Deep generative models for engineering design
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Chapter 7

Conclusion and Outlook

This thesis aims to bridge the gap between modern deep generative models and generative engineering design. This chapter summarizes all the content of the preceding chapters, responds to the main research questions raised in Chapter 1, and points out limitations and future directions.

7.1 Research Question Revisited

Chapter 1: In the introduction, this paper provides an overview for this study, including industrial design processes, generative engineering design, and the latest advances in deep generative modeling, and explains the motivation for using deep generative models to achieve generative engineering design. The main research question addressed in this paper is:

How to enable deep generative models to synthesize engineering designs?

To answer this question, we have broken it down into several sub-questions, which are discussed separately in different chapters. More precisely, this paper addresses the main question by tackling a series of challenges, namely data representation, model architecture, model training/sampling, and evaluation. A secondary objective is to apply the newly developed methods to industrial design processes and demonstrate their applicability.

Chapter 2: Although recent diffusion models have achieved impressive results on general images, their generated engineering blueprints are structurally unrecognizable, i.e., poor plausibility. We assume that this can be caused by their prioritizing strategy for better visual quality. Herein, the challenge is:

How to prioritize plausibility in generation with deep generative models?

We observe that there is a range of noise levels associated with structure formation. Therefore, we design a new noise scheduling scheme for the diffusion model for training and sampling to focus on this selected noise level range. Our evaluation results show that this helps improve the rationality of the generated results. This proposed noise scheduling method is called plausibility-oriented diffusion model (PoDM).

Chapter 3: In the previous chapter, we discover the issue of poor plausibility in the generated designs, which are evaluated manually. This raise the following research question:

How to automatically evaluate the plausibility of designs generated by deep generative models?

Leveraging the advantage of denoising autoencoders in focusing on capturing underlying structures during training, we propose Fréchet Denoised Distance (FDD) as a new evaluation metric, which shows reliable performance in aligning with human judge on plausibility.

Chapter 4: High dependence on training autoencoders to enable deep generative models on high-dimensional data leads to significant computational costs and imperfect decoding results. Thus, the research question is:

How to use deep generative models to generate high-dimension designs more efficiently?

Several learning-free decomposition algorithms can achieve the same encoding-decoding function with adjustable information loss, such as singular value decomposition (SVD). Inspired by this, we design an SVD-based generation framework, SpoDify, which achieves performance comparable to state-of-the-art methods without training an autoencoder.

Chapter 5: Given that CAD is the most widely used data format in engineering design processes, enabling DGM for generative engineering design must address the following research question:

How to enable deep generative models to directly synthesize CAD-native representation?

Existing work has directly generated B-Rep data (native CAD representation), but this progress relies on learning on structured point clouds sampled from geometries. Here, we address this limitation by proposing NeuroNURBS, a method that decomposes NURBS-based geometries into latent features that can be used for downstream tasks. This method demonstrates significant efficiency advantages in terms of storage, computation and speed.

Chapter 6: Industrial design encompasses many complex structures and knowledge. When using generative models to simulate engineer construction, our major concern is:

How can DGMs be beneficial for real-world industrial design applications?

Here, we use the car A-pillars and rims as examples to demonstrate how the methods we developed (SA-ALAE, PoDM, and SpoDify) can assist engineers in designing complex structures at certain stages of the design process. Through the attempts in Chapter 6, our research provides insights into the application of DGMs to real-world engineering design processes, thereby answering the core research question of this thesis.

7.2 Limitations and Future Work

While DGMs develop in a swift speed, applying the technologies for generative engineering design still faces several challenges. We list the limitations and future directions below, for more specific discussions, we refer to the conclusion sections of corresponding chapters.

Available dataset. Currently, despite the publication of numerous engineering design datasets, e.g., 2D design images (BIKED [137], Seeing3DChairs [7], etc.), sequential construction operations in sequence (DeepCAD [182], Fusion 360 Gallery [180], etc.), 3D B-Reps (ABC [76], DeepCAD in B-Rep [187], etc.), the existing open-source datasets for generative design are insufficient. More specifically, in industrial design scenarios, design datasets often exhibit more complex structures (e.g., B-Rep with over 3 000 NURBS surfaces) but less in diversity. In this context, the challenge of achieving DGM shifts from generating diverse simple designs to effectively learning the complex data distribution of a single target. We note that the most advanced DGM currently used for B-Rep generation has been evaluated as having excellent performance, but the entities it generates have been deemed to be unreasonable designs. Here, we ask whether this problem is caused by poor DGM performance or excessive diversity in the training data set. Additionally, when we are developing the NeuroNURBS framework, these datasets cannot provide sufficient high-degree NURBS surfaces to challenge the model. Therefore, the potential of NeuroNURBS is underestimated. Considering that during the historical design phase, a significant amount of designs were created in a verifiable digital format, the release of new datasets containing these historical designs may be helpful in further advancing this field.

Generating feasible designs. Our work on PoDM is just a small step towards understanding the structure generated by DGM. We refer to the performance of generating reasonable designs as “plausibility”. However, in actual industrial design scenarios, engineering design needs to present feasible, manufacturable structures. In order for a design to be feasible and manufacturable, it must meet a large number of critical requirements, such as ease of assembly, sufficient strength, compliance with safety standards, etc. Currently, research in this field still struggles to explain why and how DGM generates realistic samples. To address this, we believe that the future direction is to iteratively generate designs, evaluate feasibility and design performance at each step, and feed the evaluation results back into the next iteration. On this, we have presented our insights in Section 2.4.

Conditional design generation. This thesis evaluates proposed models often under unconditional generation, as we aim to improve the generation efficiency and to enable the generation of special design representations for research purposes. However, in real-world industrial design processes, conditional design generation is required. Recent studies [88, 92] have achieved the generation of desired designs under specific condition (e.g., text descriptions, sketches, or mesh inputs), but industrial users prefer more intuitive inputs (e.g., dragging), which we have demonstrated in Section 2.4 but only for 2D images. To address this limitation, we believe that the future direction is to enable more intuitive input and evaluate the accuracy of the editing.

Design representation. This work begins with two-dimensional blueprints and delved into three-dimensional meshes and B-Reps, fully exploring the representational possibilities of design. However, to use DGM in real-world design cases, the current representation types are far from sufficient. More specifically, representing B-Reps with hierarchical structures leads to unnecessary large data volumes and poses challenges for the reversal process. Although recent work has achieved promising results [187], this framework suffers from high inefficiency during generation and poor performance when generating complex structures with thousands of surfaces. To address this issue, we believe that developing new representation methods or new concept of how B-Reps are formed, such as introducing interactions and combination functions between solids to form B-Rep volumes, may be helpful.

7.3 The Future of DGMs in Generative Engineering Design.

The limitations mentioned previously expose a significant gap but also reveal the enormous potential for growth in the field of DGM-based generative design. Our work is completed during a period when generative models began to shine, with researchers in the field continuously surpassing previous methods. It may take only a short time for the future directions discussed in this section to be surpassed, but we will still offer our insights.

Firstly, due to the development of large language models (LLMs), current LLMs can operate on a high diversity of data by treating it as "language", such as code, tabular data, and even images, referred to as large multimodal models (LMMs). In fact, in historical industrial design processes, there is a rich repository of design data in various forms, e.g., code (JT and STEP files), engineering construction operations in sequence (from CADPART files), blueprint images (DWG files), or tabular data, which can be understood by LMMs according to recent research [185, 42, 9]. However, this concept remains in its early stages.

At the same time, there is great potential for research into using DGMs to directly learn from design data, such as B-Reps, as this enables a differentiable modeling process, which is useful for further applications such as numerical simulation. We have already provided this concept in Section 2.4. Most of the work in this thesis has been done in this direction, but it seems that there is still a long way to go. To enable more effective modeling of design data like B-Reps, DGMs need to access the natural processes of construction, including but not limited to sketching, extruding, chamfering, drilling, and interaction. We believe that these construction operations are based on engineering expertise, and it is essential for DGMs to learn this knowledge in addition to structural information. It should be noted that representing these operations in text form does not necessarily enable the DGM to understand the construction knowledge and structural dependencies. DGMs also need to consider the changes these operations make to the structure and be penalized when constructing any infeasible entities. However, how to achieve this and how to represent it remains an open question.

Moreover, the current main trend in generative modeling applications is to deepen models exponentially. This trend has led to the emergence of giant, even mega models. Designers have observed that simply increasing the size of the model can effectively force it to learn hidden information better. However, we hope this does not become the future direction of research, as recent DGM frameworks have not yet been fully developed. Researchers in this field should strive forward to bring more advancements to DGM frameworks to address remaining challenges, such as low-sample learning, out-of-distribution learning or machine reasoning.

Finally, incorporating industrial applications into consideration is an inevitable future direction for DGM research. In our work, we have observed that the development of DGMs for industrial purposes has not garnered much attention in the DGM community, while most recent work has focused on more general data representations such as point clouds, meshes, and implicit representations like neural radiative fields (NeRFs). This focus has led to DGM research often attracting widespread attention but struggling to find corresponding application cases in the real world. Meanwhile, generating engineering designs is a valuable application scenario where DGMs can make significant contributions. By bridging the gap between theoretical advancements and practical applications, we can unlock the full potential of DGMs, paving the way for innovative solutions that enhance efficiency and creativity in industrial applications.

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List of Abbreviations

ALAE	Adversarial Latent Autoencoder
B-Rep	Boundary Representation
CAD	Computer-Aided Design
CAE	Computational-Aided Engineering
CD	Chamfer Distance
DAE	Denoising Autoencoder
DDIM	Denoising Diffusion Implicit Mode
DDPM	Denoising Diffusion Probabilistic Model
DGM	Deep Generative Model
DPS	Design Plausibility Score
FDD	Fréchet Denoised Distance
FID	Fréchet Inception Distance
FMH	Free Motion Headform
FPS	Frames per Second
GAN	Generative Adversarial Network
GED	Generative Engineering Design
GenAI	Generative Artificial Intelligence
HIC	Head Injury Criterion
KDD	Kernel Denoised Distance
LDM	Latent Diffusion Model
LLM	Large Language Model
LMM	Large Multimodality Model
MMD	Maximum Mean Discrepancy
MSE	Mean Squared Error
NeRF	Neural Radiance Fields

NURBS	Non-Uniform Rational B-Splines
NWD	Neural Wavelet-domain Diffusion
ODE	Ordinary Differential Equation
PDR	Plausible Design Rat
PoDM	Plausible-oriented Diffusion Mode
ReLU	Rectified Linear Unit
SA-ALAE	Self-Attention Adversarial Latent Autoencoder
SDE	Stochastic Differential Equation
SDF	Signed Distance Field
SVD	Singular Value Decomposition
SVM	Support Vector Machine
VAE	Variational Autoencoder