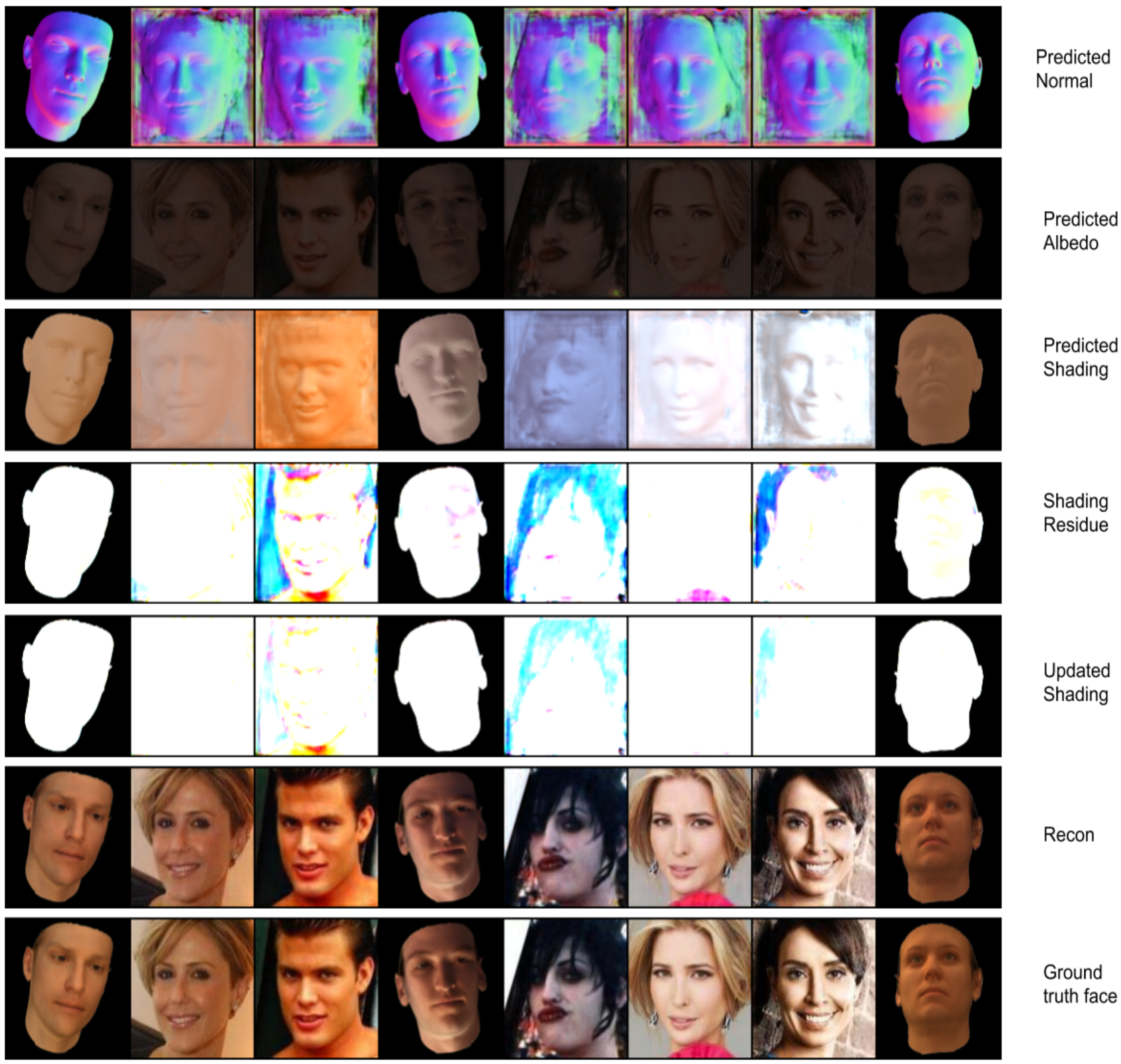

Figure 26: Demonstrating important of albedo loss in GAN based approach. Without Albedo loss, intensity of albedo is learned by new shading model instead of albedo. See, Albedo and Shading Residue in image.

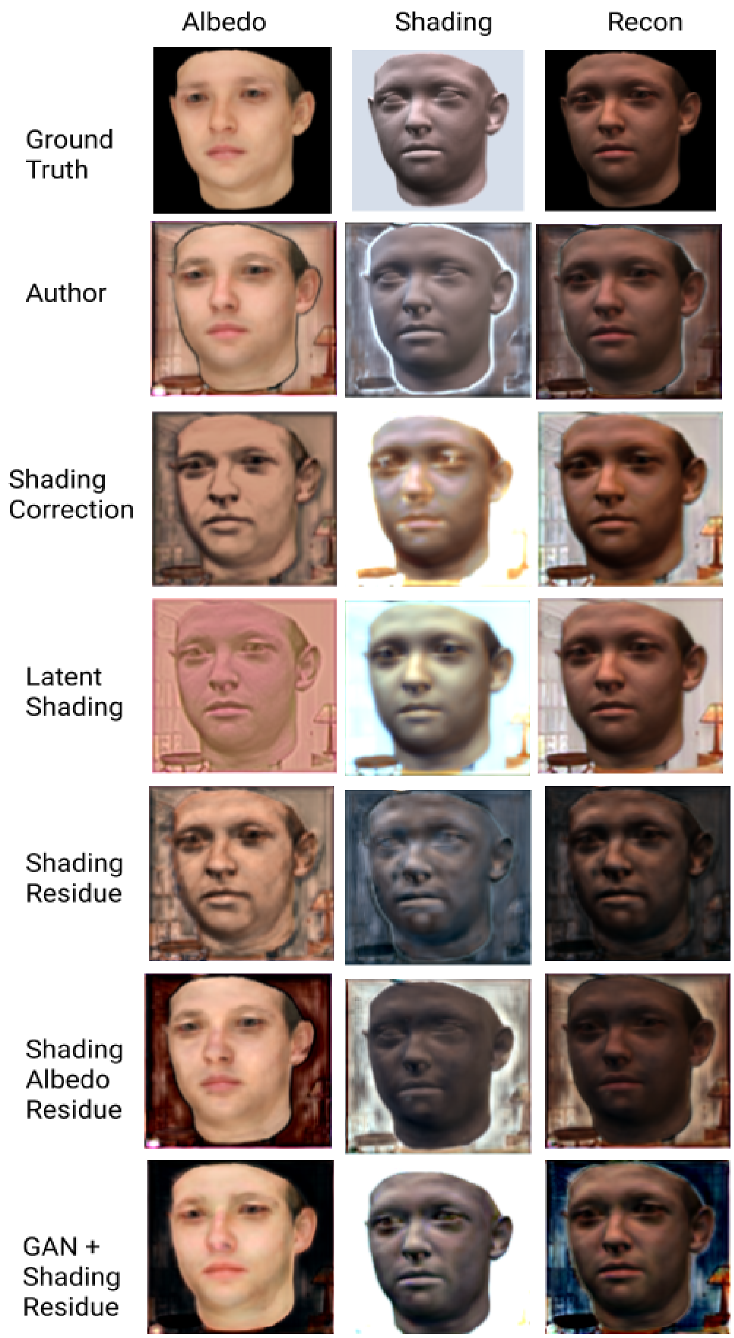

Figure 27: Comparing All experiments on Synthetic dataset for Albedo, Final Shading and Reconstruction.

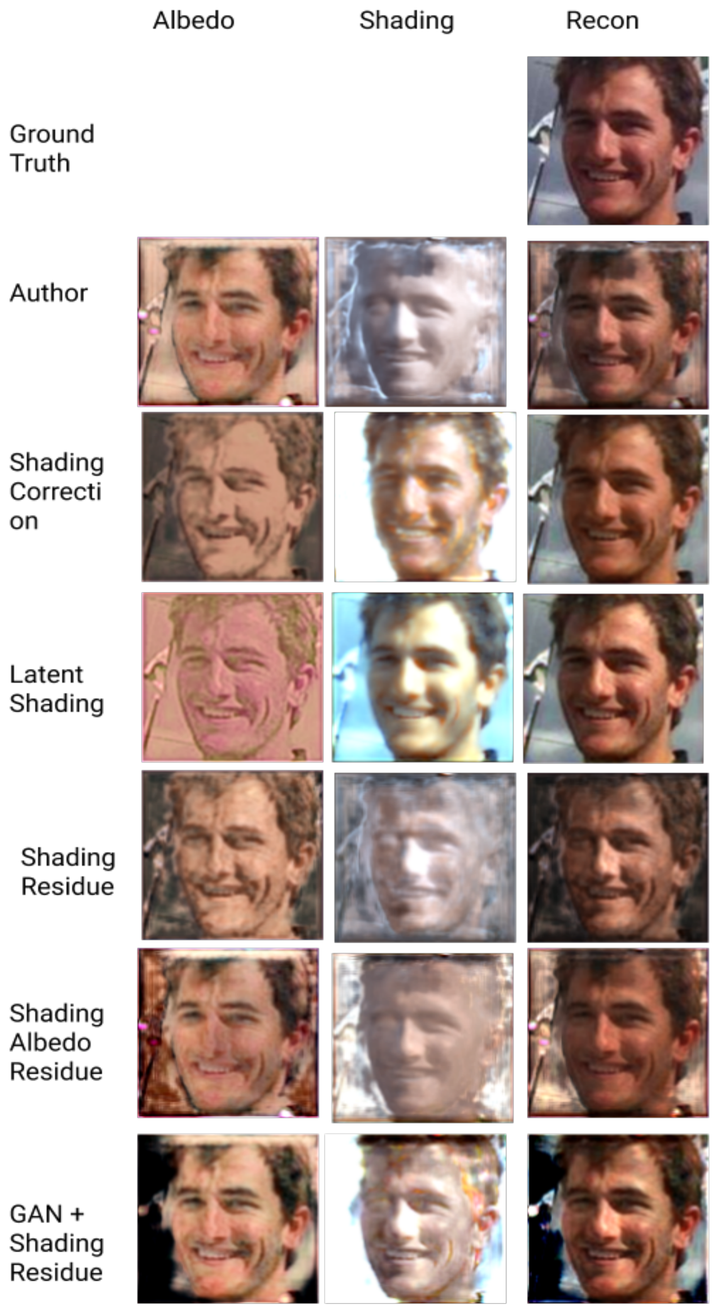

Figure 28: CelebA 1: Comparing All experiments on CelebA sample for Albedo, Final Shading and Reconstruction

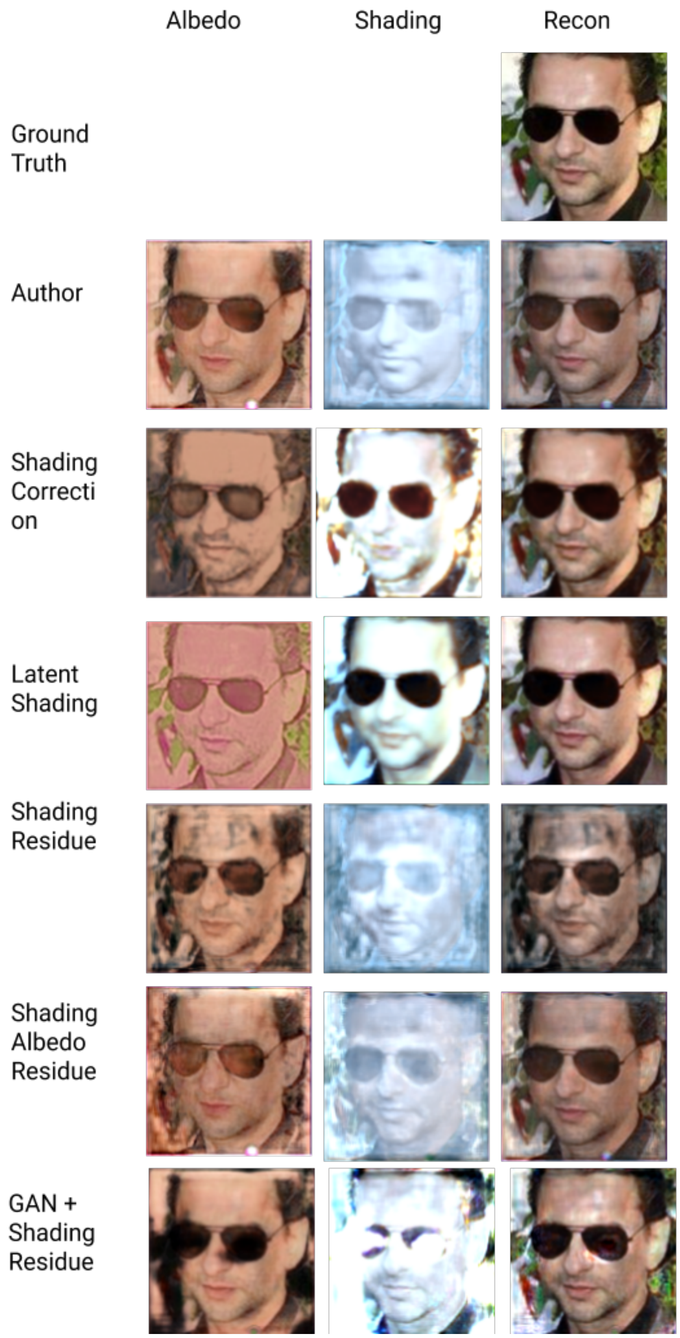

Figure 29: CelebA 2: Comparing All experiments on CelebA sample for Albedo, Final Shading and Reconstruction

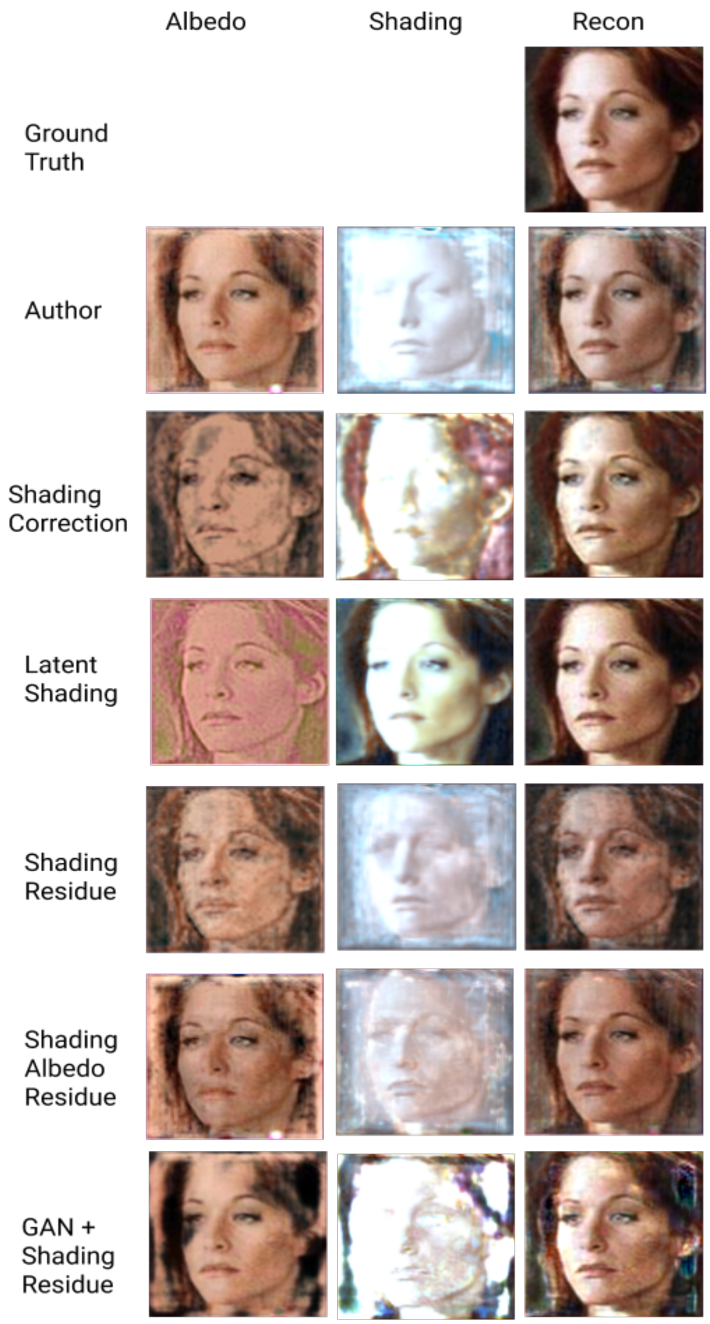

Figure 30: CelebA 3: Comparing All experiments on CelebA sample for Albedo, Final Shading and Reconstruction

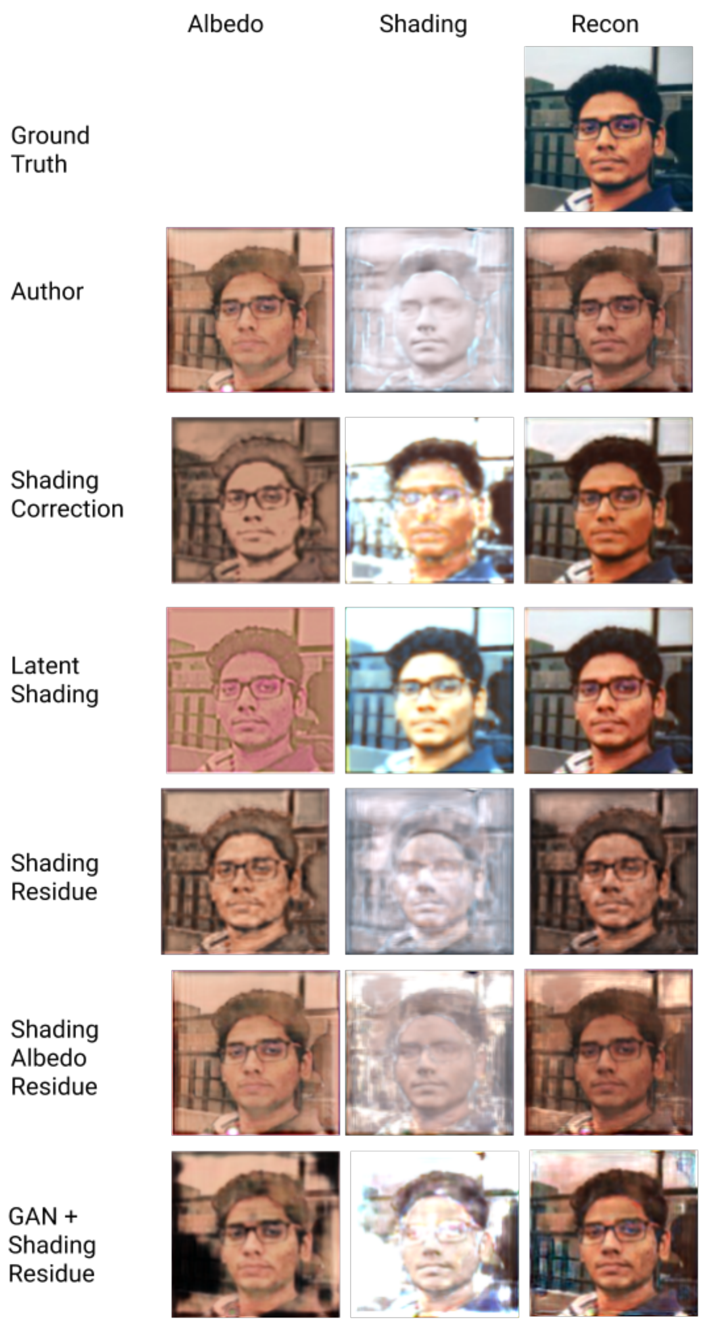

Figure 31: Real world sample: Comparing All experiments on real world sample for Albedo, Final Shading and Reconstruction

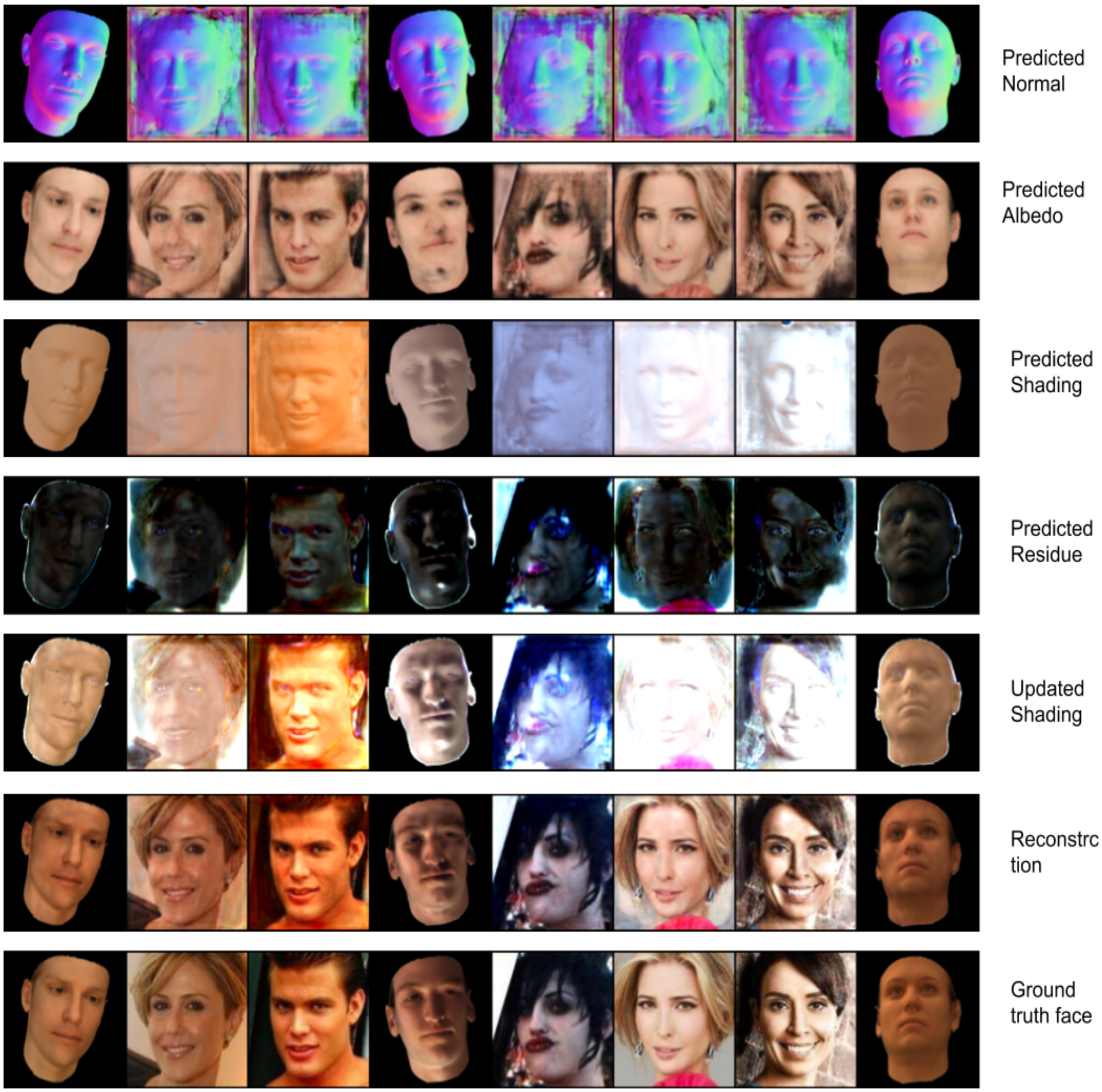

Figure 32: GAN based model Result samples: Shows generated Albedo, Residue, Shading, Updated new shading and reconstruction. Normal and SH is not learned.

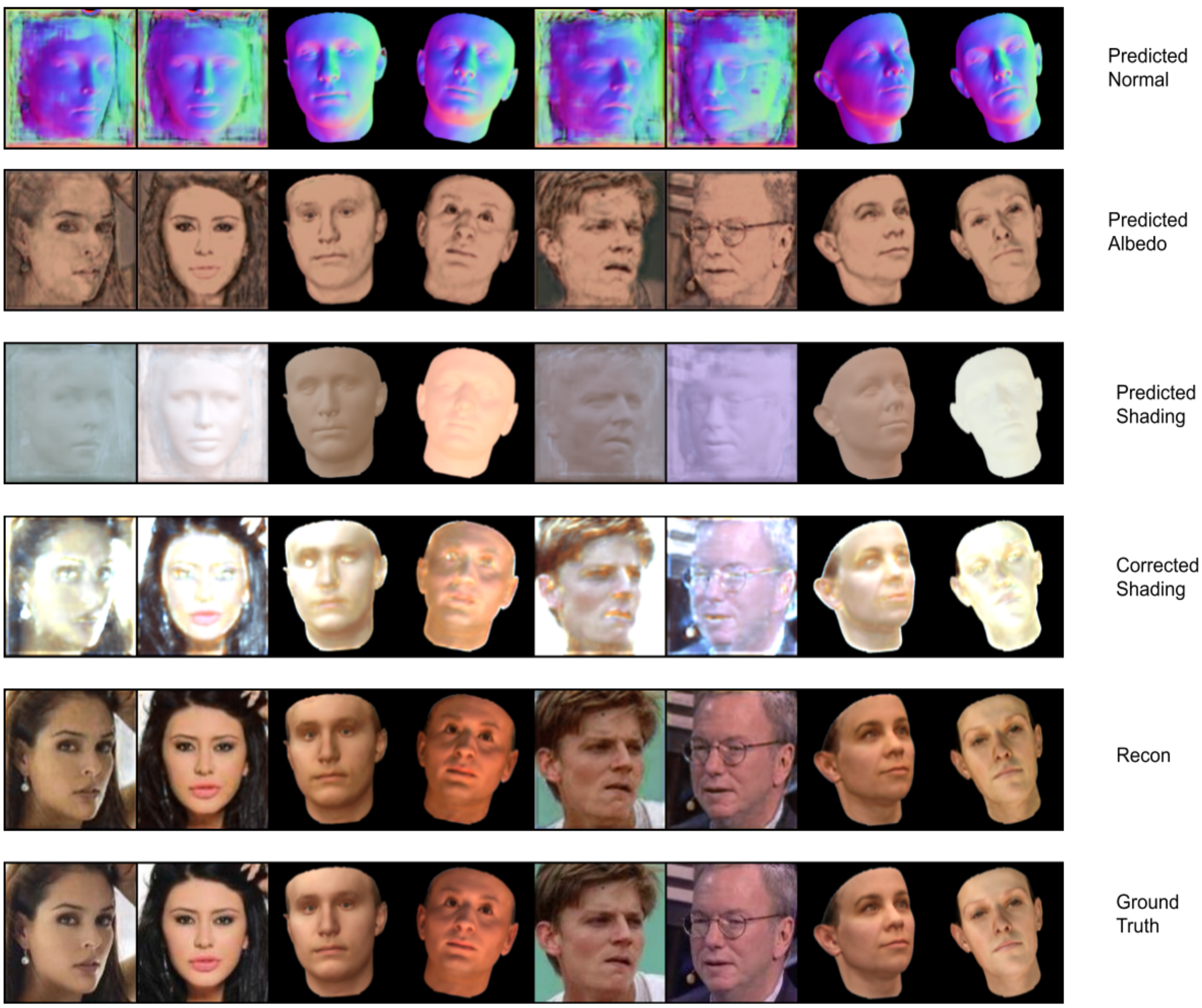

Figure 33: Shading Correcting model Result samples: Shows generated Albedo, Residue, Shading, Updated new shading and reconstruction. Normal and SH is not learned.

Figure 34: Latent shading generation model Result samples: Shows generated Albedo, Residue, Shading, Updated new shading and reconstruction. Normal and SH is not learned.

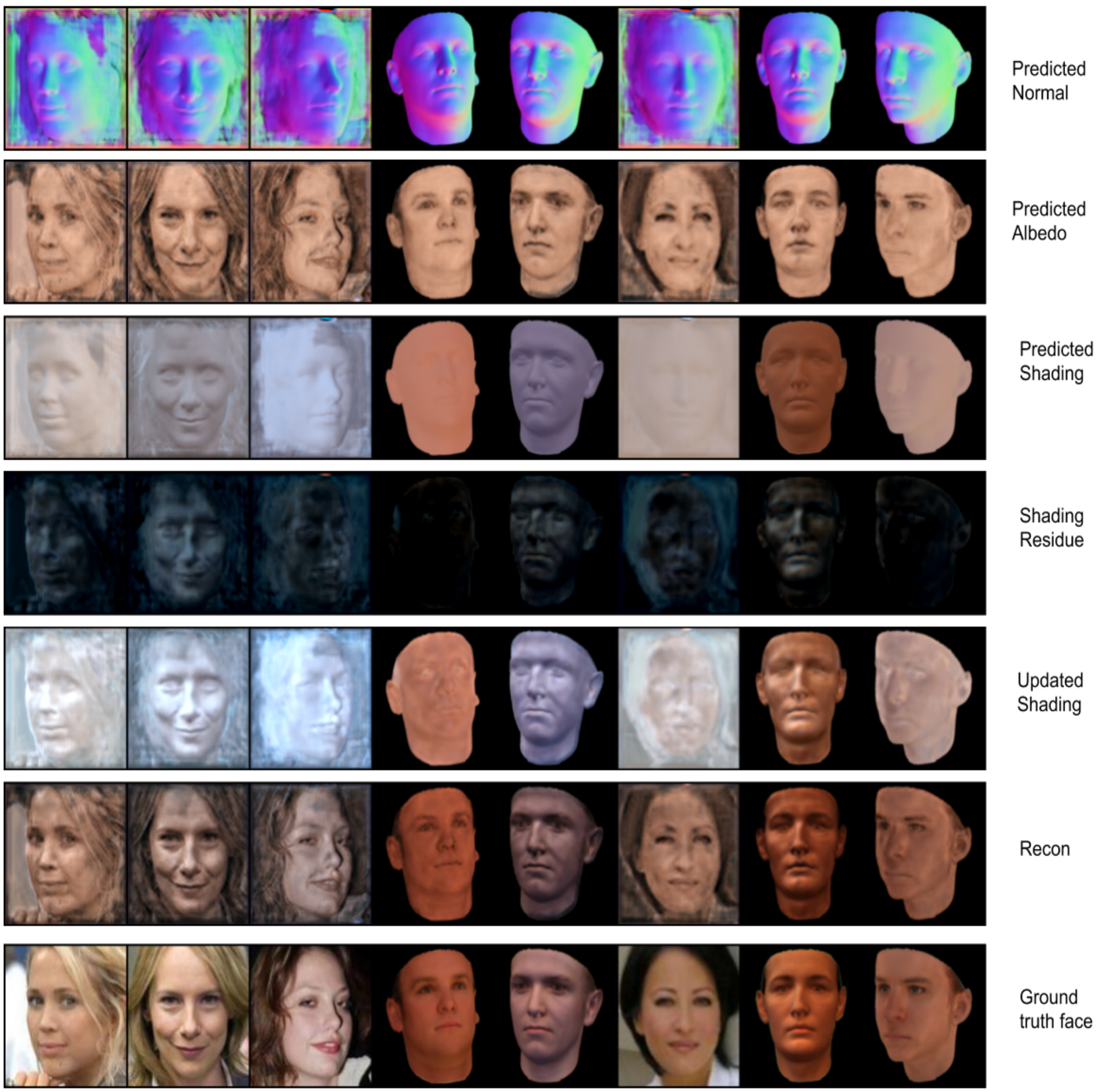

Figure 35: Shading Residue model Result samples: Shows generated Albedo, Residue, Shading, Updated new shading and reconstruction. Normal and SH is not learned.

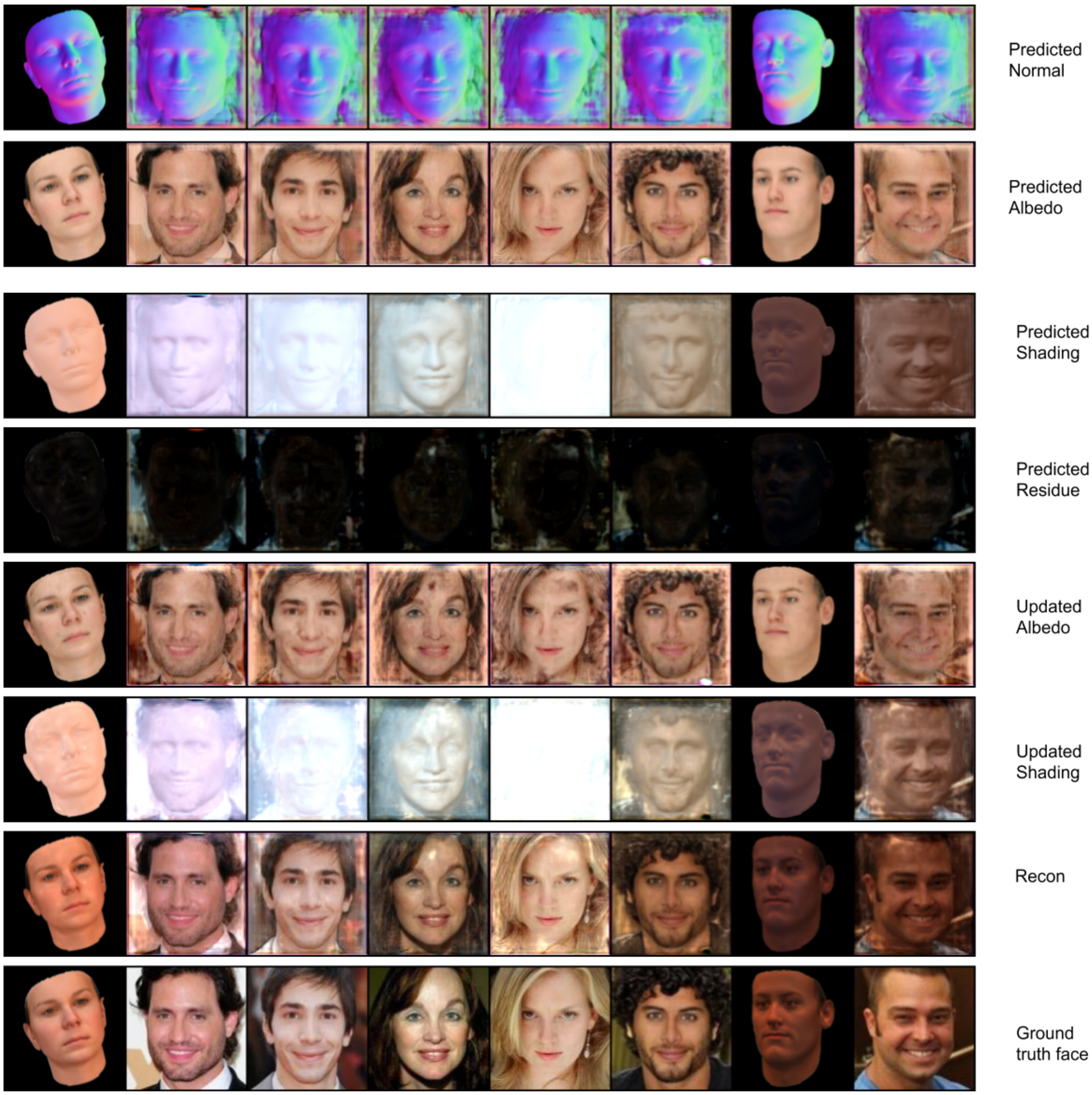

Figure 36: Shading-Albedo Residue model Result samples: Shows generated Albedo, Residue, Shading, Updated new shading and reconstruction. Normal and SH is not learned.