Improving Illumination Estimation using Shading Residue

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Abstract

SfSNet[1] estimates Albedo, Normal and Spherical Harmonics attributes for given face image. Due to lack of Shading loss, we see some of the residue pushed down into Albedo. In this project, we work on improving albedo in SfSNet setting by computing residue pushed into albedo and add it into shading (shading is computed using normal and spherical harmonics). We propose that learned shading residue can help to remove albedo residue and get updated shading with desired residue. With the ground truth albedo, we can achieve this with shading loss similar to normal and albedo loss. But, in case of lack of ground truth, we propose to achieve the same with only re-construction loss and using generative adversarial networks[2] to remove residue from albedo- we are using Cycle-GAN[3] based training paradigm for albedo generation. We are using pretrained model provided by SfSNet. We also experiment with supervised approach for albedo with very less weight for albedo loss with shading residue network. We also introduce latent lighting representation Spherical Harmonics 2.0 to assess if it can improve existing shading or generate shading altogether.

1 Introduction

Learning face attributes 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.

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 1 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.

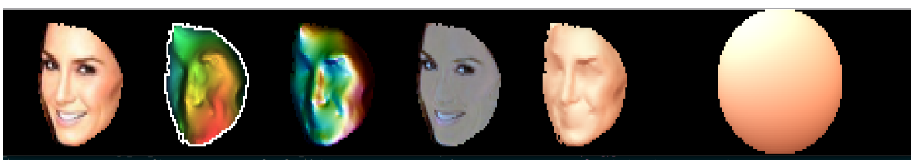

Figure 1: Input image, Shape, Normal, Shading, Reflectance and SH based lighting respectively

4 Baseline

We implemented base SfSNet and Skip connection based model for baseline and ground up for our work. Figure 3 demonstrates SfSNet pipeline and figure 2 demonstrates Skip connection based model.

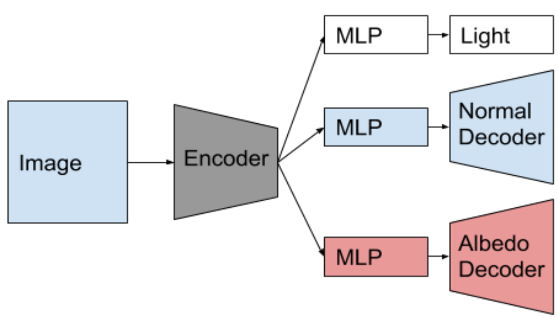

Figure 2: SkipNet

Training procedure is as follow:

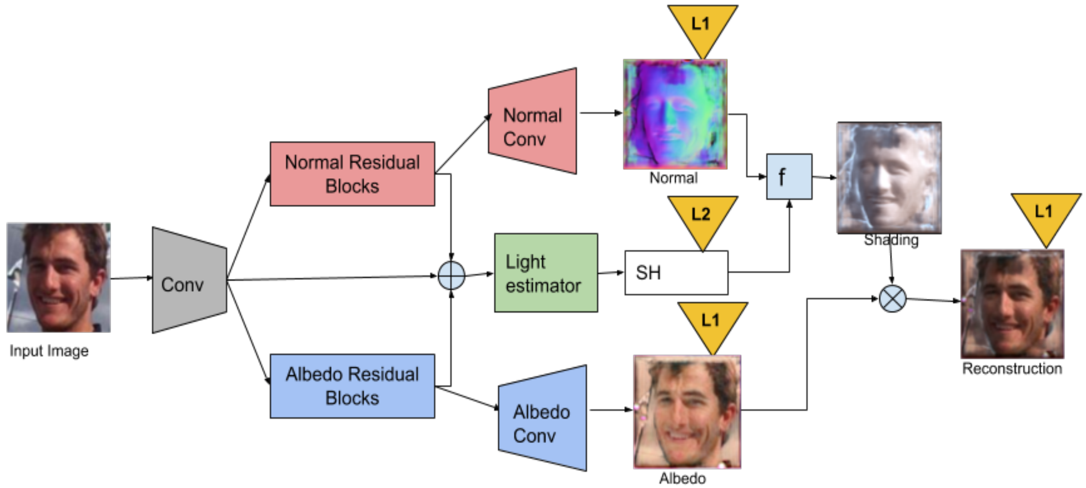

Figure 3: SfSNet Model

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 3 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 uses L1 losses for Normal and Albedo. It does not uses any loss for shading as it computed using normal and spherical harmonics which is trained using L1 and L2 loss respectively and hence, supervision for Spherical Harmonics 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-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 hamazard product, gradients are equally distributed to shading and albedo. This leads to some of the image features being pushed to albedo.

Question is, why features are 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.

Solution for residue issue could be to add neural network to compute possible residue being generated and add that into shading. This will help images features coming from shading and hence, in backpropogation, residue will not be added into albedo. We have performed extensive experiments in this area. In next section, we will go over these experiments.

6 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 4 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 5

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

Figure 4: Synthetic dataset

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.

7.1 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 6 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 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).

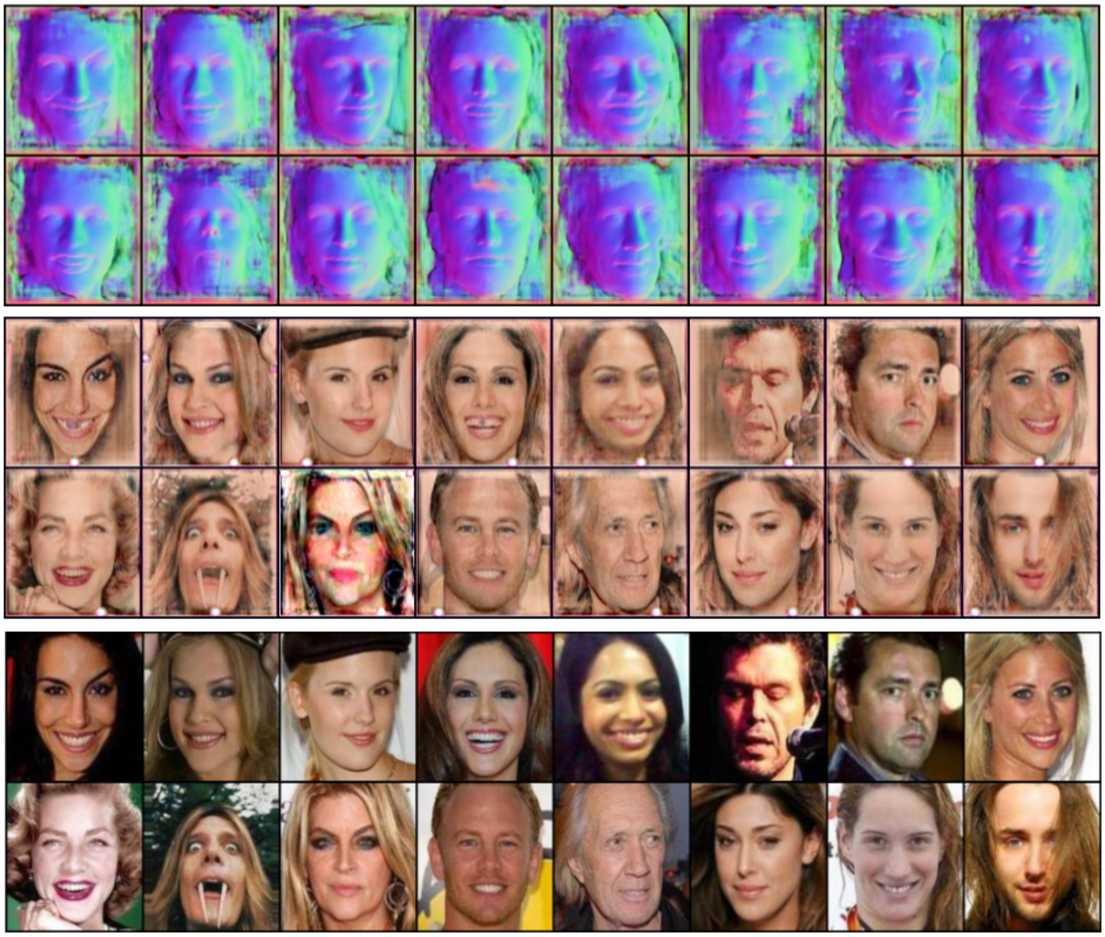

Figure 5: CelebA Pseudo-Supervision dataset

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 13 and 14 shows interpolation and comparison for celeba and synthetic image.

Plot 7 shows training loss for gan based model. Plot 8 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

7.2 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.

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.

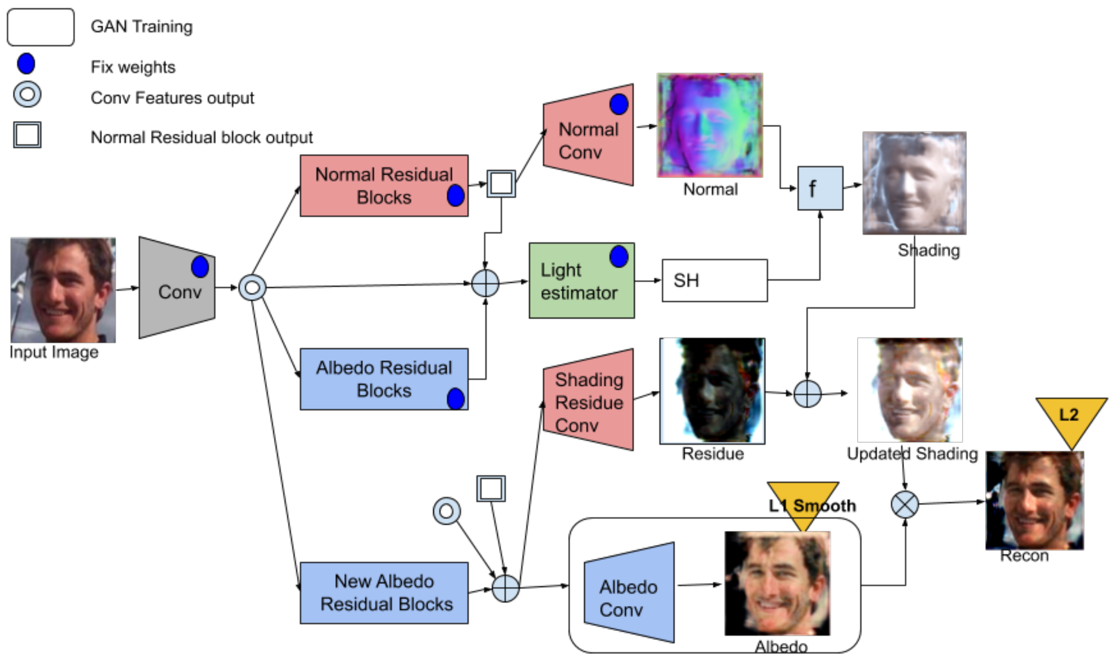

Figure 6: GAN based model

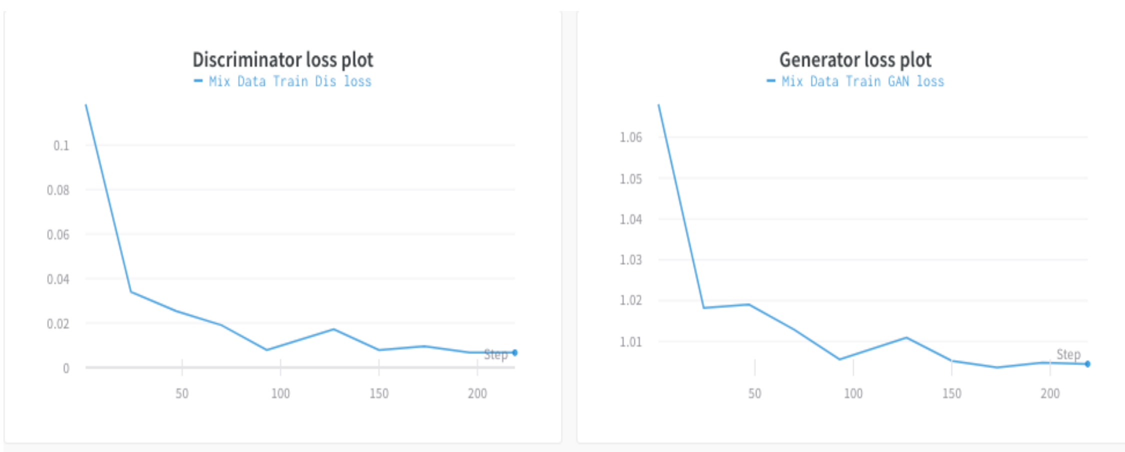

Figure 7: GAN model: GAN loss

Figure 9 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/d5imq0b2

7.3 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.

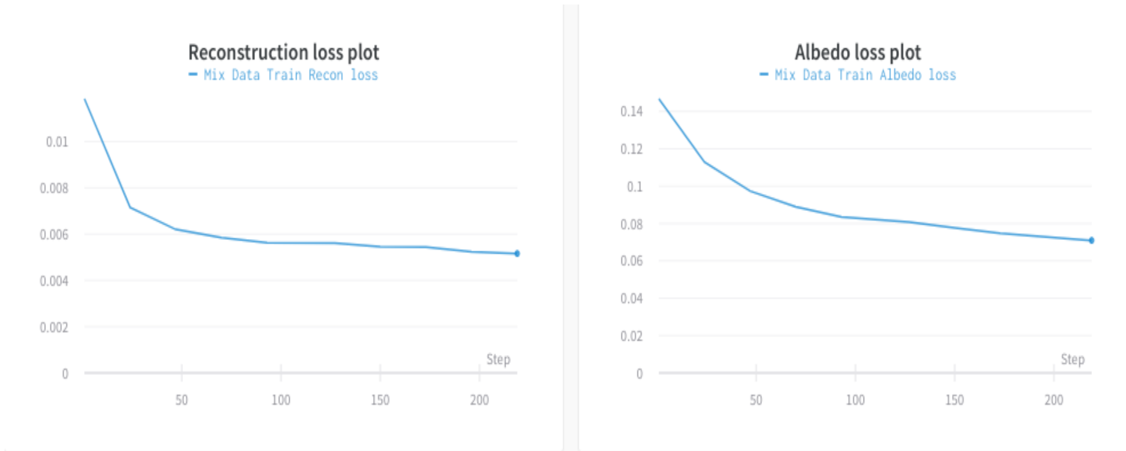

Figure 8: GAN Model: Reconstruction and albedo loss plot

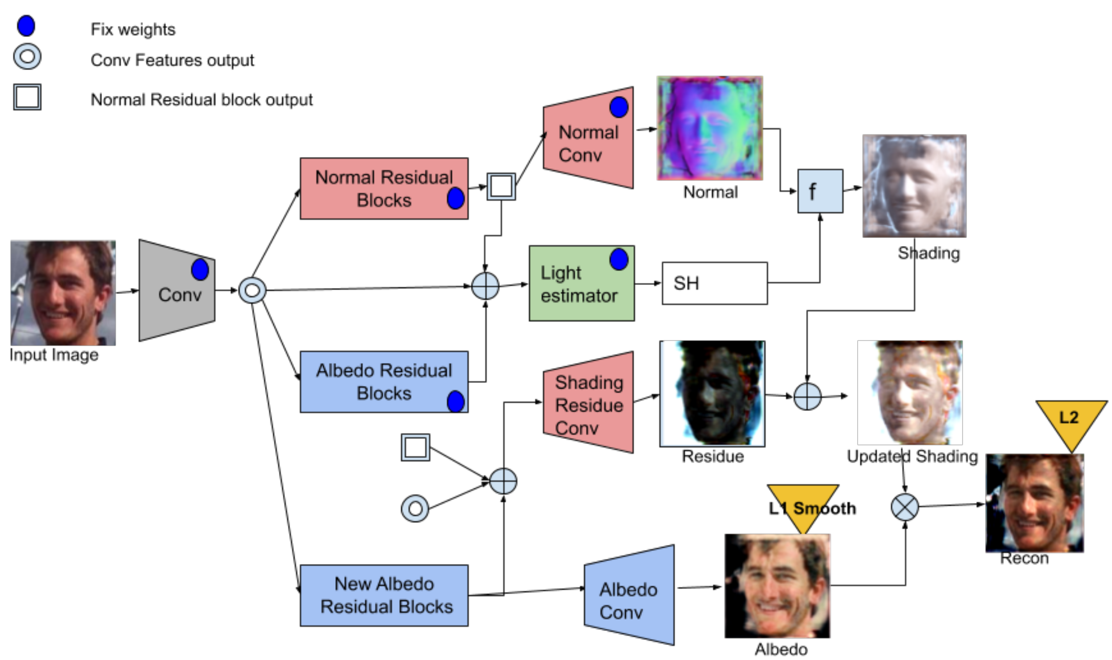

Figure 9: Shading Residual model

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 10 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.

7.4 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.

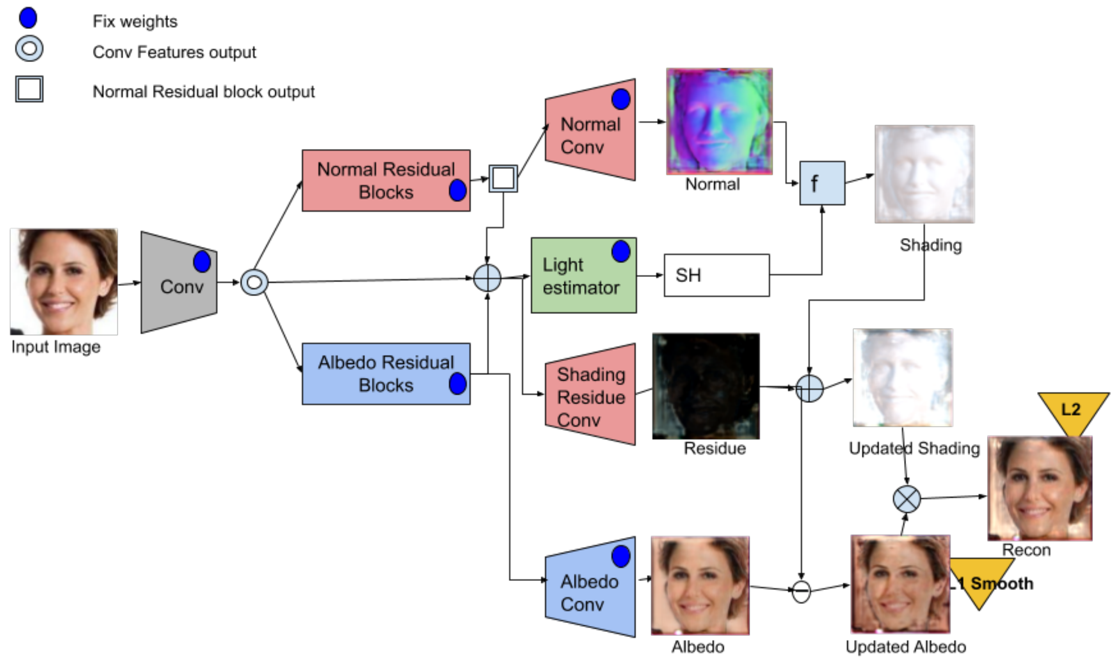

Figure 10: Shading-Albedo Residual model

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 11 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

7.5 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 12 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

8 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

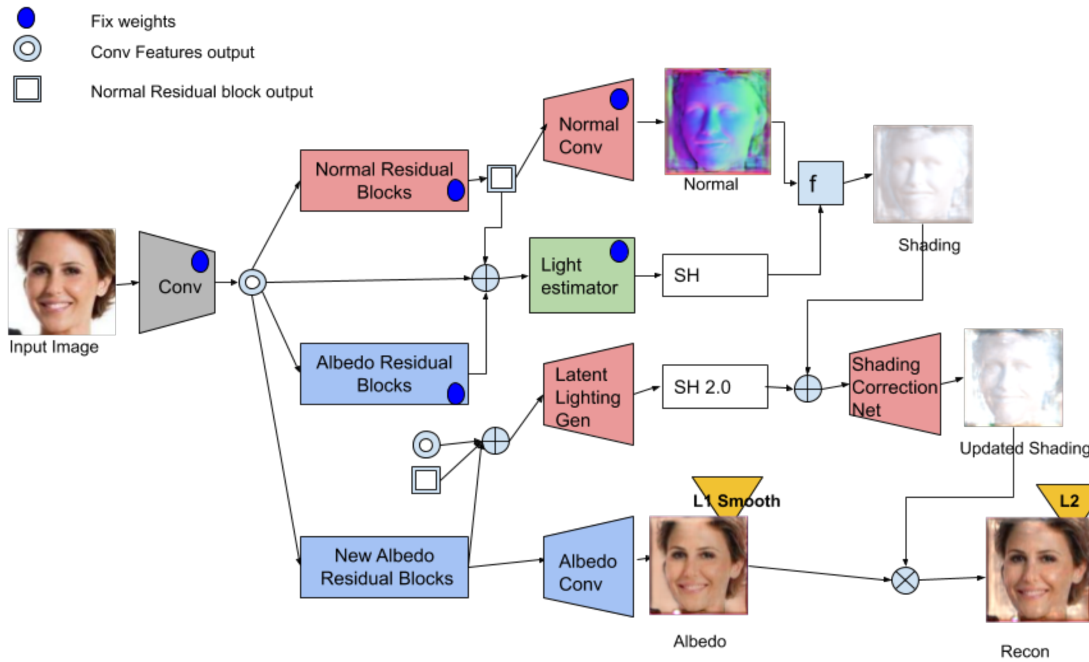

Figure 11: Shading Correcting model

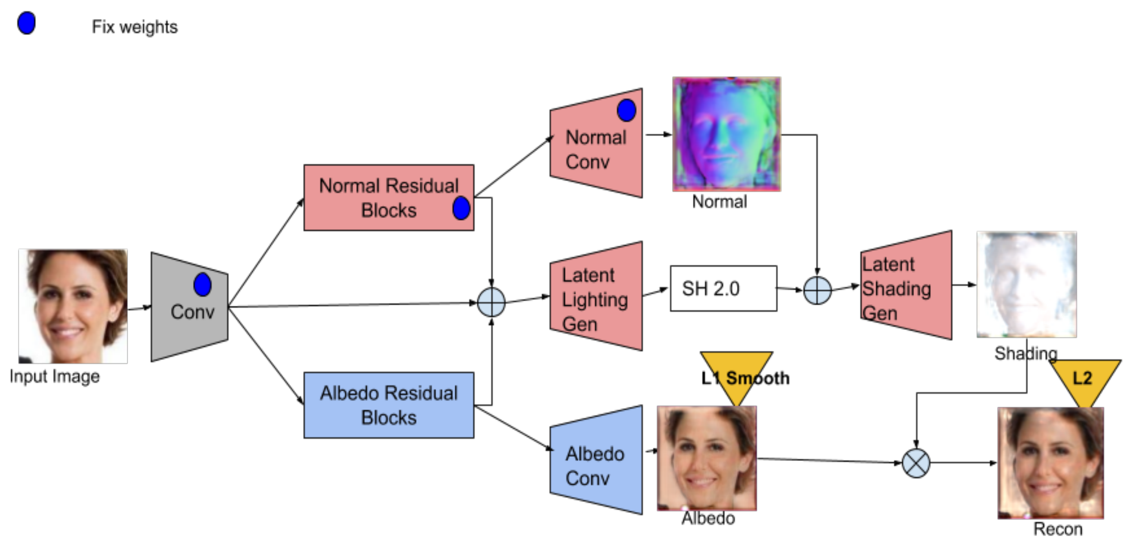

Figure 12: Latent Shading generation using SH 2.0

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.

8.1 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 29 shows predicted albedo, shading, residue, updated shading and reconstruction with this method. Figure 13 and 14 shows results on GAN based method on unseen samples on celeba and synthetic images.

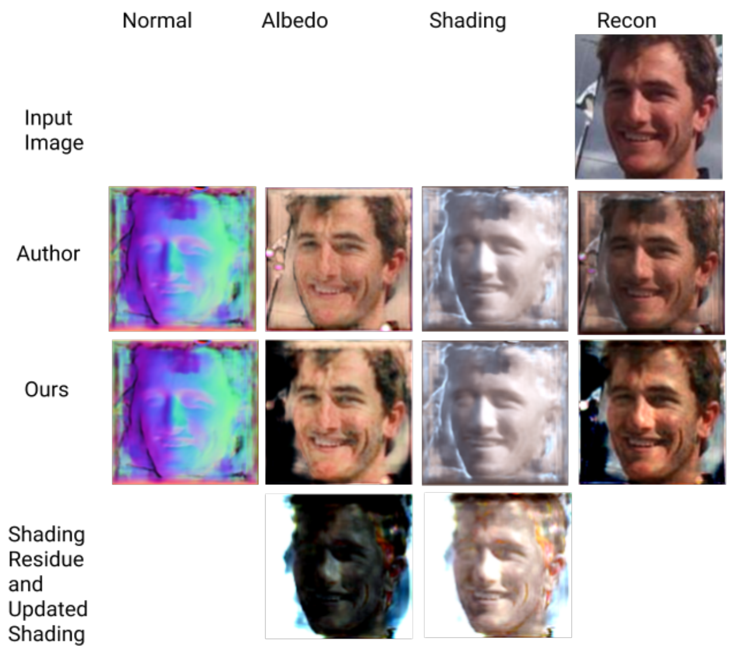

Figure 13: GAN based model result for CelebA

8.2 Shading residue network

Shading residue output had few artifacts in albedo generation and were constistent across the samples. This was adressed by GAN basde method. Artifcats were due to training method and shoudl be removed with fine-tuning.

Figure 15 and 16 shows output of residual based network. We have added more examples of sample output in appendix.

We can see that residue indeed captures the missing shading and shading is updated partially. But albedo was not completely accurate and some artifact was observed in it.

8.3 Shading-Albedo Residue network

This approach did not perform better than only shading residue. We have more strong control over residue in this case, but this residue needs to be updated by shading loss as shading is incorrected added and also we don't have ground truth albedo to ensure residue in indeed correct.

Figure 17 and 18 shows output of residual based network. We have added more examples of sample output in appendix.

8.4 Shading Correction Network

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

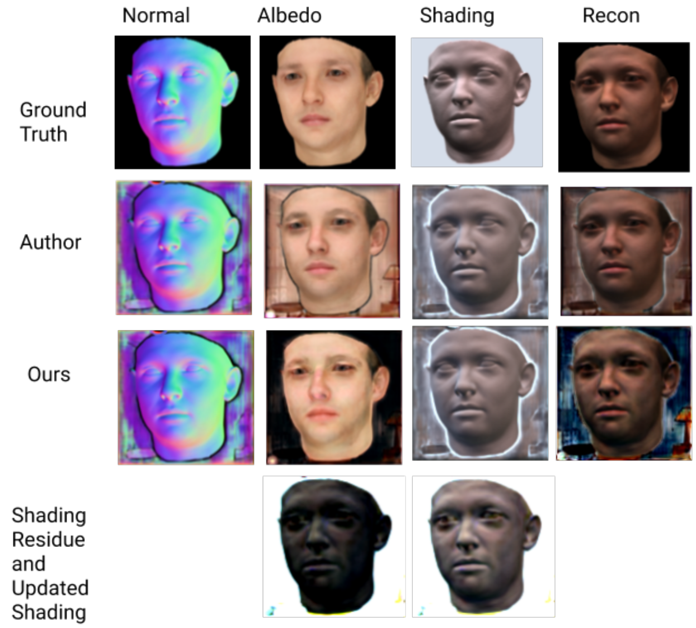

Figure 14: GAN based model result for Synthetic dataset

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, during back-prop, image features are pushed into shading.

Figure 19 and 20 shows output of shading correcting network on celeba and synthetic data respectively. We have added more examples of sample output in appendix.

8.5 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 21 and 22 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.

9 Analysis and Comparison

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

As captured in figure 24, for synthetic images, GAN based approach outperforms all other methods leadig to better shading capture and reconstruction. This could be due to less albedo loss weight that was used for 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. Albedo loss weight of 0.5 lead to more training of albedo and resulting into few artifacts being observed in shading residue based albedo which are also passed into the reconstructed image. Due to less gan and albedo loss, albedo learned in GAN based method is closer to ground truth than any other method. Shading-Albedo residue based

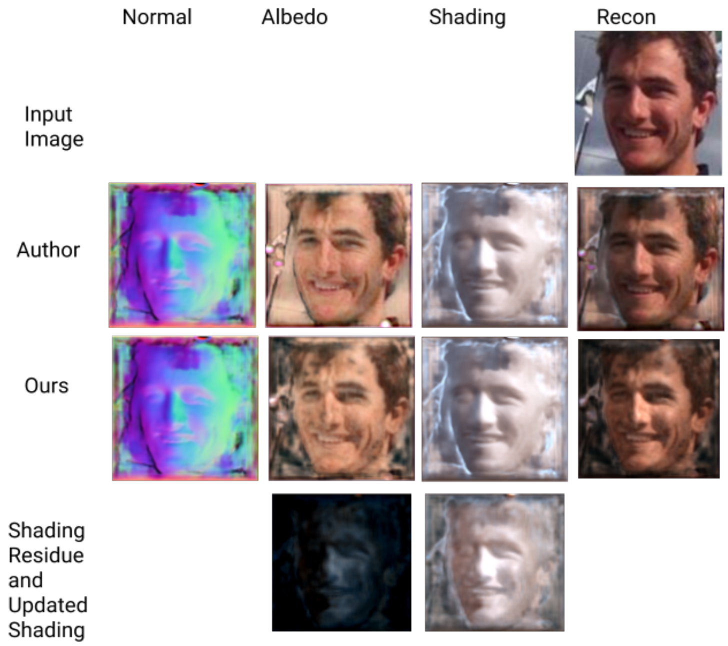

Figure 15: Shading Residual based model result for CelebA

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 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 featuers 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 25, 28, 26 and 27, Shading residue network performed best from our experiments. This is acceptable as network is only fine-tuning albedo and learning residue which is much simpler than heavy 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 23 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

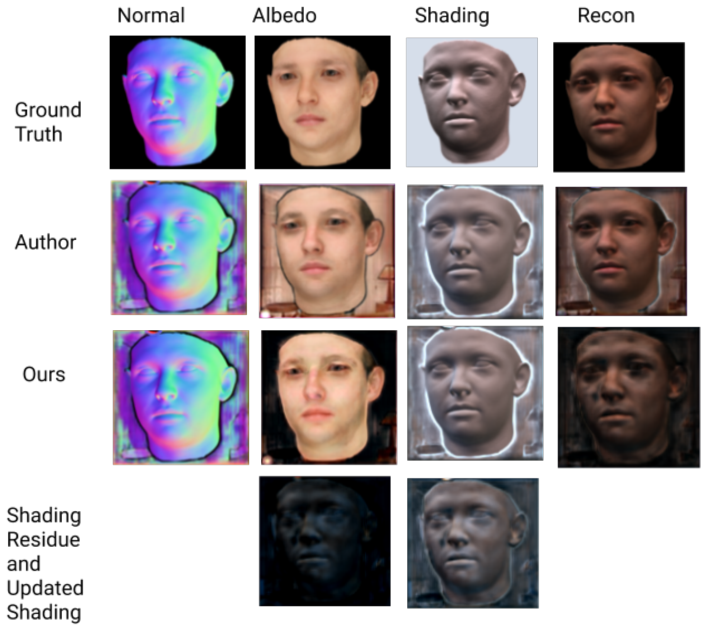

Figure 16: Shading Residual based model result for Synthetic dataset

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.

10 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.

11 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

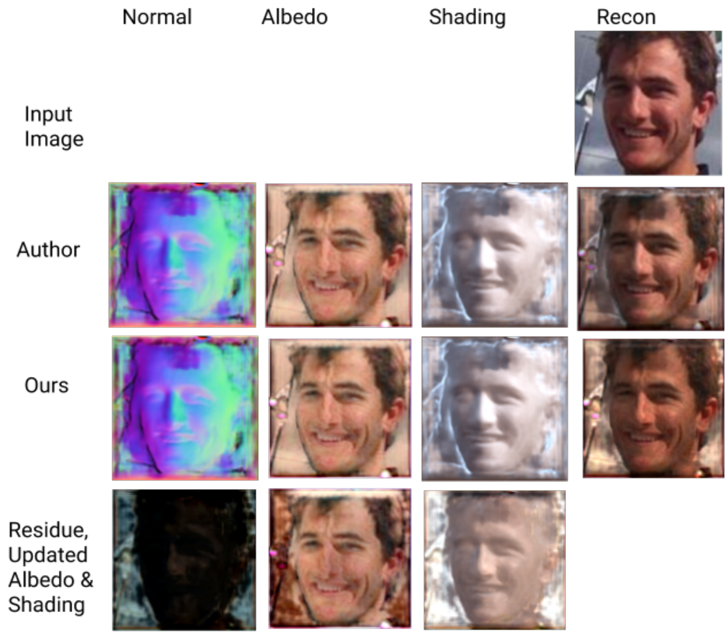

Figure 17: Shading-Albedo Residual based model result for CelebA

(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) Add L1 smoothing loss with more weight for albedo

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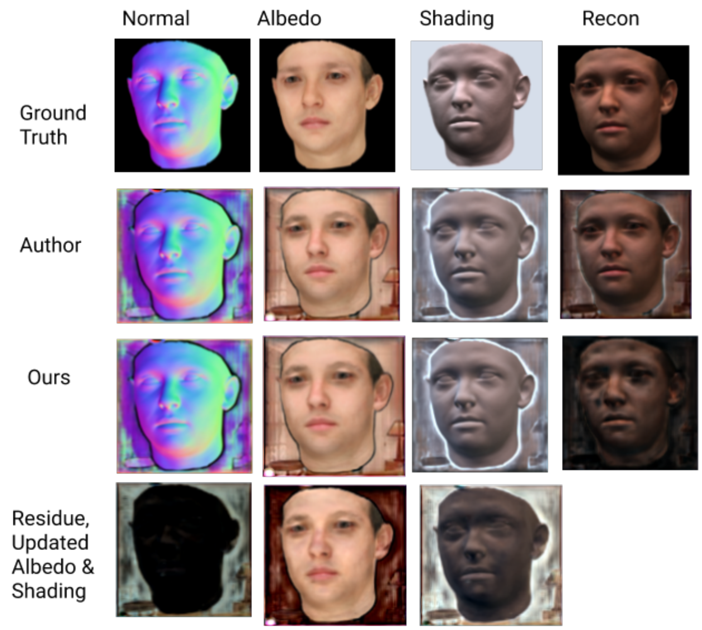

Figure 18: Shading-Albedo Residual based model result for Synthetic dataset

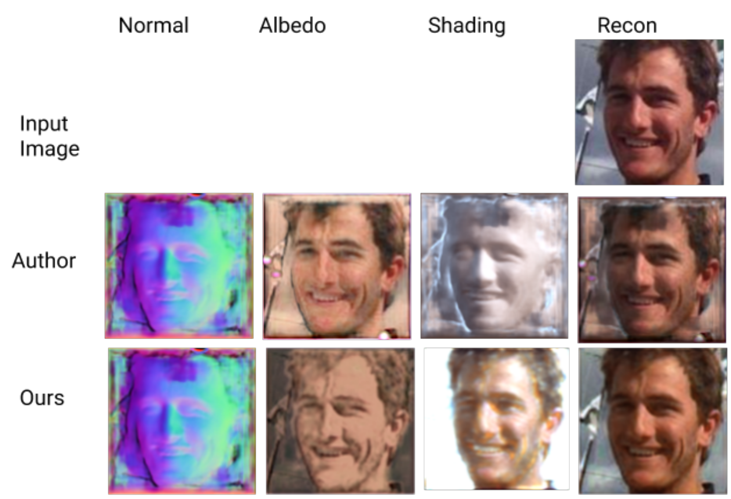

Figure 19: Shading correcting model result for CelebA

12 Appendix

12.1 More examples of sample output

Following, we go over more sample output of each of the model described above. Figures 30, 31, 32, 33, 29 shows sample output for shading correcting, latent shading generation, shading residue, shading-albedo residue and gan based approach respectively.

12.2 Source code

1. Baseline SFSNet and SkipNet https://github.com/bhushan23/SfSNet-PyTorch

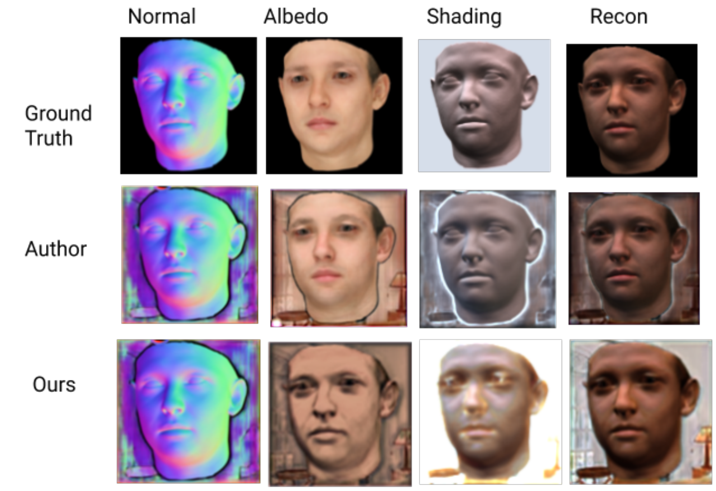

Figure 20: Shading correcting model result for Synthetic dataset

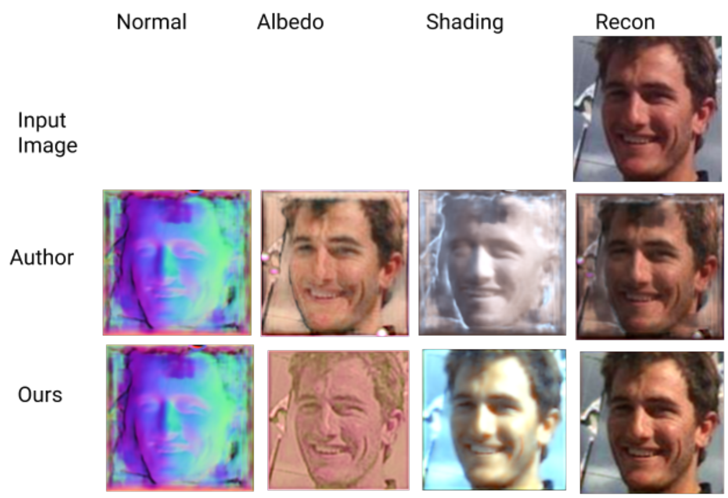

Figure 21: Shading generation using SH 2.0 result for CelebA

2. All experiments- https://github.com/bhushan23/SC-Net

Figure 22: Shading generation using SH 2.0 result for Synthetic dataset

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 training procedue 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

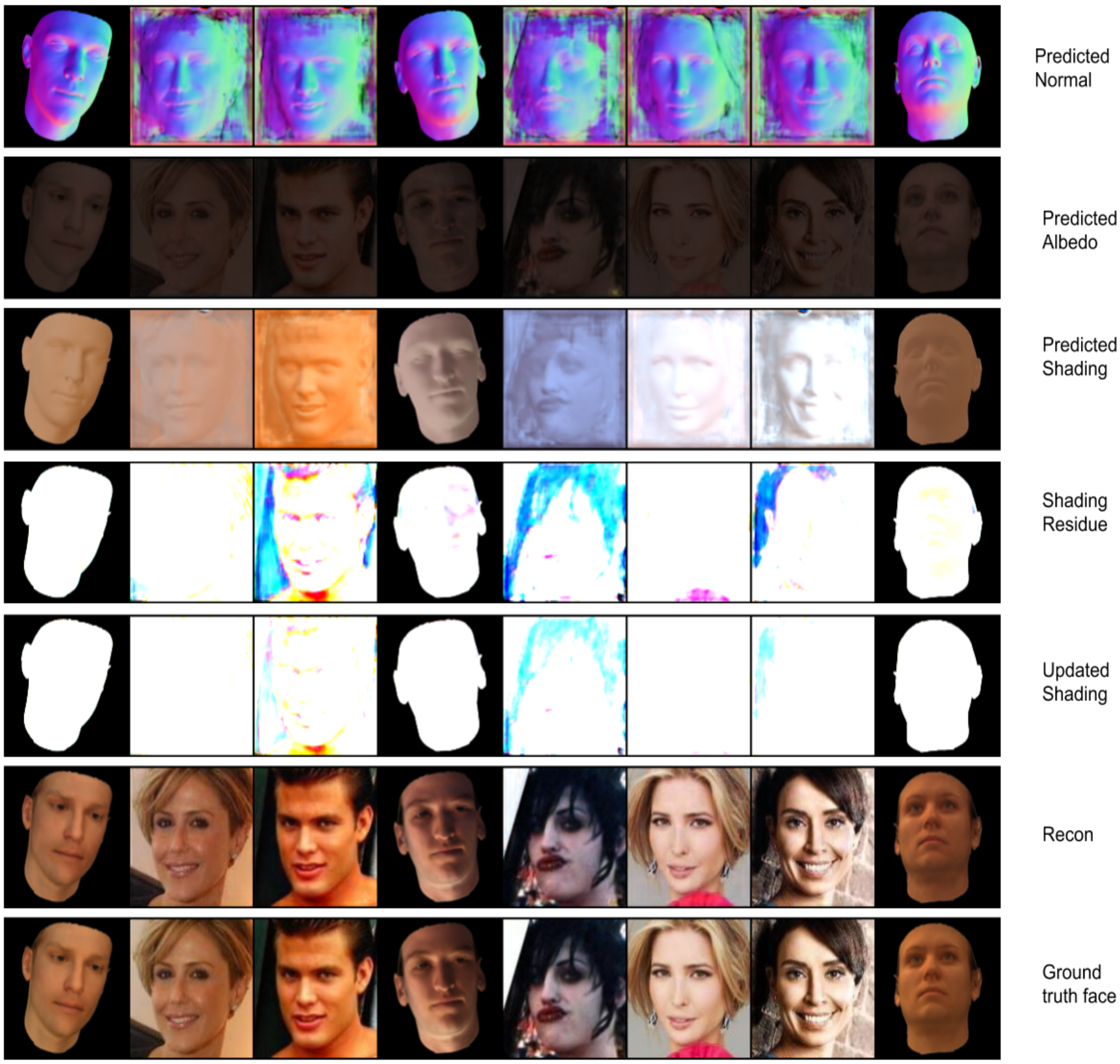

Figure 23: Results of GAN based model without albedo loss

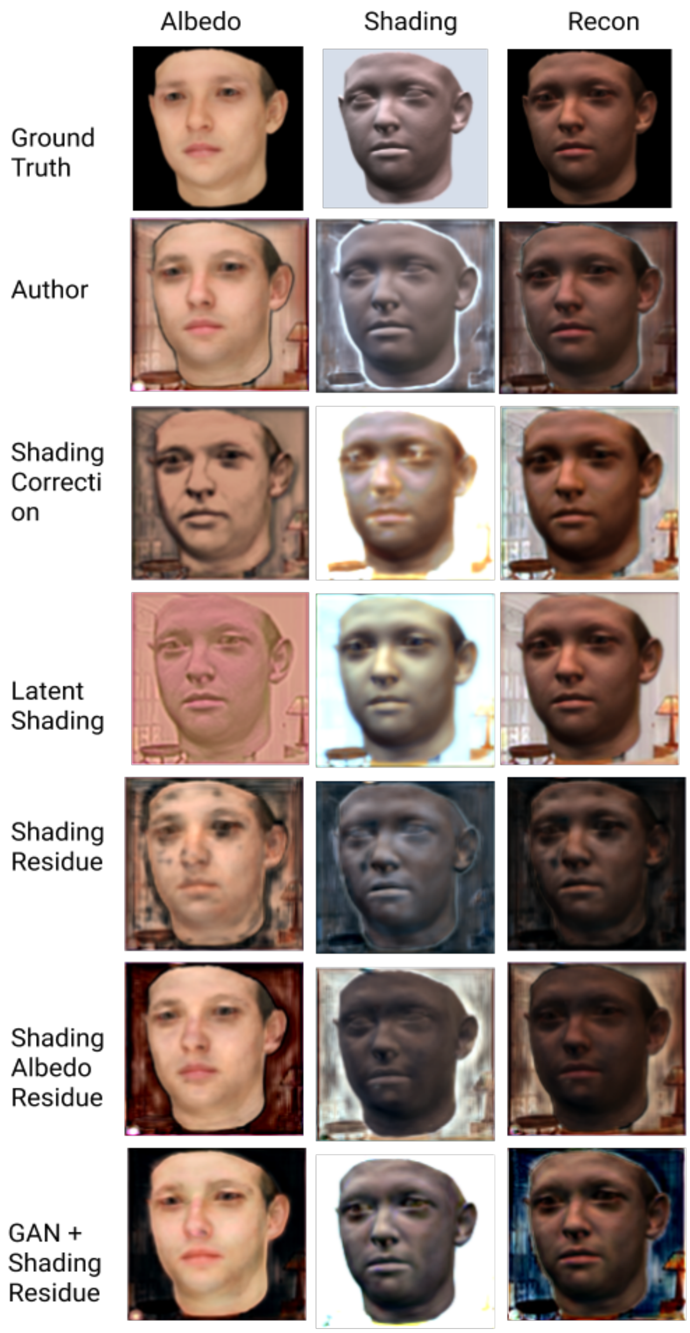

Figure 24: Results comparison: Synthetic dataset

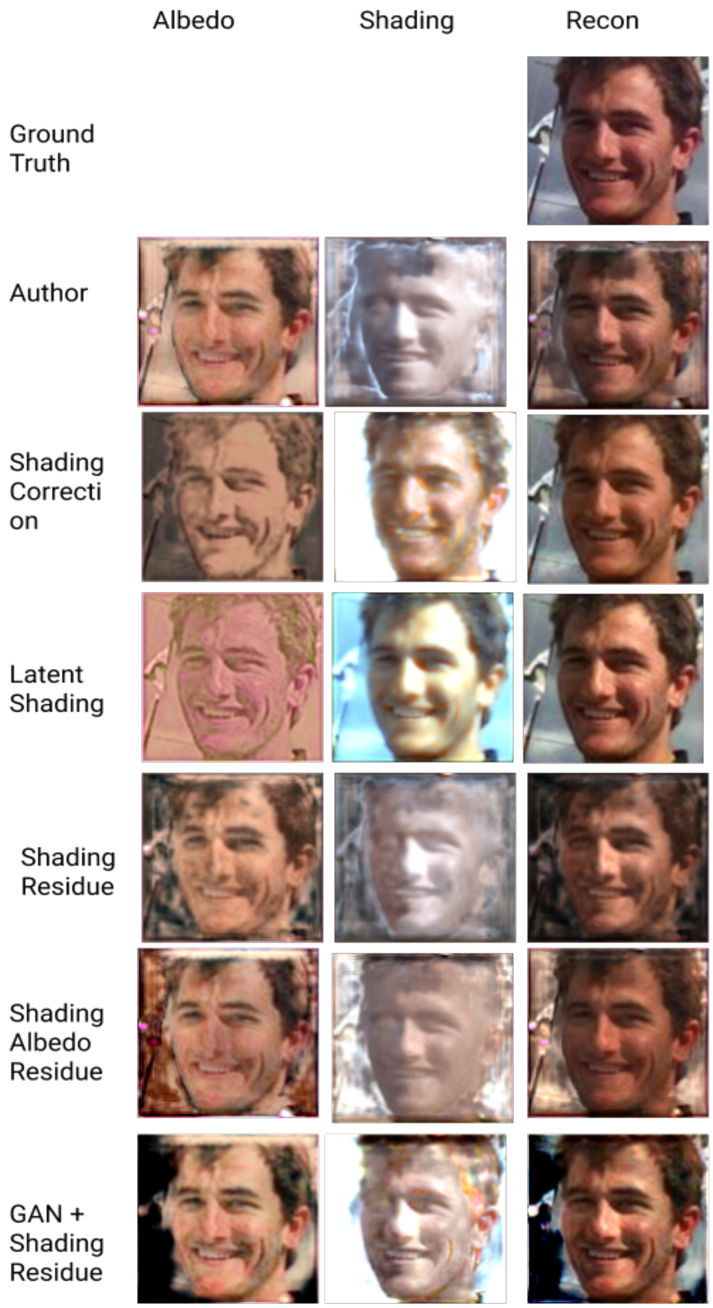

Figure 25: Results comparison: CelebA sample 1

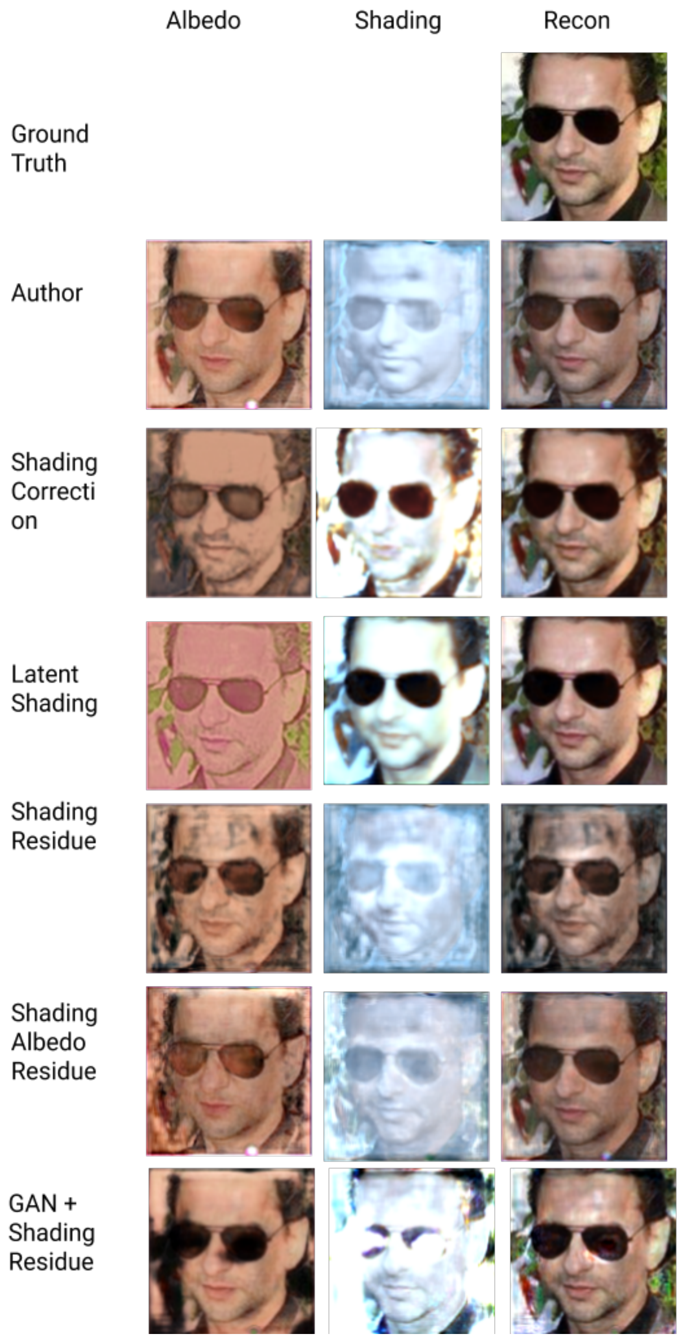

Figure 26: Results comparison: CelebA sample 2

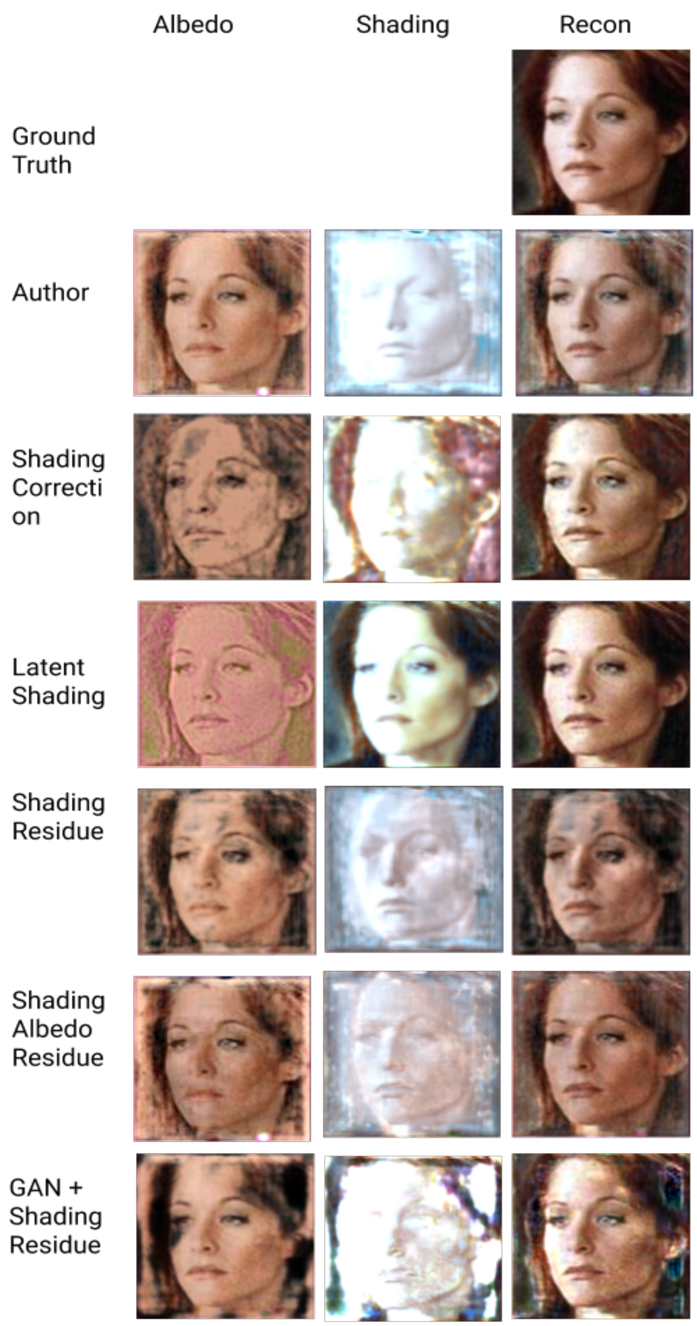

Figure 27: Results comparison: CelebA sample 3

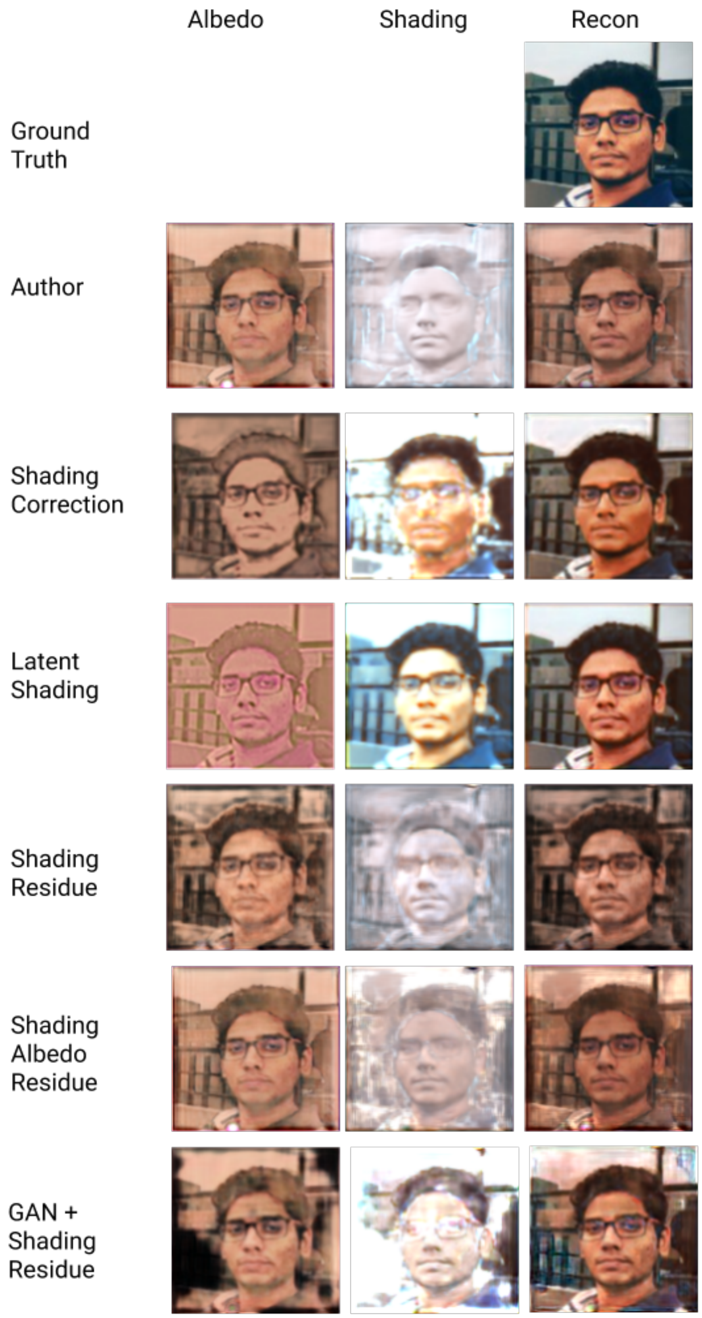

Figure 28: Results comparison: Real sample 1

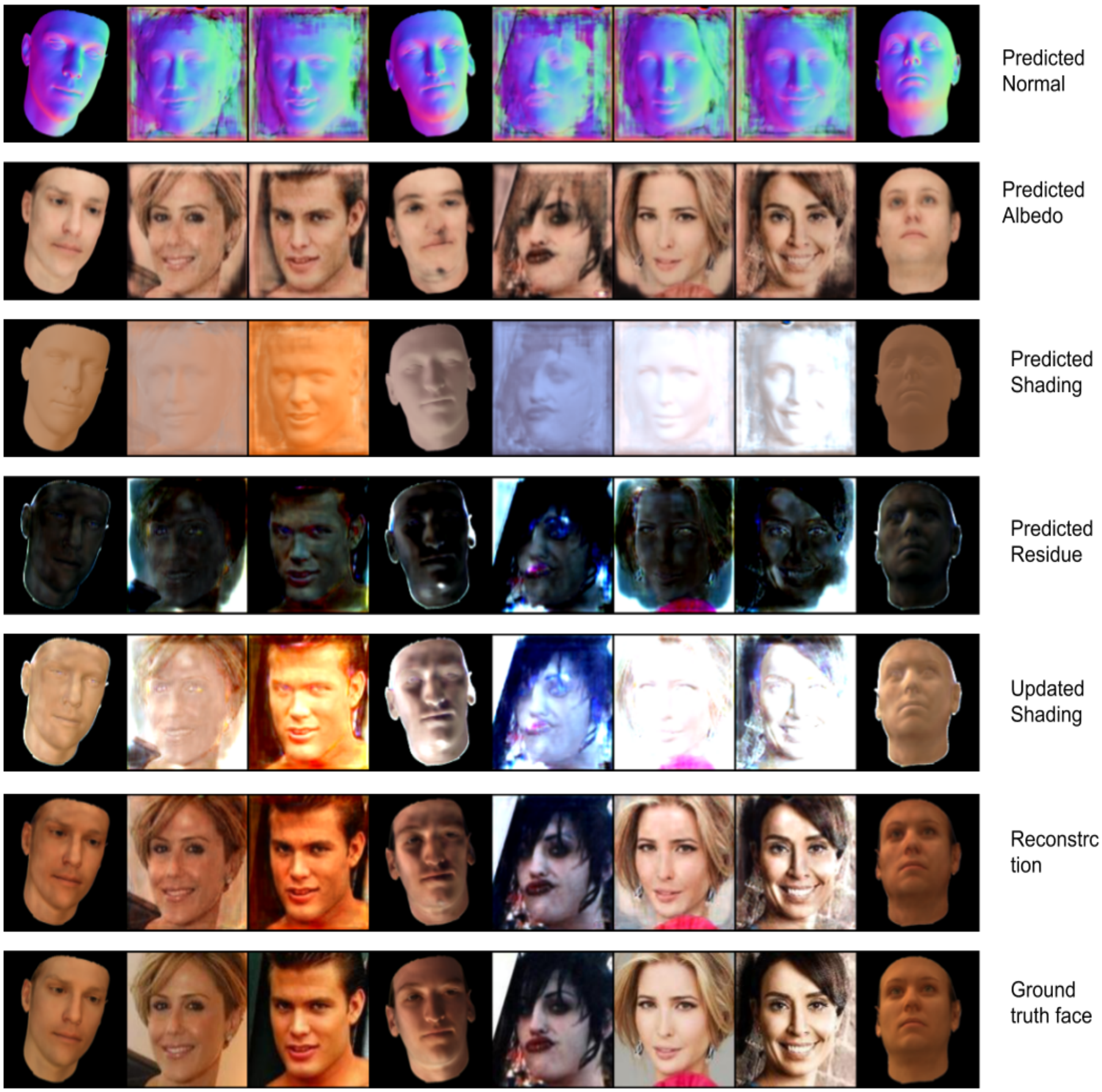

Figure 29: GAN based model Result samples

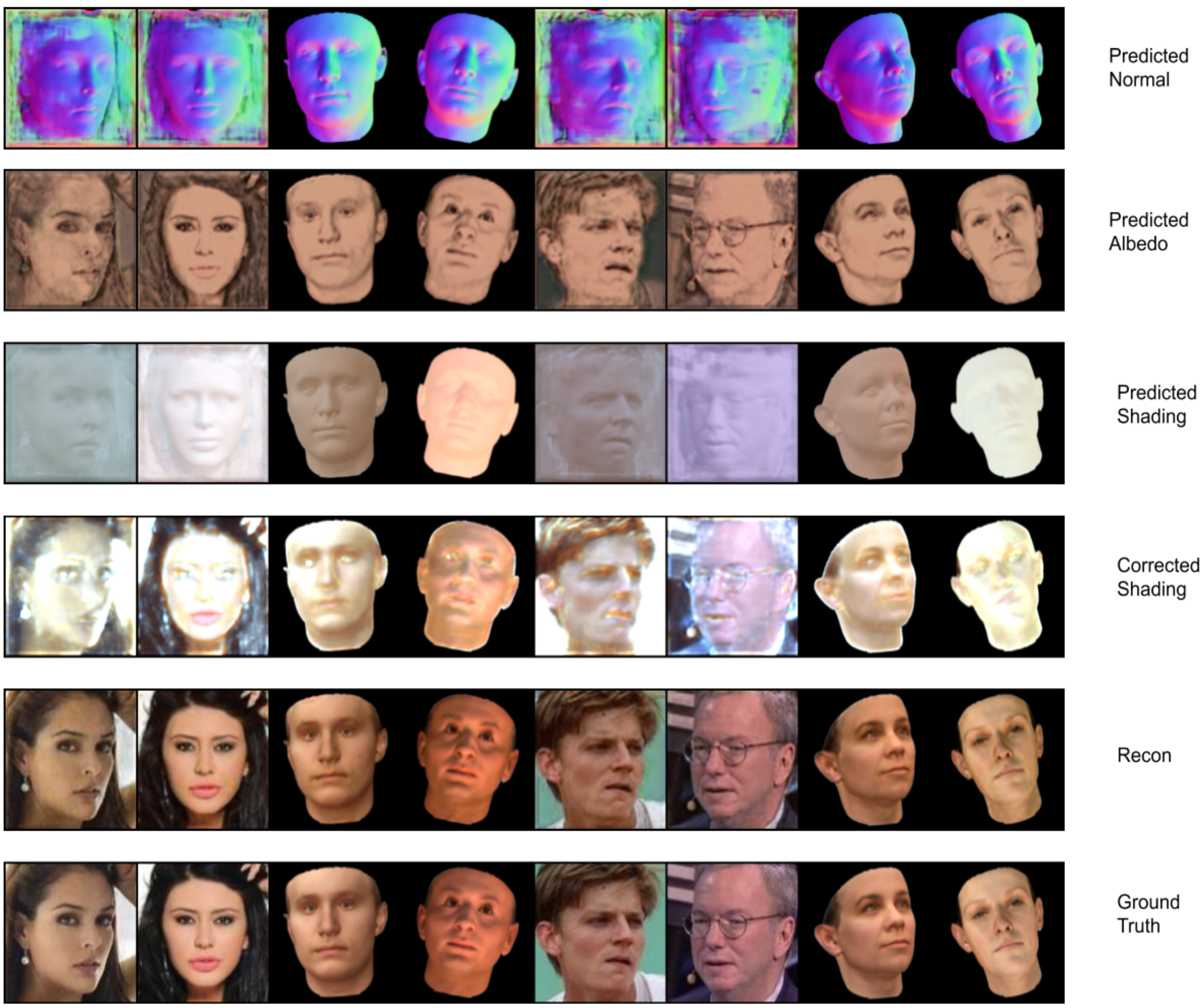

Figure 30: Shading Correcting model Result samples

Figure 31: Latent shading generation model Result samples

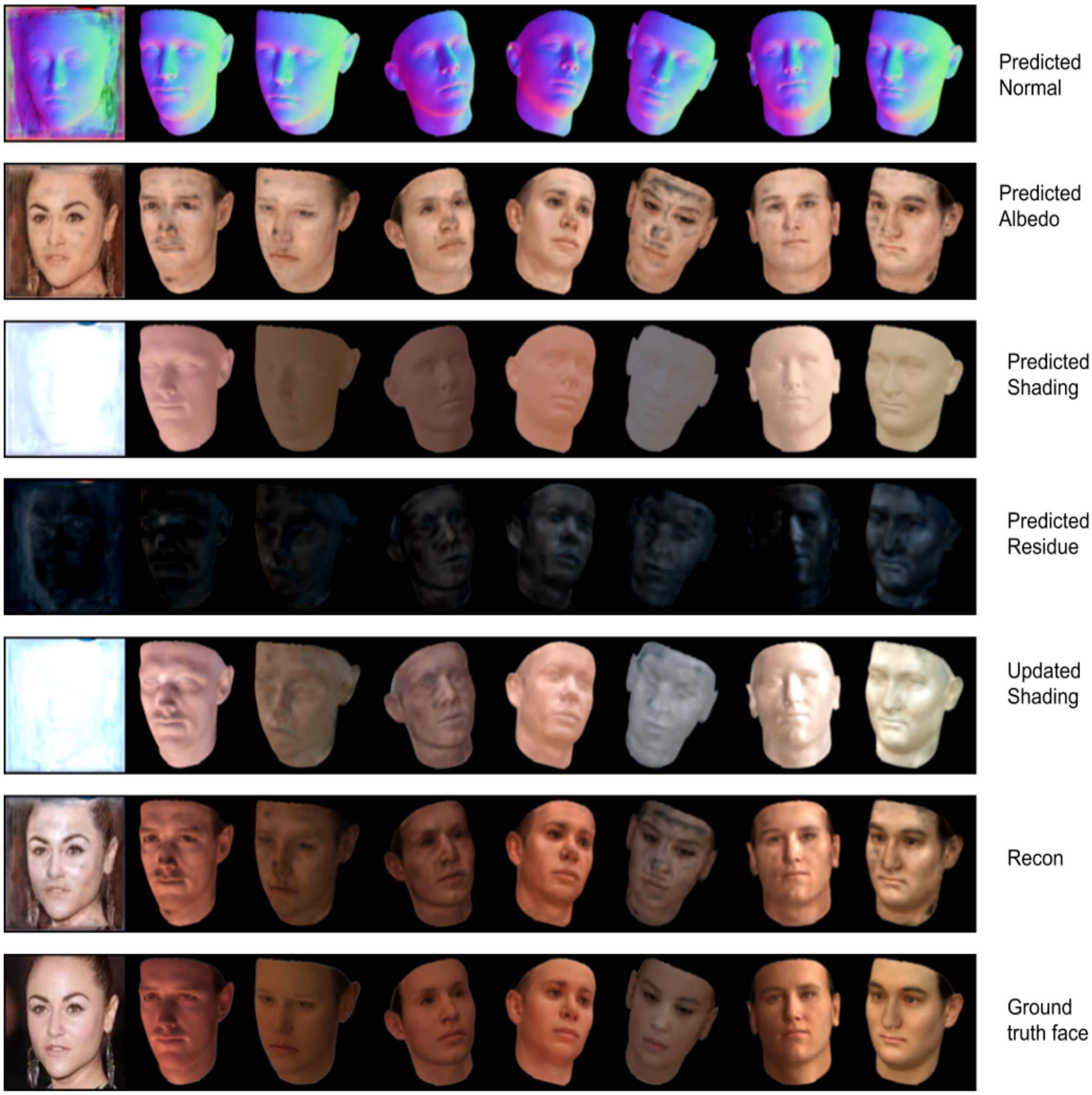

Figure 32: Shading Residue model Result samples

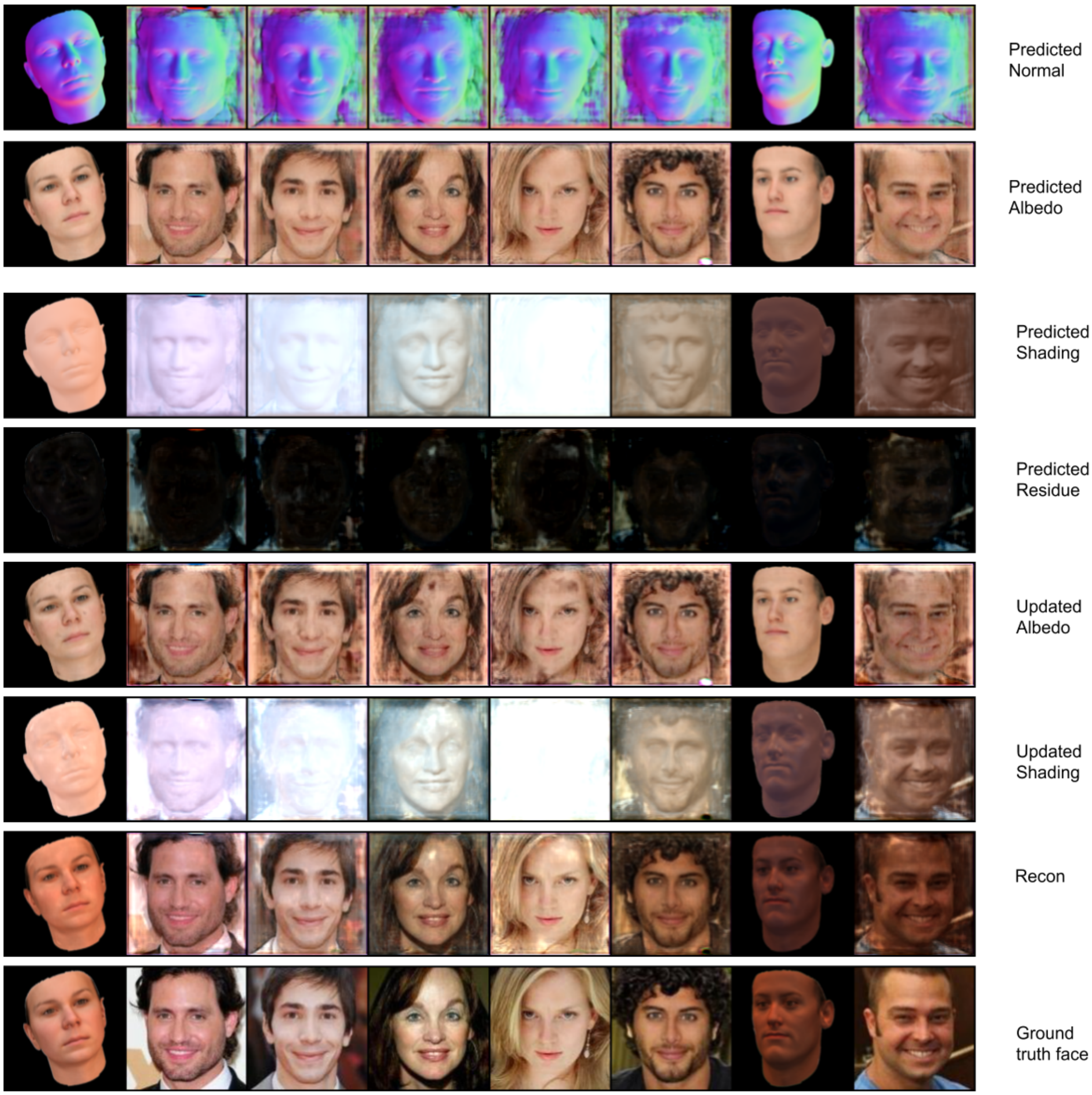

Figure 33: Shading-Albedo Residue model Result samples