Learning Three-dimensional Flow for Interactive Aerodynamic Design

Nobuyuki Umetani\textsuperscript{1}, Bernd Bickel\textsuperscript{2}
Motivation

• Predicting aerodynamics at an interactive rate
Aerodynamics is Important
Computational Fluid Dynamics

- Traditional workflow is expensive & slow

input

3D shape

mesh generation

output

- Cd value
- pressure field
- velocity field

\[
\begin{align*}
\mu \left( \frac{\partial u}{\partial t} + u \cdot \nabla u - f \right) &= \nabla^2 u + \nabla p \\
\nabla \cdot u &= 0
\end{align*}
\]
Replacing CFD with ML

- 3D shape
- Input parameter
- Regressor
- Output parameter
- Uncertainty parameterization
- Output
  - Cd value
  - Pressure field
  - Velocity field
Parameterization Problem

- Shape need to be represented by fixed dimensional vector/tensor
Parameterization Problem

- Triangle mesh / NURBS are not suitable for ML
  - Topology / #points are not constant
Related Work: Voxel Model

- Difficult to handle *detailed* 3D shape

[3D GAN, 2016] [Girdhar et al., 2016] [O-CNN, Wang et al., 2017]
[liu et al., 2017] [OctNet, Riegler et al., 2017]
Related Work: Point-based Model

- Ordering of the point is not consistent

[PointNet, Qi et al, 2017]

[PointNet++, Qi et al, 2017]  [Gadelha et al., 2017]
[DeformNet, Kurenkov et al, 2017]  [Fan et al, 2017]
Our Approach: Mesh Representation

• PolyCube as a template quad mesh
• Deforming the quad mesh into the input shape
3D Shape as “Height Field”

- “Height field” from a PolyCube in normal directions

[Umetani 2018], Normal Meshes [Guskov et al. 2000]
Hierarchical Projection

• We repeat subdivision and projection

• Key observation: concave shape is locally convex
Parameterization Example
Parameterization Example
Parameterization Example
Parameterization Example
Parameterization Example
Parameterization Example
Parameterization Example
Parameterization Example
Parameterization Example
Overview of Our Approach

3D shape

• pressure field
• velocity field
• Cd value

input parameter

 regressor

output parameter

input

output
Challenge for Velocity Field Learning

• Velocity changes rapidly at the boundary
Challenge for Velocity Field Learning

• Velocity changes rapidly at the boundary
Challenge for Velocity Field Learning

- Velocity changes rapidly at the boundary

\[ V \sim V_{\infty} \quad V \sim 0 \]
Challenge for Velocity Field Learning

- Regular grid has too much nonlinearity

\[ V \approx V_\infty \]

\[ V \approx 0 \]
Parameterization of the Velocity Field

We cannot use fixed grid
Parameterization of the Velocity Field

We cannot use fixed grid

We use conformable grid
Parameterization of the Velocity Field

- Continuous representation of velocity field 😊

3D Mean Value Coordinate [Tao et al, 2005]
Parameterization Result

Airplane
Parameterization Result

Dolphin
Challenges

- 3D shape
- parameterization
- input parameter
- uncertainty
- regressor
- output parameter
- parameterization
- output
  - Cd value
  - pressure field
  - velocity field
Challenges

3D shape input

- \( C_d \) value
- Pressure field
- Velocity field

3D shape output

- \( C_d \) value
- Pressure field
- Velocity field

\[ C_d \propto \frac{F}{A} \]

- \( F \): drag force
- \( A \): area
Cd Value is Important

• Car design is strongly influenced by the Cd value

1951

Citroen 2CV
Cd=0.51

1980

Ford Mercury
Cd=0.36

1995

Ford Falcon
Cd=0.31

2005

Ford Fusion
Cd=0.275

2017

Tesla Model3
Cd=0.23
Preview of Result

C_d = 0.31
Preview of Result

predicted error range
Regression: Gaussian Process (GP)

- GP: non-parametric Bayesian regression model
  - Handles nonlinearity well 😊
  - Learning from few samples without over-fitting 😊
  - Prediction of error 😊
Regression: Gaussian Process (GP)

- GP: non-parametric Bayesian regression model

Interpolation weight is determined by distances

\[ C_d = 2.5 \]

\[ C_d = 2.7 \]

\[ C_d = 2.7 \]

\[ C_d = ? \]

\[ C_d = 2.8 \]
Regression: Gaussian Process (GP)

- GP: non-parametric Bayesian regression model

Covariance (similarity of the distributions) is determined by distances

\[ C_d = 2.5 \]

\[ C_d = 2.7 \]

\[ C_d = 2.8 \]
Regression: Gaussian Process (GP)

• Standard deviation gives how “confident” the prediction is

\[
C_d = \quad \begin{array}{c}
\text{less confident} \\
\end{array}
\]

\[
C_d = \quad \begin{array}{c}
\text{confident} \\
\end{array}
\]
Distance Metric Optimization

- Distance metric is optimized for maximizing likelihood of the training data
The Weights in the Distance Metric

$$Distance(h_0, h_1) \propto \| w(h_0 - h_1) \|$$

height difference

separation location

distributed weight for heights

stagnant

separated flow

weight low

weight high
Training Data

- 889 CFD simulation for car shapes from ShapeNet
- Each simulation takes 3 hours computed on Amazon AWS
- All data available

http://www.nobuyuki-umetani.com/
Accuracy

\[ \sigma = 0.01 \]
Live Demo!
Shape with Genus One Topology

PolyCube

Cd=0.31
3D Printed Hood Ornament
Limitations

• Prediction limited by training data
• Highly concave shape

Future Work

• Convolution operation on the PolyCube
• Application to more complex phenomena
  – thermal convection, acoustics
Acknowledgement

• Anonymous reviewers
• Alec Jacobson, Ryan Schmidt, Eitan Grinspun

Funding:

• European Research Council (ERC) No 715767 -- MATERIALIZABLE
Learning Three-dimensional Flow for Interactive Aerodynamic Design

Nobuyuki Umetani, Bernd Bickel