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Supplemental Material: A Hyperspectral Space of Skin Tones for Inverse Rendering of Biophysical Skin Properties

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Abstract

This is the supplemental material for the paper A Hyperspectral Space of Skin Tones for Inverse Rendering of Biophysical Skin Properties. *It includes further analysis of the albedo space (Section 1); a discussion and tests of Kubelka-Munk to compute diffuse reflectance (Section 2), a discussion of the Look Up Tensor approach (Section 3); other implementation and rendering details (Section 4); more comparisons with related work (Section 5); and further results (Section 6).*

CCS Concepts

• ***Computing methodologies*** → ***Reflectance modeling; Reconstruction;***

1. Albedo Space Analysis. Further details

In spectral color modeling, it is efficient to represent a large spectral dataset using principal component analysis (PCA) with a lower number of dimensions [TB05]. Based on the first three principal components trained from our spectral dataset, in Figure 1, the PCA reconstructed spectra of some representative Leeds spectra are compared with the original measurements. The bottom shows the histogram of the reconstruction root mean squared errors. In addition to the Leeds dataset that only has the visible wavelength range, the IR range up to 1000 *nm* is tested using the NIST dataset [CA13], which has less data points and skin varieties though. Both datasets can be accurately represented (less than 0.03 RMSE) via the three principle componnets from our spectral manifold.

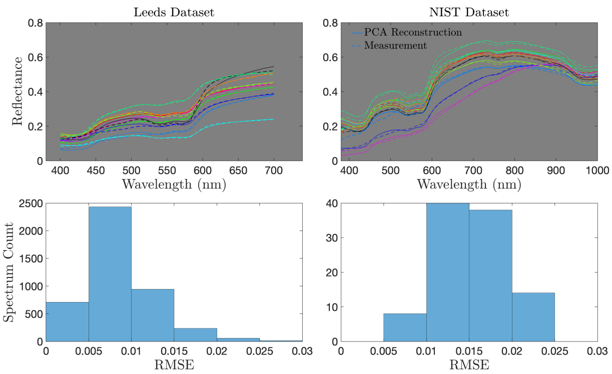

Figure 1: *PCA reconstructions for the Leeds and NIST datasets. Top rows show some representative spectral comparisons between the reconstructions using the PCA basis functions from our spectral manifold versus the spectrophotometric measurements. Bottow row show the histograms of the reconstruction RMSE across the two dataset.*

2. Kubelka-Munk

For computing the diffuse reflectance of a skin patch, we first started by using a Kubelka-Munk (KM) [KM31] layering model, following previous work [AS17].

We experimented through different variations of the KM-based model, all of them suffering from lack of expressiveness and requiring many ad-hoc parameters to tune the layering quantities. These issues with KM approaches stem mostly from the fact that the theory was initially derived for pigments, and it is known to exhibit some limitations, like inaccuracies in cases of dark shades or thin films [Cho14], that can make this technique not adequate in our context.

Moreover, there is no clear conversion between the parameters of Radiative Transfer and those of KM theories. We tested existing empirical relationships [RRG12] and more grounded derived ones from optics literature [SK14]. Unfortunately, the model is still unable to generalize to various skin types, lacks fidelity in certain areas such as the lips, and other heterogeneities (imperfections) are not really recovered (see Figure 2).

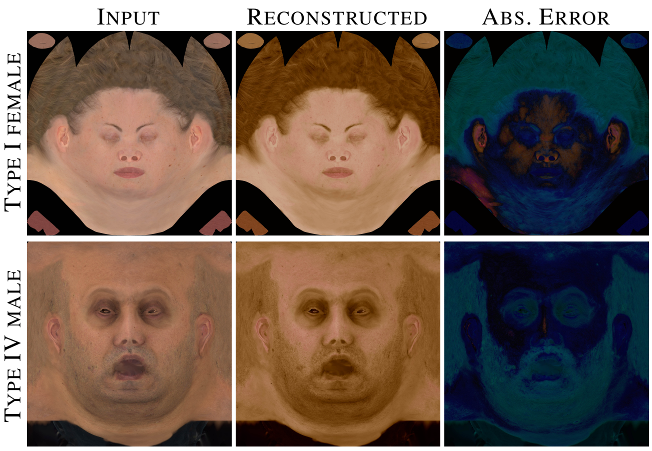

Figure 2: *Reconstruction results using a Kubelka-Munk based model [AS17] for different types of skin. The model is unable to recover the original albedo from the inferred properties (only melanin and haemoglobin volume fractions in this case), leading to noticeable shifts in the skin shades.*

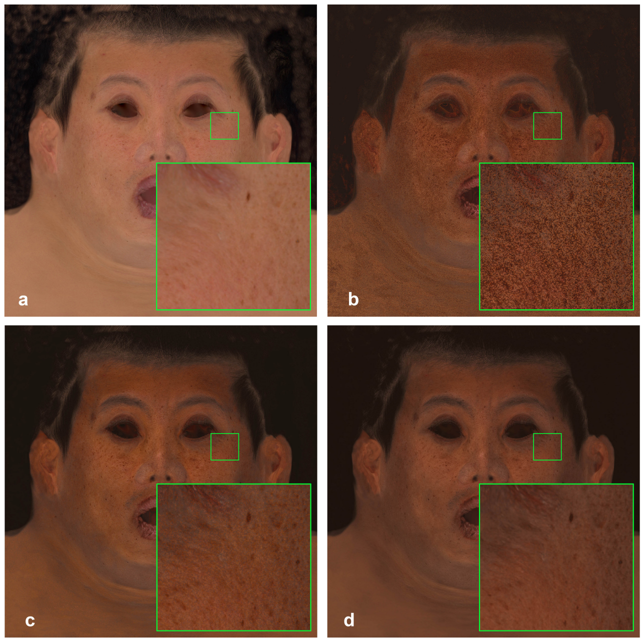

Figure 3: *The LUT approach suffers from quantization in the estimated parameters maps even for large tensors. This issue does not reveal during reconstruction, but creates artifacts and even some perceptual color shifting when edits on the skin properties are performed. An example of a x3 edit over the reconstructed melanin concentration of a Type III skin is shown. From left to right: a) original image, and reconstructions (edited melanin x3) using a b) tensor of 55296 skin tones ($V_m, V_b, t, \varphi_m, \varphi_h$) = (64, 32, 3, 3, 3), c) tensor of 256k skin tones (64, 32, 5, 5, 5), d) learned inverse mapping using 600k points to train the network. Whereas even for densely sampled tensors quantization appears, the neural approach provides smooth maps for the estimated parameters, which results in clean edits.*

3. Recovering the Skin Properties using a Look-up Tensor

We pre-compute a wide tensor of skin tones by following the sampling strategy outlined in the paper. To estimate the skin parameters given an input albedo, we search the LUT on each texel of the albedo to find the best skin parameter set that minimizes a reconstruction L_2 error. Then, we can manipulate them and query the new corresponding albedo from the LUT. This approach is able to reconstruct the skin albedo faithfully with an error close to zero. However, the inverted parameter maps are noisy and have many discontinuities, since the mapping from RGB to skin parameters is not smooth. In turn, editing operations over neighboring pixels in such extracted components can lead to unexpected abrupt changes in the reconstructed albedos (see Figure 3). We leave out of scope of this paper the assessment of different representations or data structures suitable for more efficient search strategies, that could dramatically improve the performance of this approach.

4. Implementation Details and Decisions on the Model

Using the model In Rendering In the spirit of a well known technique in production [WVH17], to preserve the skin details coming from the albedo texture, we make use of the reconstructed and edited albedo maps and compute a 3D random walk subsurface scattering solution that relies on a numerical albedo inversion around the mean free path and accounting for the anisotropy factor g (see Figure 4).

Using Albedo Maps in Rendering. The final 3D lit geometries of our virtual faces are rendered using our own skin materials inside *Blender Cycles* [Ble20]. Aside from the specular component of the skin, which we represent as a double lobe GGX [WMLT07], we follow, in the spirit of a state of the art technique in production [WVH17], a 3D random walk subsurface scattering solution that relies on a numerical albedo inversion around the mean free path and accounting for the anisotropy factor g. At this stage, we simplify the model to be single layered, dermis and epidermis combined, as a semi infinite medium. Obviously multi-layered models could be employed, for instance directly consuming the chromophores estimations, but these are out of scope of this paper. See

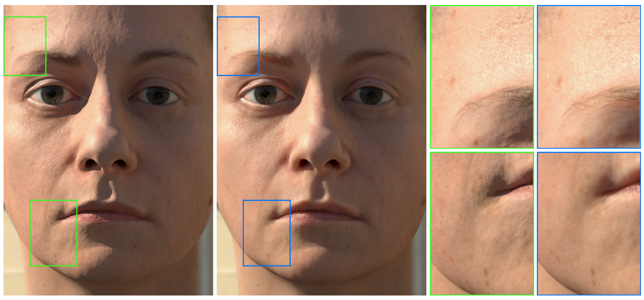

Figure 4: Lambertian vs Random Walk Subsurface Scattering in final rendering stage. *The numerical albedo inversion allows to drive the attenuation by the albedo map, ensuring skin details are preserved and not over blurred by the 3D SSS simulation.*

Figures 7, 8, and 9 for examples of path traced renders under 3 different lighting environments.

5. Further Comparisons with Previous Work

We conduct a series of comparisons with the related and recent work from [GGD*20]. Not having access to the trained models, we run our method over the the paper's images, skin patches obtained via the Antera device (under D65 illuminant) in Figure 5.

6. Further Results

We perform estimations and manipulations of skin parameters over several skin types covering the Fitzpatrick scale [Fit88]. With the LUT approach, using the largest tensor (256k skintones) resulted in varying times from 2 to 5 hours for 2k by 2k images, or more than 7 hours for 4k by 4k images, using brute force multi threaded (12) search on the tensor in an Intel Xeon W-2135 at 3.70GHz. We refer the readers to Figure 3, that showcases the problems of LUTs.

Robustness under different illuminants For completeness, we include in Figure 6 the complete set of estimated properties for the two faces under 4 color temperatures shown in Figure 9 of the paper.

Editing the Skin Parameters We show how we can manipulate directly in this space of inferred skin properties, scaling some of them up or down in an intuitive and predictable manner. We run the neural decoder on these modified quantities to reconstruct biophysical albedos, and finally render them on 3D faces. For skin types ranging from I to V, we perform large edits in hemoglobin and melanin content, with details explained in Figure 7, 8 and 9. Note the edits are naive in order to cover similar ranges for all skin types, and the *RGB* version of the model was used for these manipulations, so extreme edits can turn unnatural.

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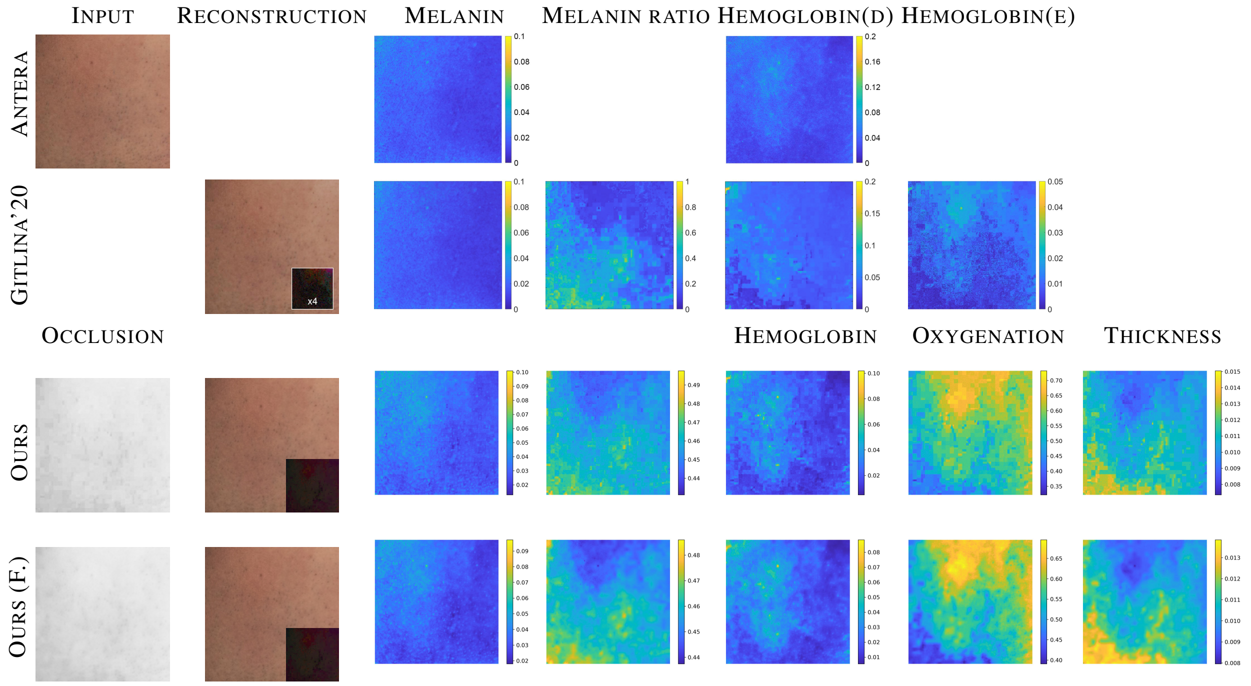

Figure 5: Comparison with the skin albedo patch from [GGD*20]. Top: *their reconstruction (MSE = 0.0130) and estimated parameters.* Middle: *ours (MSE = 1.26x10^{-05}). Note that the image contains compression and color artifacts, and does not seem to have an homogeneous lighting. This causes an excess of estimated melanin concentration (higher even in our reconstruction), in reference to what seems appropriate for that type of skin. Interestingly, the level of oxygenation appears to correlate with the extended blood concentration in the epidermis from their work.* Bottom: *our reconstruction over a filtered input (after removal of spatial and color JPEG artifacts).*

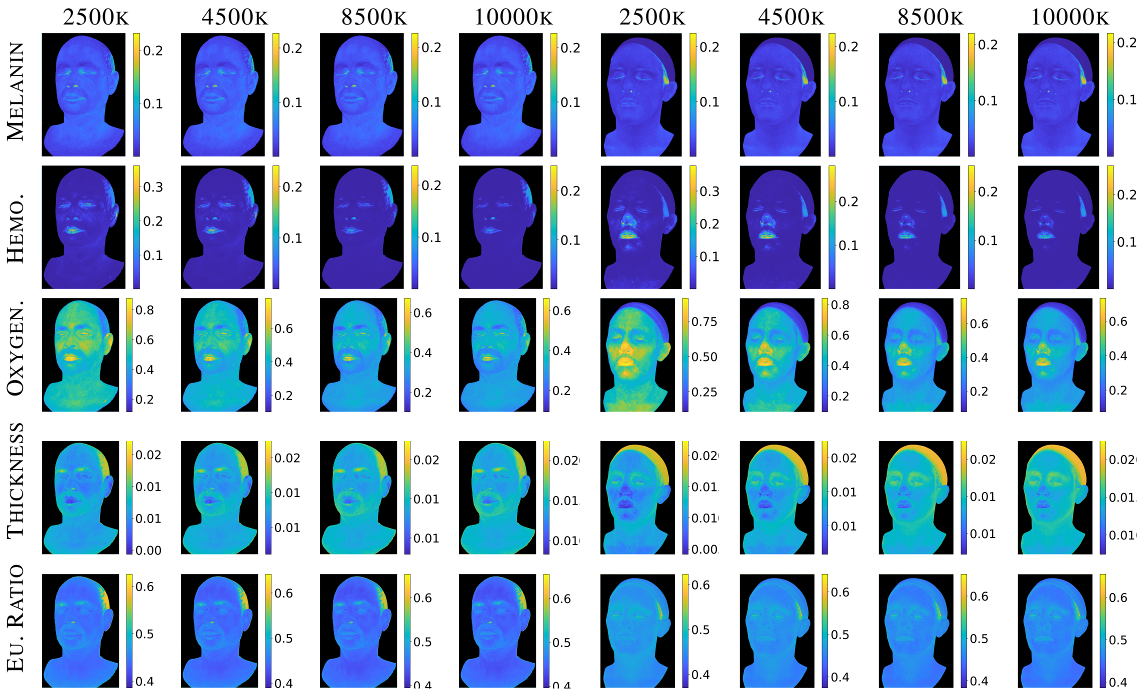

Figure 6: *Complete estimated skin properties for the faces under different color temperatures shown in the paper.*

Figure 7: *Rendering results under our most neutral lighting scenario for edited skin parameters inferred by our model over different skin types (classified according to the Fitzpatrick scale). From left to right, original, followed by different manipulations per subject, three in blood concentration and three in melanin concentration. Note that these are straight algebraic edits on the recovered skin components, with no additional artistic tweaks or touch-ups involved. Though they demonstrate that our skin model describes an expressive reflectance space, these naive edits can result sometimes in semi non natural skins.*

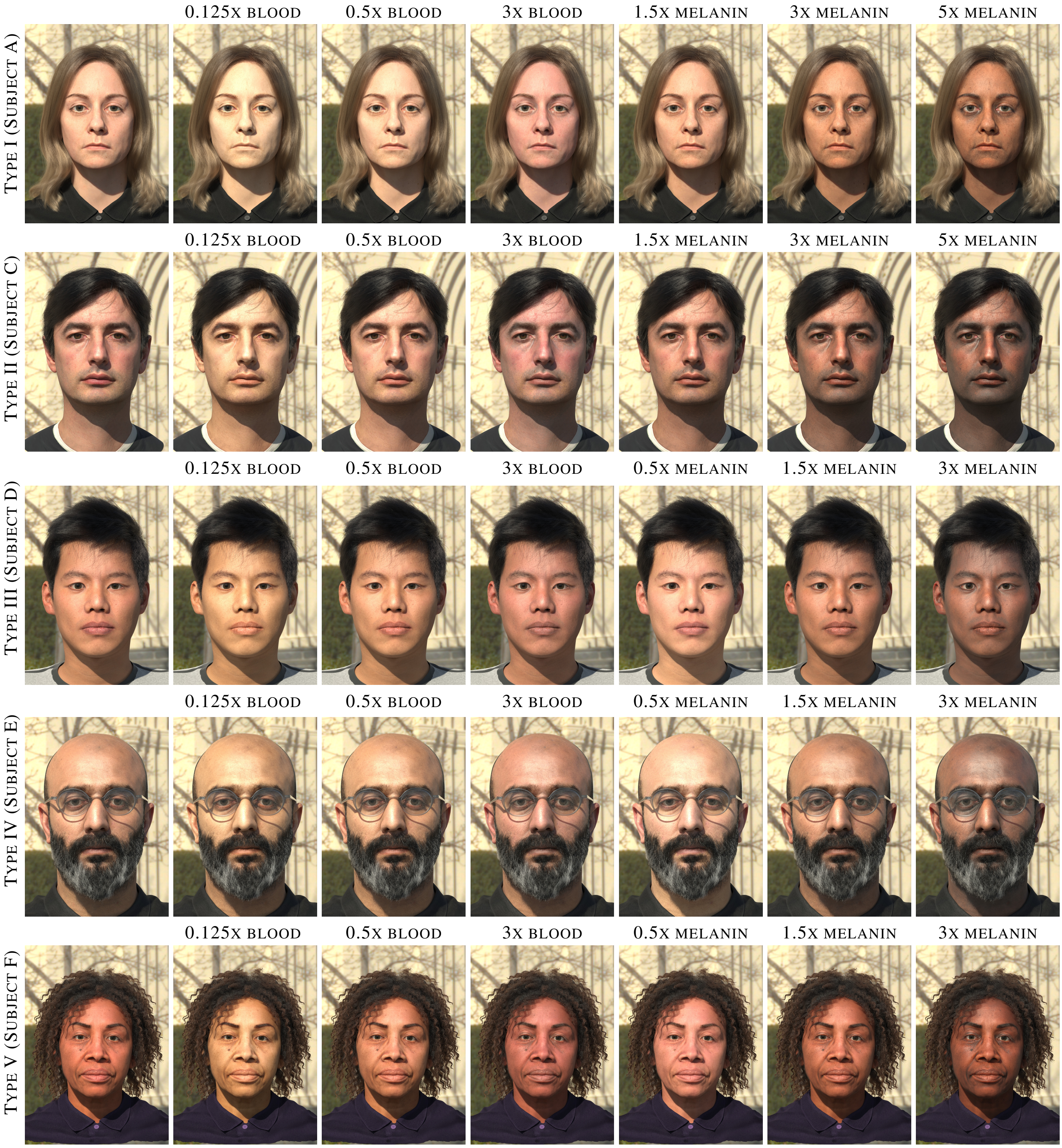

Figure 8: *Rendering results under lighting scenario 2 for edited skin parameters inferred by our model over different skin types. From left to right, original, followed by different manipulations per subject, three in blood concentration and three in melanin concentration.*

Figure 9: *Rendering results under lighting scenario 3 for edited skin parameters inferred by our model over different skin types. From left to right, original, followed by different manipulations per subject, three in blood concentration and three in melanin concentration.*