Warsaw University of Technology

FACULTY OF ELECTRONICS AND INFORMATION TECHNOLOGY

PhD Thesis

in the discipline of Information and Communication Technology

Few-Shot Human Neural Rendering with Partial Information

Kacper Kania, M.Sc.

supervisor
Tomasz Trzciński, Prof. PhD DSc.

assistant supervisor
Marek Kowalski, PhD DSc.

WARSZAWA 2025

Acknowledgements

Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Ut purus elit, vestibulum ut, placerat ac, adipiscing vitae, felis. Curabitur dictum gravida mauris. Nam arcu libero, nonummy eget, consectetuer id, vulputate a, magna. Donec vehicula augue eu neque. Pellentesque habitant morbi tristique senectus et netus et malesuada fames ac turpis egestas. Mauris ut leo. Cras viverra metus rhoncus sem. Nulla et lectus vestibulum urna fringilla ultrices. Phasellus eu tellus sit amet tortor gravida placerat. Integer sapien est, iaculis in, pretium quis, viverra ac, nunc. Praesent eget sem vel leo ultrices bibendum. Aenean faucibus. Morbi dolor nulla, malesuada eu, pulvinar at, mollis ac, nulla. Curabitur auctor semper nulla. Donec varius orci eget risus. Duis nibh mi, congue eu, accumsan eleifend, sagittis quis, diam. Duis eget orci sit amet orci dignissim rutrum.

Nam dui ligula, fringilla a, euismod sodales, sollicitudin vel, wisi. Morbi auctor lorem non justo. Nam lacus libero, pretium at, lobortis vitae, ultricies et, tellus. Donec aliquet, tortor sed accumsan bibendum, erat ligula aliquet magna, vitae ornare odio metus a mi. Morbi ac orci et nisl hendrerit mollis. Suspendisse ut massa. Cras nec ante. Pellentesque a nulla. Cum sociis natoque penatibus et magnis dis parturient montes, nascetur ridiculus mus. Aliquam tincidunt urna. Nulla ullamcorper vestibulum turpis. Pellentesque cursus luctus mauris.

Nulla malesuada porttitor diam. Donec felis erat, congue non, volutpat at, tincidunt tristique, libero. Vivamus viverra fermentum felis. Donec nonummy pellentesque ante. Phasellus adipiscing semper elit. Proin fermentum massa ac quam. Sed diam turpis, molestie vitae, placerat a, molestie nec, leo. Maecenas lacinia. Nam ipsum ligula, eleifend at, accumsan nec, suscipit a, ipsum. Morbi blandit ligula feugiat magna. Nunc eleifend consequat lorem. Sed lacinia nulla vitae enim. Pellentesque tincidunt purus vel magna. Integer non enim. Praesent euismod nunc eu purus. Donec bibendum quam in tellus. Nullam cursus pulvinar lectus. Donec et mi. Nam vulputate metus eu enim. Vestibulum pellentesque felis eu massa.

Quisque ullamcorper placerat ipsum. Cras nibh. Morbi vel justo vitae lacus tincidunt ultrices. Lorem ipsum dolor sit amet, consectetuer adipiscing elit. In hac habitasse platea dictumst. Integer tempus convallis augue. Etiam facilisis. Nunc elementum fermentum wisi. Aenean placerat. Ut imperdiet, enim sed gravida sollicitudin, felis odio placerat quam, ac pulvinar elit purus eget enim. Nunc vitae tortor. Proin tempus nibh sit amet nisl. Vivamus quis tortor vitae risus porta vehicula.

Abstract

This thesis is a series of publications that introduce novel methods for human neural rendering using limited information, focusing on Neural Radiance Fields (NeRFs) and 3D Gaussian Splatting (3DGS). It explores how these models construct 3D representations from 2D images and demonstrates ways to condition these representations for generating high-quality human renderings. We propose techniques that use simple, interpretable inputs derived from sparse training data and extends these methods to perform effectively in few-shot learning scenarios.

We begin by examining the field of neural radiance fields, addressing limitations in existing approaches and presenting contributions to controllable radiance fields. By incorporating partial and sparse data during training, it leverages the smoothness of neural networks to produce controllable, high-quality human images.

To tackle the reliance on extensive, high-quality data annotations from multi-view videos, we introduce a new method for training neural radiance fields in few-shot, multi-view settings. This approach learns internal deformation templates, which blend smoothly during inference, significantly improving image quality compared to existing baselines and enabling effective human rendering from limited input images.

The work also addresses the need for adaptable computational efficiency during inference. It proposes a fine-to-coarse learning strategy for 3D Gaussian Splatting, which upscales a latent 2D grid that stores Gaussian representations. This strategy achieves competitive results while allowing deployment on various computational devices with minimal quality loss.

In addition, we develop a novel model for controlling radiance fields through environmental lighting. By incorporating precomputed radiance transfer, this model enables physically plausible scene relighting and provides users with intuitive control over lighting in reconstructed scenes.

This research advances the state of the art in controllable neural radiance fields and expands their application to few-shot learning scenarios. These innovations enhance the possibilities for human rendering from limited information and open new directions for future research in the field.

Keywords: Neural Rendering, Neural Radiance Fields, Few-Shot Learning, Human Rendering, Partial Information, Gaussian Splatting

Streszczenie

To jest streszczenie. To jest trochę za krótkie, jako że powinno zająć całą stronę.

Słowa kluczowe: A, B, C

Lay Summary

ok

Publications in this thesis

Title	Authors	Venue	Status
CoNeRF: Controllable Neural Radiance Fields	**Kacper Kania**, Kwang Moo Yi, Marek Kowalski, Tomasz Trzciński, Andrea Tagliasacchi	CVPR 2022	Accepted
BlendFields: Few-Shot Example-Driven Facial Modeling	**Kacper Kania**, Stephan J. Garbin, Andrea Taglisacchi, Virginia Estellers, Kwang Moo Yi, Julien Valentin, Tomasz Trzciński, Marek Kowalski	CVPR 2023	Accepted
LumiGauss: High-Fidelity Outdoor Relighting with 2D Gaussian Splatting	Joanna Kaleta, **Kacper Kania**, Tomasz Trzciński, Marek Kowalski	WACV 2025	Accepted
CLoG: Leveraging UV Space for Continuous Levels of Detail	**Kacper Kania**, Rawal Khirodkar, Shunsuke Saito, Kwang Moo Yi, Julieta Martinez	CVPR 2025	Under Review

Contents

List of Abbreviations and Symbols

List of Figures

List of Tables

π	Stała matematyczna równa stosunkowi obwodu okręgu do jego średnicy
I	Natężenie prądu elektrycznego

Chapter 1

Introduction

With the advent of deep learning, research have been exploring varying ways to apply it to computer graphics. One of the most recent and promising approaches is neural rendering. Neural rendering is a field that combines deep learning and computer graphics to generate realistic images of 3D scenes. The neural radiance field (NeRF) is a popular neural rendering technique that represents a 3D scene as a continuous function that maps 3D coordinates to radiance values. NeRF has shown impressive results in generating photorealistic images of 3D scenes. However, NeRF has limitations in terms of memory and computational requirements, which makes it difficult to scale to large scenes.

To alleviate the problem, Kerbl *et al.* [18] proposed a new technique—3D Gaussian Splatting (3DGS). 3DGS is a neural rendering technique that represents a 3D scene as a set of 3D Gaussian that are splatted to an image space using algorithm proposed by Zwicker *et al.* [45]. In contrast to NeRF, 3DGS is more memory efficient and can be used to render large scenes. It can also render scenes with millions of points in real-time on a single GPU.

In this thesis, we focus on those two milestone techniques in neural rendering and address their fundamental problem—lack of controllability.

1.1 Motivation and challenges

NeRF and 3DGS are both impressive techniques that can generate realistic images. However, a single scene representation needs to be trained on a high-end GPU for hours or even days just to render a novel view at the inference time. However, any type of controllability is difficult to achieve with those models. That includes changing the lighting conditions, subject's attributes or even the scene itself. We see imbuing those models with controllability as a an important step towards making them more useful in practice. Our proposed models are designed to address this issue.

One may ask why the controllability is a feat sought after to be researched. We see the inspiration in how human artists work. Imagine an artist working on 3D game where they need an asset, like a 3D mesh, to be created. Such a mesh takes much effort since it includes modeling, creating a UV map which can then be textured. After the process is finish, the artist's supervisor may task him to change the model to some extent which requires the artist to redo all the effort again. Such a process is not limited to 3D assets as meshes and could be applied to 3DGS or NeRF. However, 3DGS and NeRFs are volumetric in nature. Our exploited and well-established practices no longer apply to them since volumetric representations do not have the underlying surface representation. For that reason, we see a couple of avenues which we explore in this thesis.

Firstly, Park *et al.* [26] proposed NeRFies, a model that creates a volumetric representation of a person from a self-captured sequence with a phone camera. Since the inception of NeRFs [23], it was among the first works the achieved such a high quality of reconstructions from a casual videos. In its primal form, NeRFies were unable to control the avatar in any other way than by a linear interpolation of latent embeddings that embedded the video's time dimension. The follow-up work, HyperNeRF [27] handles this issue by projecting the learnable embeddings with D onto a lower-dimensional space $\mathbb{R}^d$ where $d \ll D$. After the assumption that the d=2 is enough to explain the sequence variability, that projected embedding becomes a 2-dimensional space that can be traversed in an interpretable way. However, that space is not intuitive since the projection is a non-linear operation and one cannot predict how values affect the results. To mitigate that issue, we propose to leverage smoothness of Multilayer Perceptrons (MLPs) [26, 36] to constrain the projection via sparse supervision. We realize our approach as a weakly-supervised MLP that out of many images from the sequence (we assume at least 100 frames in our work) only a few are provided with a coarse annotation. Such annotations denote what values a chosen attribute takes and where its effect spans in the image space. We show that our method, which we dubbed CoNeRF [16] and published at the CVPR 2022 conference, imbues NeRFs with a flexible editability feature without the lose of the rendering quality.

Secondly, approaches such as CoNeRF [16], EditNeRF [21] or FigNeRF [39] focus solely on static elements of the scene, hence their controllability is limited to changing colors or textures in general. HyperNeRF [27] arises as a potential solution due to its ability to model object deformations. However, our initial experiments showed that those changes cannot handle motions that affect a subject globally, *e.g.*, jumping jacks performed by a person. To solve the issue, Fang *et al.* [4] proposes to model the deformation via a multi-scale voxel structure which works well in the synthetic setting, such as the one proposed by Pumarola *et al.* [29].

There exists a plethora of works that approach the problem from the another angle—instead of modeling the motion purely from data, they use a template model in the form of a 3D mesh to canonicalize deformed points [44]. Such methods rely on the accuracy of the *registration*, *i.e.*, fitting the template mesh to subject. Since the registration methods [5, 43] are imperfect estimators, they inherently contain registration errors. Those deviations are exacerbated by learnable radiance field models which assume a perfectly calibrated scene. The authors of those approaches usually mitigate the issue with additional latent space [8, 16, 22] that requires thousands of video frames to learn an avatar of high-fidelity that reacts correctly to deformations such as wrinkles on the forehead. At the same time, performing the registration on the large scale is costly [1]. In this thesis, we seek a remedy for those obstacles. We propose a method that is data-efficient, easy to improve with a minimal user input and can model realistic deformation dependent changes in the subject. Inspired by classical methods in character texturing [25] and motion modeling [19], we propose BlendFields [13], an *homage* to traditional blendshapes [19]. We build on VolTeMorph's [6] approach to point canonicalization to provide a data-efficient way to control the character. We further introduce a physically-based mixture of predefined, learned from data wrinkle templates that represent expression-dependent skin deformations. Our proposed was acknowledged by the reviewers and was accepted to the CVPR 2023 conference.

Thirdly, having the texture and coarse mesh-based controllability, we strive for control scene settings directly. The inverse rendering of 3D scenes is an ill-posed problem where many different lighting settings may explain the same light effects [28]. To facilitate solving the problem, many approaches use datasets of single object's images captured under different lighting conditions [2, 32, 40]. These approaches cannot decouple albedo from the lighting effects [2, 40] or need additional neural networks to predict correct shadows [32] which limits methods' practicality. We propose to use recently proposed 2D Gaussian Splatting [11] which exhibit remarkable quality of the surface reconstruction. Together with our precomputed radiance transfer from classical computer graphics approaches [30, 33], our LumiGauss achieves state-of-the-art reconstruction quality with the ability to render novel lighting conditions with high fidelity. Our work received positive reviews for the WACV 2025 conference.

Finally, volumetric representation are computationally intensive to render, compared to the traditional mesh representation. For NeRFs [23], it takes seven days on V100 NVidia GPU to train for single scene, and more than 60 seconds to render a single image—way beyond any practical applications. Although many approaches have been proposed to speed up the rendering process [7, 10, 24, 31, 41], they usually make a trade-off between memory requirements, quality, and rendering speed. 3D Gaussian Splatting [18] (3DGS) rose as an alternative to NeRF, offering both high-quality rendering at interactive frame rates. However, those frame rates could be achieved with the most advanced GPU units available at that time. As we see the potential in 3DGS to be a viable canonical representation for 3D data, akin to 3D meshes, a need for its adaptability to different computational resources exists. Meshes can be adapted easily with levels of detail (LoD) approaches that remove detail from meshes that do not affect the general object's perception if necessary.

1.2 Research objectives

In this thesis, we explore different avenues of radiance field controllability. With this goal in mind, we aim at answering the following research questions:

(**RQ 1**) Can we imbue a Neural Radiance Field (NeRF) with a controllability by providing sparse annotations to the training dataset? How many annotations suffice to learn smooth interpolation capabilities between controlled values?

(**RQ 2**) Are extreme facial expressions known from the literature sufficient to learn expression-dependent details that extrapolate to expressions unseen at the training time?

(**RQ 3**) Is it possible to learn an underlying radiance transfer function of a scene from images taken in "in-the-wild" setting? Can such a transfer function generalize to unknown environment maps?

(**RQ 4**) How to learn a single 3D Gaussian Splatting (3DGS) representation that can be adapted to different computational regimes at inference time in a feed-forward mode?

Each of these questions is a representative of possible among many others controllability directions for radiance fields. In case of this thesis, we present summarize our methods as controls of: texture [13, 16], shape [13], lightning [12] and use of resources [14]. To answer (**RQ 1**), we describe our CoNeRF [16]. It is one of the pioneering works that uses sparsely annotated frames to continuously control the subject in a post-hoc manner. We leverage the fact that MLP used in NeRFs are smooth functions biased towards low frequency signals [36]. For that reason, NeRF can learn to interpolate smoothly the annotation signal between frames of high similarity. We show that this assumption is sufficient to obtain both novel view synthesis and novel attribute synthesis with a single model.

We further move towards answering (**RQ 2**). We introduce BlendFields [13], achieving two primary goals: ability to generalize unknown expressions via a predefined face mesh template, and a mixture model of training expressions that can produce spatially coherent, expression-dependent wrinkles on the face from as few as three expressions. In our work, we build on VolTeMorph [6] to achieve to former, and focus on the latter contribution. Inspired by texture maps in classical computer graphics pipelines [25], we define a set of learnable radiance fields, each being overfit to a particular extreme expression from the training set. We define an extreme expression as one of the possible expressions involving the most facial muscles. Building on VolTeMorph [6] allows us to use an underlying tetrahedral mesh to compute physical quantities such as the volume change of tetrahedra under a given expression. We use those quantities to linearly interpolate between the pretrained radiance fields. We mix the tetrahedra independently which makes rendering novel expressions possible. For example, BlendFields can render one of the eyebrows raised while maintaining the other in a natural position, which is a difficult expression to make for majority of people.

Our LumiGauss [12] answers (**RQ 3**). In contrary to common approaches [32], we posit that the radiance transfer function known among computer graphics researchers [30] can be learned from unconstrained photo collection under varying lighting conditions. To this end, we use 2DGS [11] which gives us a smooth shape representation, difficult to achieve when using 3DGS [18]. With the use of contributed priors, we induce learning Gaussian's Spherical Harmonics such that they correctly react to changing environment maps. Not only our approach is fast to train, but renders realistic scenes and object's shadows even under novel lighting conditions.

All the contributions so far are affected by a specific disadvantage—a single model needs to be trained from scratch and it can be deployed only on high-end hardware. We then ask if we can train a single model that is adaptable at inference time to different hardware regimes (**RQ 4**). We propose CLoG [14] as a potential remedy. Our approach uses the fact that one can constrain the number of Gaussians in 3DGS [18] to a specific number, such that it can be formed as a 2D grid by simple reshape operation. With a specific training coarse-to-fine training protocol we contributed, the model learns a representation that converges to a high-quality volumetric structure. In the second training stage, we leverage the fact that Gaussians's can be spatially sorted in such a manner that their descriptors are placed next to each other if they are similar. That forms a low-frequency image which can be modulated with an off-the-shelf continuous upsampling architecture [37]. The architecture outputs a new grid of the given resolution. We show in our work that such an approach achieves remarkable results and can output any number of Gaussians at inference time with high quality.

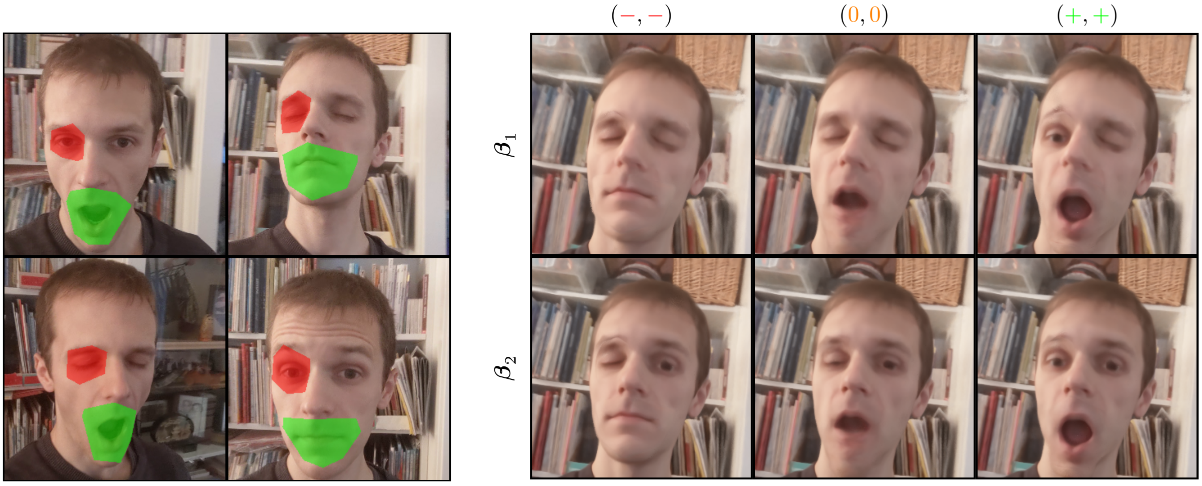
1.3 Contributions

Building on those questions, we structure this thesis in several chapters corresponding to the answers. An answer is in a form of a scientific article where we introduce the following:

- A novel approach for controlling trained radiance fields with the use of sparsely annotated images from a casually captured data.
- A new model capable of blending trained radiance fields from multi-view frames in an interpretable way and extrapolating to novel human expressions for the trained subject.
- The first use of Gaussian Splatting methods that learns a coherent shape representation of a subject and an ability to distill the varying lighting conditions in the data to a radiance transfer function.
- A novel paradigm for learning Gaussian Splatting models as 2D grids to achieve flexibility to adapt the model to different computational regimes at inference time.

1.3.1 Texture from Partial Information

Existing NeRF-based approaches in 2021 were simple models—they were overfit to a single subject, for a new subject the model needed to be retrained from scratch, and the editability



(a) annotated samples

(b) renderings from the trained model

Figure 1. Example with annotations and controlled attributes – We show an example of how our CoNeRF is capable of controlling attributes selected sparse annotations at the training time. Top row shows possible value combinations (− denoting closed eye, 0 neutral position and + an open eye) and $\{\boldsymbol{\beta}_1, \boldsymbol{\beta}_2\}$ possible values of attributes that are not explicitly learned from the annotations but purely from data (please see Chapter 3 for further explanation).

capabilities were limited [21]. NeRFactor [42] could be considered a more sophisticated model. However, it worked only for simple scene with calibrated scenes and could not handle any motion.

We approach those issues in our CoNeRF [16] published at the CVPR 2021 conference. Inspired by HyperNeRF [27], we propose to revisit the weak supervision in the context of radiance fields. Specifically, under an assumption that one can provide a few of sparse annotations to the dataset, we can leverage the smoothness of the neural networks to propagate the annotation across the dataset. The annotations also consist of what regions in the image space it refers to and hence we can train a semantic segmentation radiance fields that decouples attribute controls. We show an example in Fig. 1 where the left side represents the annotations present in the data and the right one possible manipulations at the inference time. We note that those annotations are easy to make in a matter of a few minutes for a single dataset. However, the complexity of the annotations grows with the number of attributes to control.

1.3.2 Expression from Few-Shot Learning

CoNeRF [16] is capable of rendering complex motions given sufficient amount of data and provided annotations. However, motions as the ones a person performs daily when speaking are infeasible in practice. We propose a solution to target that issue. We introduce BlendFields [13] from the CVPR 2023 proceedings which learns motion-dependent face deformation from data. We build on VolTeMorph [6] which uses existing face template models, such as FLAME [20], to learn a single canonical representation, akin to the canonicalization module in CoNeRF. Internally, BlendFields creates a tetrahedral cage around the face model. For each sample along the ray in NeRF, it moves the points to a "neutral position", chosen once prior to the training procedure. Such a procedure comes insufficient to model realistic facial features, such as wrinkles. We contribute a novel approach to modeling those deformations. We compute a deformation gradient of each tetrahedra for a given expression which is a physically-based and easy to interpret quantity. The value serves us to smoothly transition face regions textures to appropriate colors. We obtain the colors from NeRFs branches, each overfit to particular expression. In principle, BlendFields predicts face bases which are conditioned on the face expression vector to output the final point color. Our framework works well even when only a few "extreme" expressions are provided such as grinning face with closed eyes and wide open mouth with open eyes.

1.3.3 Light from Unconstrained Images

In both approaches above, we tackle the problem of texture controllability. They assume an ideal case scenario where a capture can be taken in an idealized environment with constant camera exposure and lighting. Moreover, the produced colors are blended together, making the change of light impossible in practice. We then ask the questions if we can decouple an intrinsic color of the subject and change of that color stemming from the environment light. We answer that question with our LumiGauss [12] published at the WACV 2025 conference that, indeed, we can achieve that by learning the radiance transfer function directly from data. For that end, we train a 2DGS [11] model to obtain a smooth and spatially coherent surface of objects. On top of the other attributes known from 3DGS [18], we imbue our Gaussians with additional features corresponding to the radiance transfer, expressed as Spherical Harmonics [9]. We show in our experiments that such a formulation is sufficient to train a model that reacts to changing environment maps in a realistic manner and renders images of higher fidelity than prior approaches.

1.3.4 Levels of Detail in One Model

All the contributions above require considerable computation hardware to be trained on and then run inference in near real-time frame rates. Drawing an inspiration from the gaming industry where Levels of Details (LoD) for meshes is used heavily, we introduce CLoG [14]. Our approach trains a single Gaussian Splatting model such that it can be modulated at inference time and adapted to the target computational requirements with a minimal loss on the rendering quality. That allows us to democratize the use of 3DGS and deploy a single model even on handheld devices. We show later that even under a strict case where only 2,000 Gaussians[1] can be used, the object is still recognizable. The most important contribution of our model is that it is continuous by design while the existing baselines assume prior the training the model how many LoD the model should comprise at inference. To change the size of particular LoD in those

[1]Common 3DGS models can achieve from 10^5 to even 10^6 Gaussians.

baselines requires training the whole model from scratch, imposing a significant computational burden.

1.4 Thesis outline

This thesis is structured as follows. We start by introducing the preliminaries related to the Neural Radiance Fields and Gaussian Splatting in Chapter 2—a common theme in all works that appear later. We then move towards describing CoNeRF [16] in Chapter 3, our approach to control trained neural radiance fields by using sparse annotations. In Chapter 4, we describe BlendFields [13] that can produce realistic expression-dependent texture from just a few multi-view frames of the subjects. Chapter 5 introduces the LumiGauss [12], a Gaussian Splatting model that learns a radiance transfer function for novel lighting rendering capabilities. Finally, we bring a general method, CLoG [14], that uses Gaussian Splatting to learn continuous levels of detail while training only a single model. We conclude the thesis in Chapter 6 where we also explore possible future avenues that can be undertaken.

1.5 Publications not included in the thesis

We attach a list of articles that are related to and can be used to in neural rendering approaches:

- **Kania, K.**, Zięba, M., and Kajdanowicz, T., "UCSG-NET – Unsupervised Discovering of Constructive Solid Geometry Tree," *NeurIPS*, vol. 33, pp. 8776–8786, 2020,
- **Kania, K.**, Kowalski, M., and Trzciński, T., "TrajeVAE: Controllable Human Motion Generation from Trajectories," *arXiv preprint arXiv:2104.00351*, 2021,
- Stypułkowski, M., **Kania, K.**, Zamorski, M., Zięba, M., Trzciński, T., and Chorowski, J., "Representing Point Clouds with Generative Conditional Invertible Flow Networks," *Pattern Recognition Letters*, vol. 150, pp. 26–32, 2021,
- Xia, S., Yue, J., **Kania, K.**, Fang, L., Tagliasacchi, A., Yi, K. M., and Sun, W., "Densify Your Labels: Unsupervised Clustering with Bipartite Matching for Weakly Supervised Point Cloud Segmentation," *arXiv preprint arXiv:2312.06799*, 2023,
- Esposito, S., Xu, Q., **Kania, K.**, Hewitt, C., Mariotti, O., Petikam, L., Valentin, J., Onken, A., and Mac Aodha, O., "GeoGen: Geometry-Aware Generative Modeling via Signed Distance Functions," in *CVPRW*, 2024, pp. 7479–7488,
- Spurek, P., Winczowski, S., Zięba, M., Trzciński, T., **Kania, K.**, and Mazur, M., "Modeling 3D Surfaces with a Locally Conditioned Atlas," in *ICCS*, Springer, 2024, pp. 100–115.

Chapter 2

Background

2.1 Neural Rendering

2.2 Neural Radiance Field

2.3 3D Gaussian Splatting

Chapter 3

CoNeRF: Controllable Neural Radiance Fields

Chapter 4

BlendFields: Few-Shot Example-Driven Facial Modeling

Chapter 5

LumiGauss: Relightable Gaussian Splatting in the Wild

Figure 2. Teaser – LumiGauss reconstructs environment maps and object surfaces from *in-the-wild* images. Our model decouples the scene color and its normals (*second and fourth column in the top row*). At inference, it can synthesize novel views (*bottom row*) and realistic lighting (*first and third columns in the bottom*) with high-fidelity shadows (*second and fourth columns in the bottom*).

Chapter 6

Final remarks and discussion

6.1 Conclusions

6.2 Future work

Bibliography

[1] Cao, C., Simon, T., Kim, J. K., Schwartz, G., Zollhoefer, M., Saito, S.-S., Lombardi, S., Wei, S.-E., Belko, D., Yu, S.-I., *et al.*, “Authentic Volumetric Avatars from a Phone Scan,” *ToG*, vol. 41, no. 4, pp. 1–19, 2022 (cit. on p. 5).

[2] Chen, X., Zhang, Q., Li, X., Chen, Y., Feng, Y., Wang, X., and Wang, J., “Hallucinated Neural Radiance Fields in the Wild,” in *CVPR*, 2022, pp. 12 943–12 952 (cit. on p. 5).

[3] Esposito, S., Xu, Q., **Kania**, **K.**, Hewitt, C., Mariotti, O., Petikam, L., Valentin, J., Onken, A., and Mac Aodha, O., “GeoGen: Geometry-Aware Generative Modeling via Signed Distance Functions,” in *CVPRW*, 2024, pp. 7479–7488 (cit. on p. 10).

[4] Fang, J., Yi, T., Wang, X., Xie, L., Zhang, X., Liu, W., Nießner, M., and Tian, Q., “Fast Dynamic Radiance Fields with Time-Aware Neural Voxels,” in *SIGGRAPH Asia 2022 Conference Papers*, 2022, pp. 1–9 (cit. on p. 4).

[5] Feng, Y., Feng, H., Black, M. J., and Bolkart, T., “Learning an Animatable Detailed 3D Face Model from In-The-Wild Images,” *ToG*, vol. 40, no. 4, pp. 1–13, 2021 (cit. on p. 4).

[6] Garbin, S. J., Kowalski, M., Estellers, V., Szymanowicz, S., Rezaeifar, S., Shen, J., Johnson, M. A., and Valentin, J., “VolTeMorph: Real-time, Controllable and Generalizable Animation of Volumetric Representations,” in *CGS*, Wiley Online Library, vol. 43, 2024, e15117 (cit. on pp. 5, 6, 8).

[7] Garbin, S. J., Kowalski, M., Johnson, M., Shotton, J., and Valentin, J., “FastNeRF: High-Fidelity Neural Rendering at 200FPS,” in *ICCV*, 2021, pp. 14 346–14 355 (cit. on p. 5).

[8] Grassal, P.-W., Prinzler, M., Leistner, T., Rother, C., Nießner, M., and Thies, J., “Neural Head Avatars From Monocular RGB Videos,” in *CVPR*, 2022, pp. 18 653–18 664 (cit. on p. 4).

[9] Green, R., “Spherical harmonic lighting: The gritty details,” in *Archives of the game developers conference*, vol. 56, 2003, p. 4 (cit. on p. 9).

[10] Hedman, P., Srinivasan, P. P., Mildenhall, B., Barron, J. T., and Debevec, P., “Baking Neural Radiance Fields for Real-Time View Synthesis,” in *ICCV*, 2021, pp. 5875–5884 (cit. on p. 5).

[11] Huang, B., Yu, Z., Chen, A., Geiger, A., and Gao, S., "2D Gaussian Splatting for Geometrically Accurate Radiance Fields," in *ACM SIGGRAPH 2024 Conference Papers*, 2024, pp. 1–11 (cit. on pp. 5, 6, 9).

[12] Kaleta, J., Kania, K., Trzcinski, T., and Kowalski, M., "LumiGauss: High-Fidelity Outdoor Relighting with 2D Gaussian Splatting," 2025 (cit. on pp. 6, 9, 10).

[13] Kania, K., Garbin, S. J., Tagliasacchi, A., Estellers, V., Yi, K. M., Valentin, J., Trzciński, T., and Kowalski, M., "BlendFields: Few-Shot Example-Driven Facial Modeling," in *CVPR*, 2023, pp. 404–415 (cit. on pp. 5, 6, 8, 10).

[14] Kania, K., Khirodkar, R., Saito, S., Yi, K. M., and Martinez, J., *CLoG: Leveraging UV Space for Continuous Levels of Detail*, 2024 (cit. on pp. 6, 7, 9, 10).

[15] **Kania, K.**, Kowalski, M., and Trzciński, T., "TrajeVAE: Controllable Human Motion Generation from Trajectories," *arXiv preprint arXiv:2104.00351*, 2021 (cit. on p. 10).

[16] Kania, K., Yi, K. M., Kowalski, M., Trzciński, T., and Tagliasacchi, A., "CoNeRF: Controllable Neural Radiance Fields," in *CVPR*, 2022 (cit. on pp. 4, 6, 8, 10).

[17] **Kania, K.**, Zięba, M., and Kajdanowicz, T., "UCSG-NET – Unsupervised Discovering of Constructive Solid Geometry Tree," *NeurIPS*, vol. 33, pp. 8776–8786, 2020 (cit. on p. 10).

[18] Kerbl, B., Kopanas, G., Leimkühler, T., and Drettakis, G., "3D Gaussian Splatting for Real-Time Radiance Field Rendering," *TOG*, vol. 42, no. 4, pp. 139–1, 2023 (cit. on pp. 3, 5, 7, 9).

[19] Lewis, J. P., Anjyo, K., Rhee, T., Zhang, M., Pighin, F., and Deng, Z., "Practice and Theory of Blendshape Facial Models," in *Eurographics 2014 - State of the Art Reports*, Lefebvre, S. and Spagnuolo, M., Eds., The Eurographics Association, 2014 (cit. on p. 5).

[20] Li, T., Bolkart, T., Black, M. J., Li, H., and Romero, J., "Learning a model of facial shape and expression from 4D scans," *SIGGRAPH Asia*, vol. 36, no. 6, 194:1–194:17, 2017 (cit. on p. 8).

[21] Liu, S., Zhang, X., Zhang, Z., Zhang, R., Zhu, J.-Y., and Russell, B., "Editing Conditional Radiance Fields," in *ICCV*, 2021, pp. 5773–5783 (cit. on pp. 4, 8).

[22] Martin-Brualla, R., Radwan, N., Sajjadi, M. S., Barron, J. T., Dosovitskiy, A., and Duckworth, D., "NeRF in the Wild: Neural Radiance Fields for Unconstrained Photo Collections," in *CVPR*, 2021, pp. 7210–7219 (cit. on p. 4).

[23] Mildenhall, B., Srinivasan, P. P., Tancik, M., Barron, J. T., Ramamoorthi, R., and Ng, R., "NeRF: Representing Scenes as Neural Radiance Fields for View Synthesis," *Communications of the ACM*, vol. 65, no. 1, pp. 99–106, 2021 (cit. on pp. 4, 5).

[24] Müller, T., Evans, A., Schied, C., and Keller, A., "Instant Neural Graphics Primitives with a Multiresolution Hash Encoding," *ToG*, vol. 41, no. 4, 102:1–102:15, Jul. 2022 (cit. on p. 5).

[25] Oat, C., “Animated Wrinkle Maps,” in *SIGGRAPH*, ser. SIGGRAPH ’07, San Diego, California: Association for Computing Machinery, 2007, pp. 33–37, ISBN: 9781450318235 (cit. on pp. 5, 6).

[26] Park, K., Sinha, U., Barron, J. T., Bouaziz, S., Goldman, D. B., Seitz, S. M., and Martin-Brualla, R., “Nerfies: Deformable Neural Radiance Fields,” in *ICCV*, 2021, pp. 5865–5874 (cit. on p. 4).

[27] Park, K., Sinha, U., Hedman, P., Barron, J. T., Bouaziz, S., Goldman, D. B., Martin-Brualla, R., and Seitz, S. M., “HyperNeRF: A Higher-Dimensional Representation for Topologically Varying Neural Radiance Fields,” *ToG*, vol. 40, no. 6, 2021 (cit. on pp. 4, 8).

[28] Patow, G. and Pueyo, X., “A Survey of Inverse Rendering Problems,” in *Computer graphics forum*, Wiley Online Library, vol. 22, 2003, pp. 663–687 (cit. on p. 5).

[29] Pumarola, A., Corona, E., Pons-Moll, G., and Moreno-Noguer, F., “D-NeRF: Neural Radiance Fields for Dynamic Scenes,” in *CVPR*, 2021, pp. 10 318–10 327 (cit. on p. 4).

[30] Ramamoorthi, R. and Hanrahan, P., “An efficient representation for irradiance environment maps,” in *Proceedings of the 28th annual conference on Computer graphics and interactive techniques*, 2001, pp. 497–500 (cit. on pp. 5, 6).

[31] Reiser, C., Peng, S., Liao, Y., and Geiger, A., “KiloNeRF: Speeding Up Neural Radiance Fields With Thousands of Tiny MLPs,” in *ICCV*, 2021, pp. 14 335–14 345 (cit. on p. 5).

[32] Rudnev, V., Elgharib, M., Smith, W., Liu, L., Golyanik, V., and Theobalt, C., “Neural Radiance Fields for Outdoor Scene Relighting,” in *European Conference on Computer Vision*, Springer, 2022, pp. 615–631 (cit. on pp. 5, 6).

[33] Slomp, M. P. B., Oliveira Neto, M. M. d., and Patrício, D. I., “A gentle introduction to precomputed radiance transfer,” *Revista de informática teórica e aplicada. Porto Alegre. Vol. 13, n. 2 (2006), p. 131-160*, 2006 (cit. on p. 5).

[34] Spurek, P., Winczowski, S., Zięba, M., Trzciński, T., **Kania, K.**, and Mazur, M., “Modeling 3D Surfaces with a Locally Conditioned Atlas,” in *ICCS*, Springer, 2024, pp. 100–115 (cit. on p. 10).

[35] Stypułkowski, M., **Kania, K.**, Zamorski, M., Zięba, M., Trzciński, T., and Chorowski, J., “Representing Point Clouds with Generative Conditional Invertible Flow Networks,” *Pattern Recognition Letters*, vol. 150, pp. 26–32, 2021 (cit. on p. 10).

[36] Tancik, M., Srinivasan, P. P., Mildenhall, B., Fridovich-Keil, S., Raghavan, N., Singhal, U., Ramamoorthi, R., Barron, J. T., and Ng, R., “Fourier Features Let Networks Learn High Frequency Functions in Low Dimensional Domains,” in *NeurIPS*, 2020 (cit. on pp. 4, 6).

[37] Vasconcelos, C. N., Oztireli, C., Matthews, M., Hashemi, M., Swersky, K., and Tagliasacchi, A., "CUF: Continuous Upsampling Filters," in *CVPR*, 2023, pp. 9999–10 008 (cit. on p. 7).

[38] Xia, S., Yue, J., **Kania**, **K.**, Fang, L., Tagliasacchi, A., Yi, K. M., and Sun, W., "Densify Your Labels: Unsupervised Clustering with Bipartite Matching for Weakly Supervised Point Cloud Segmentation," *arXiv preprint arXiv:2312.06799*, 2023 (cit. on p. 10).

[39] Xie, C., Park, K., Martin-Brualla, R., and Brown, M., "FiG-NeRF: Figure-Ground Neural Radiance Fields for 3D Object Category Modelling," 2021 (cit. on p. 4).

[40] Yang, Y., Zhang, S., Huang, Z., Zhang, Y., and Tan, M., "Cross-Ray Neural Radiance Fields for Novel-view Synthesis from Unconstrained Image Collections," in *Proceedings of the IEEE/CVF International Conference on Computer Vision*, 2023, pp. 15 901–15 911 (cit. on p. 5).

[41] Yu, A., Li, R., Tancik, M., Li, H., Ng, R., and Kanazawa, A., "Plenoctrees for Real-time Rendering of Neural Radiance Fields," in *ICCV*, 2021, pp. 5752–5761 (cit. on p. 5).

[42] Zhang, X., Srinivasan, P. P., Deng, B., Debevec, P., Freeman, W. T., and Barron, J. T., "NeRFactor: Neural Factorization of Shape and Reflectance Under an Unknown Illumination," 2021 (cit. on p. 8).

[43] Zielonka, W., Bolkart, T., and Thies, J., "Towards Metrical Reconstruction of Human Faces," in *ECCV*, Springer, 2022, pp. 250–269 (cit. on p. 4).

[44] Zielonka, W., Bolkart, T., and Thies, J., "Instant Volumetric Head Avatars," in *CVPR*, 2023, pp. 4574–4584 (cit. on p. 4).

[45] Zwicker, M., Pfister, H., Van Baar, J., and Gross, M., "EWA volume splatting," in *Proceedings Visualization, 2001. VIS'01.*, IEEE, 2001, pp. 29–538 (cit. on p. 3).