GENERATION OF OPTIMIZED CAR SHAPES FOR AERODYNAMICS USING NEURAL NETWORKS

école normale supérieure paris—saclay | université PARIS-SACLAY

Bastien Jacques*, Carlos Bermejo Barbanoj†, Elias Cueto†

*(Author) Ecole Normale Supérieure Paris-Saclay   †(Supervisor) Aragon Institute of Engineering Research (I3A)

Instituto Universitario de Investigación Universidad Zaragoza | Universidad Zaragoza

INTRODUCTION

Reducing vehicle aerodynamic drag is crucial to lower greenhouse gas emissions. However, conventional shape optimization methods are time-consuming and computationally expensive.

In this work, we introduce GenNet, a deep learning model based on an autoencoder that simultaneously predicts vehicle drag coefficients and enables the rapid generation of optimized shapes through interpolation in the latent space.

$$C_d = \frac{F_d}{\frac{1}{2}\rho U^2 A}$$

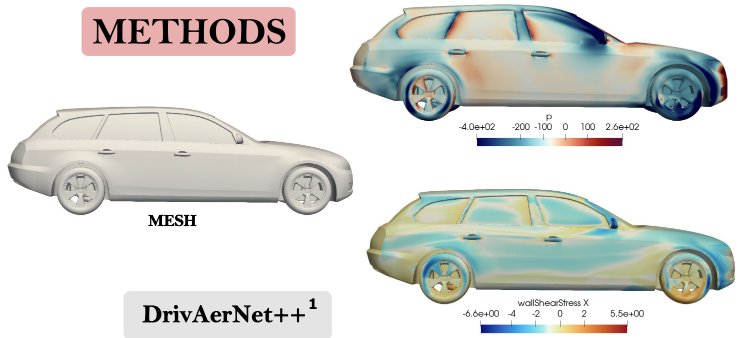
$$F_d = -\int_{\partial\Omega} p\,\mathbf{n}\cdot\mathbf{e}_x\,dS + \int_{\partial\Omega} \boldsymbol{\tau}\,\mathbf{n}\cdot\mathbf{e}_x\,dS$$

METHODS

Computional Fluid Dynamics (CFD) simulations using OpenFoam:

- Pressure Field

- Shear Stress Field



DrivAerNet++[1]

Signed Distance computation from the **centered** and **normalized mesh** of each vehicule using **250,000 sampling points**

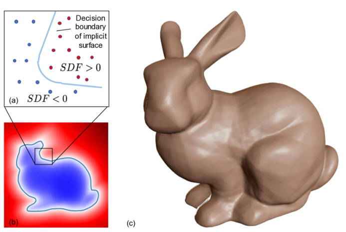
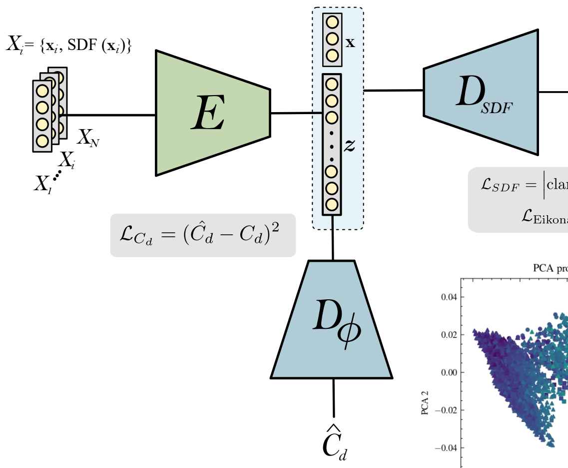


Image from Park et al., DeepSDF, 2019[2]

$$\mathbf{SDF}(x_i, \partial\Omega) = \begin{cases} -\text{dist}(\underline{x}_i, \partial\Omega) & \text{if } \underline{x}_i \in \Omega \\ +\text{dist}(\underline{x}_i, \partial\Omega) & \text{if } \underline{x}_i \notin \Omega \end{cases}$$

MODEL

Two-head autoencoder:[4] The **encoder** (E) maps the geometry of a vehicle into a **latent vector** z_{lat}. The **physics decoder** (D_ϕ) predicts the **drag coefficient** C_d. The **SDF decoder** (D_{SDF}) predicts the **Signed Distance Function** (SDF) associated with a point in space x and the latent vector.

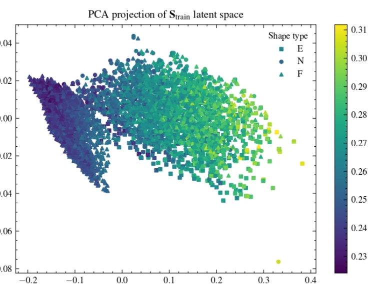


$$\mathcal{L}_{SDF} = \left|\text{clamp}(\widehat{SDF}, \delta) - \text{clamp}(SDF, \delta)\right|^2 \quad [2]$$

$$\mathcal{L}_{\text{Eikonal}} = (||\nabla SDF|| - 1)^2 \quad [3]$$

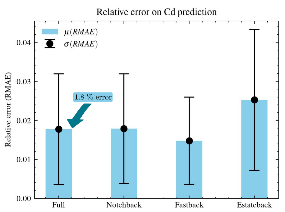
$$\mathcal{L}_{C_d} = (\hat{C}_d - C_d)^2$$

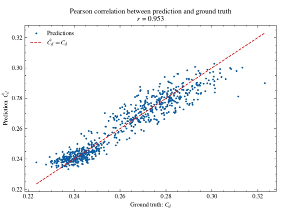
$$\mathcal{L} = \mathcal{L}_{SDF} + \lambda\mathcal{L}_{C_d} + \lambda_{\text{E}}\mathcal{L}_{\text{Eikonal}}$$



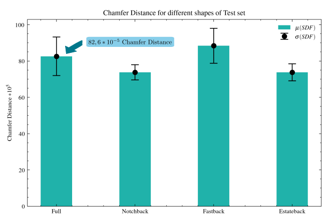
RESULTS

$$\text{MRAE} = \frac{1}{N}\sum_{i=1}^{N}\frac{|C_d^{(i)} - \hat{C}_d^{(i)}|}{|C_d^{(i)}|}$$





$$r = \frac{\text{Cov}(C_d, \hat{C}_d)}{\sigma_{C_d}\cdot\sigma_{\hat{C}_d}}$$

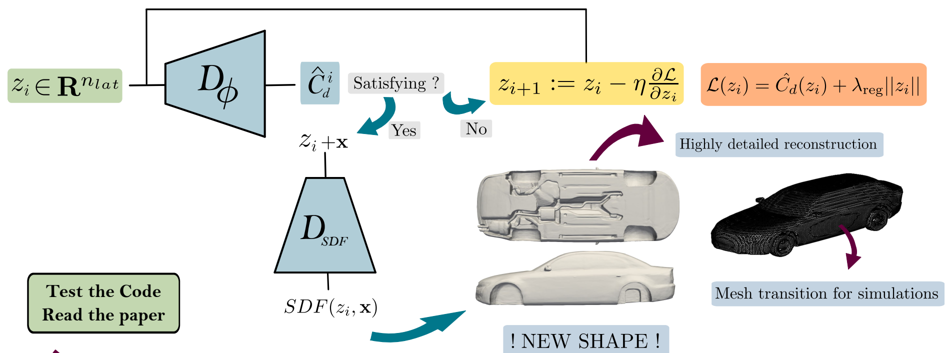


[1,2,5,6,7,8]

Method	CD×10³ (mean)	Pred. C_d ?	n_{SDF}	Benchmark
OGN	0.167	✗	-	ShapeNet, ModelNet40
AtlasNet-Sph.	0.210	✗	-	ShapeNet
AtlasNet-25	0.157	✗	-	ShapeNet
DeepSDF	0.084	✗	500k	ShapeNet, FAUST
GenNet (Ours)	**0.826**	✓	250k	DrivAerNet++

$$\text{Chamfer}(P, Q) = \frac{1}{|P|}\sum_{p\in P}\min_{q\in Q}\|p-q\|_2^2 + \frac{1}{|Q|}\sum_{q\in Q}\min_{p\in P}\|q-p\|_2^2$$

MODEL INFERENCE AND OPTIMIZATION



Test the Code
Read the paper

References

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CONCLUSION

GenNet enables rapid generation of aerodynamic car shapes via implicit representation and drag coefficient prediction.
Scaling to larger datasets could lead to real-world design tools for energy-efficient vehicle shapes.

bastien.jacques@ens-paris-saclay.fr