Universiteit Leiden
The Netherlands

Deep generative models for engineering design

Fan, J.

Stellingen

Behorende bij het proefschrift

Deep Generative Models for Engineering Design

1. A parametric noise scheduling strategy in diffusion models improves the plausibility of generated structural designs over default schedules, achieving higher plausible design rates [Chapter 2].
2. Evaluating generative outputs in a denoising autoencoder's latent space aligns better with human judgments than general metrics like FID [Chapter 3].
3. Spectral-domain diffusion modeling with a small number of eigenfeatures preserves geometric fidelity in high-dimensional shape generation while lowering latent dimensionality and computation [Chapter 4].
4. Diffusion models trained on spectral latent representations (mesh eigenfeatures) generalize better under limited data than models trained on raw meshes or point clouds [Chapter 4].
5. Developing generative models through the latent space obtained by encoding NURBS parameters enhances both computational efficiency and memory utilization compared to UV-grid parameterization methods, while also improving surface regularity and reducing artifacts. [Chapter 5].
6. Generative models operating on parametric CAD representations enable more controllable and interpretable design synthesis than mesh-based approaches.
7. While deep learning based on B-Reps can directly access their spatial structure, learning from operation sequences more accurately reflects engineering knowledge and generates editable design solutions.
8. Generating CAD code leverages LLMs' growing general knowledge to facilitate engineering design and knowledge-based synthesis.
9. Integrating AI-for-simulation with AI-for-CAD establishes differentiable design workflows that yield optimized solutions via gradient-based learning.
10. Embedding AI-driven generative tools in CAD shifts engineers' roles from manual geometry creation toward higher-level design supervision and decision-making.

Jiajie Fan
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