

# VehicleSDF: A 3D generative model for constrained engineering design via surrogate modeling

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# **Introduction and motivation**

We want to integrate Generative AI tools in all stages of design.

Concept	Basic	Detailed
	CAD Model	Engineering Drawings

# **Use case 2**: Stylizing realistic images using ControlNet<sup>[3]</sup>

input







Can use AI tools today!

Need to incorporate complex engineering design constraints

We aim to integrate engineering constraints into a 3D generative model for vehicle design, considering design parameters, engineering performance, and **styling** simultaneously.

# Methodology

Auto-decoder model<sup>[1]</sup> was trained to estimate signed distance function using ShapeNet dataset.



To get an ideal latent z corresponding to target parameters, a MLP was trained to estimate parameters from optimized latent z.



Vehicle geometric parameters were extracted automatically from mesh.



# **Experiments and results**

Generating 3D shapes satisfying target parameters



# Comparison of target parameters during optimization

Table 1: Comparison of target geometric parameters and during optimization

Parameters	$p_0$	$p_1$	$p_2$	$p_3$	$p_4$	$p_5$	$p_6$	MSE
Initial	1.000	0.331	0.396	0.053	0.598	0.194	0.208	$5.97  imes 10^{-4}$
Intermediate	1.000	0.306	0.425	0.039	0.599	0.203	0.199	$1.03 \times 10^{-4}$
Final	1.000	0.280	0.431	0.037	0.600	0.200	0.200	$2.86\times10^{-8}$
Target	1.000	0.280	0.430	0.037	0.600	0.200	0.200	-

#### Drag estimator results:









(a) Automatic parameter extractor

(b) Examples of extracted parameters

# **Use case 1**: Estimating drag coefficient from 3D model<sup>[2]</sup>



#### Estimating drag and stylizing realistic car-design image





[1] Jeong Joon Park, Peter Florence, Julian Straub, Richard Newcombe, and Steven Lovegrove. Deepsdf: Learning continuous signed distance functions for shape representation. In Proceedings of the IEEE/CVF conference on computer vision and pattern recognition, pages 165–174, 2019.

[2] Binyang Song, Chenyang Yuan, Frank Permenter, Nikos Arechiga, and Faez Ahmed. Surrogate modeling of car drag coefficient with depth and normal renderings. In International Design Engineering Technical Conferences and Computers and Information in Engineering Conference, volume 87301, page V03AT03A029. American Society of Mechanical Engineers, 2023.

[3] Lvmin Zhang, Anyi Rao, and Maneesh Agrawala. Adding conditional control to text-to-image diffusion models. In Proceedings of the IEEE/CVF International Conference on Computer Vision, pages 3836–3847, 2023.

https://arxiv.org/pdf/2410.18986