GPU-ACCELERATED DEEP LEARNING FRAMEWORK FOR CYBER-ENABLED MANUFACTURING

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Outline

Design for Manufacturing

Volumetric Representations for CAD Models

Deep Learning based Design for Manufacturing

Explainable Deep Learning

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Reducing Product Cost

• Design has a large influence on final product cost

• DFM helps identify production issues early

Source: David Stienstra (Rose-Hulman)
Challenges

• Traditional DFM method involves rule based analysis

• Depends on the experience of the engineers

• Several rules for different processes
Artificial Intelligence for Design for Manufacturing

• Use deep learning to learn non-manufacturable features in a CAD model
  • Learn from examples of manufacturable and non-manufacturable models

• Advantages
  • No explicit hand-crafting of rules
  • Learn complicated rules that are difficult to codify
Feasibility Demonstration – Drilling Holes

• Common manufacturing operations

• Fewer set of design rules
  • Can manually create ground-truth data

• Complex design rules
  • Depth to diameter ratio
    • Blind vs. through holes
  • Proximity of holes to object boundaries
Boundary Representation (B-Rep) CAD Models

- De-facto representation for CAD models
- Can be easily tessellated into triangles for rendering
- Difficult to interpret volumetric information
  - Size of a feature
  - Internal location of a feature
Voxel Representation

• Binary occupancy information
  • Augmented with extra geometry information

• Can be used as direct input to a convolutional neural network

• Require a fast method to voxelize a large number of CAD models
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Volumetric Voxelization

• Overlay a regular voxel grid on the object

• Test point membership of the voxel bounding-box center points, classify as *in* or *out*
Point Membership Classification (PMC) Using GPU Slicing

- Use standard PMC using odd ray intersection test
- Slice the object perpendicular to an arbitrary axis
- Render the sliced object and count the number of pixels
- Extend to 3D; Each pixel corresponds to a grid point in a 2D slice
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Explainable Deep Learning
Learning Local Features

• Local Feature learning is different from object recognition

• Variation in features affect the object classification

• Learning the features by semi-supervised learning

Need for 3D Convolutional Nets

• Hierarchical feature extraction from volumetric representation

• Capability to learn features with object classification

• Amenable to model interpretability due to learning of spatial location
Deep Learning Based Design for Manufacturing

- Binary definition of manufacturability (binary cross-entropy loss)
- Choice of input resolution depending on the GPUs
- Architecture
  - 3D convolutional layer and 3D max. pooling layer
  - ReLU activation with output layer having Sigmoid activation
Deep Learning Based Design for Manufacturing

(a) (b) (c) (d) (e) (f)

DLDFM

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Results

Representative Test Data Non-Manufacturable

- DLDFM (binary)
- DLDFM (Orthogonal Distance Fields)
- DLDFM (binary + normals)

Representative Test Data Manufacturable

- DLDFM (binary)
- DLDFM (Orthogonal Distance Fields)
- DLDFM (binary + normals)

Legend:
- Green: True Negative (Predicted Non-Manufacturable, Actually Non-Manufacturable)
- Red: False Positive (Predicted Manufacturable, Actually Non-Manufacturable)
- Black: True Positive (Predicted Manufacturable, Actually Manufacturable)
- Yellow: False Negative (Predicted Non-Manufacturable, Actually Manufacturable)
Results

Non-Representative Test Data Non-Manufacturable

- DLDFM (binary)
- DLDFM (Orthogonal Distance Fields)
- DLDFM (binary + normals)

Non-Representative Test Data Manufacturable

- DLDFM (binary)
- DLDFM (Orthogonal Distance Fields)
- DLDFM (binary + normals)

- True Negative (Predicted Non-Manufacturable, Actually Non-Manufacturable)
- False Positive (Predicted Manufacturable, Actually Non-Manufacturable)
- True Positive (Predicted Manufacturable, Actually Manufacturable)
- False Negative (Predicted Non-Manufacturable, Actually Manufacturable)
Results

DLDFM (orthogonal distance fields)

DLDFM (binary + normals)

DLDFM (binary)

True Positive (Predicted Manufacturable, Actually Manufacturable)
True Negative (Predicted Non-Manufacturable, Actually Non-Manufacturable)
False Negative (Predicted Non-Manufacturable, Actually Manufacturable)
False Positive (Predicted Manufacturable, Actually Non-Manufacturable)
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Explainable Deep Learning
Model Interpretability

• Possible methods
  • Back-propagation
  • Guided back-propagation, saliency map, etc.

Disadvantage: Not class discriminative

• Grad-CAM
  • Class discriminative

References:


3D Grad-CAM

• Perform global average pooling and back-propagate the activations

Input: Volumetric Representation

Output: Manufacturability

(Yes/No)
Insights from GradCAM
One Hole
Manufacturable

Insight:
3D Grad-CAM is class discriminative
Insight:
DLDFM can predict manufacturability of multiple features simultaneously.

Two Holes
Manufacturable (both)
Insight:

DLDFM can predict manufacturability of individual features

Two Holes
Non-Manufacturable (due to one of them)
Insight:
DLDFM can predict manufacturability of interacting features by generalizing the rules.

Two Holes
Non-Manufacturable (due to interaction between them)
L-Shaped Block with Hole
Non-Manufacturable (close to external face)

**Insight:**
DLDFM can predict manufacturability based on a local feature instead of external geometry.
Cylindrical-Shaped Block with Hole
Non-Manufacturable (close to external cylindrical face)

**Insight:**
DLDFM can predict manufacturability based on a local feature even with complicated external geometry.
Demo
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Questions?