Battles with Overhang in 3D Printing
by Deformation, Orientation & Decomposition

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Example of 3D Printed Products

Boeing Air-Ducting Parts

Air-Intake for a Turbine
Additive Manufacturing

- Defined by ASTM as:
  - Process of joining materials to make objects from 3D model data, usually layer upon layer

- Six Different Types of AM:
  - Lasers: Stereolithography Apparatus (SLA), Selective Laser Sintering (SLS)
  - Nozzles: Fused Deposition Modeling (FDM)
  - Print-heads: Multi-jet Modeling (MJM), Binder-jet Printing (3DP)
  - Cutters: Laminated Object Modeling (LOM)

- Mainly used for Rapid Prototyping (Past)
- More and More used for ‘Mass’-Production (Present)
Supporting Structures for Overhangs

In many scenarios, models are fabricated by **Single Material**

**Multi-Materials:**
Resolvable materials for supporting structure

**Single Material:**
Using structures to support
Problems Caused by Supports

- **Stereolithograph Apparatus** (SLA), **Fused Deposition Modeling** (FDM) and **Selective Laser Sintering** (SLS) need supports
  - Layer-based
  - Single Material
  - Print@Overhangs

Problems:
- Hard to remove
- Surface damage
- Material waste
Outline – Battles

- Changing the designed shape (by deformation) for support-free printing
- Finding a ‘best’ printing orientation
- Determining an optimized sequence of printing
  - Solid region decomposition based discrete multi-axis 3D printing
  - Volume-to-surface and surface-to-curve decomposition for continuous multi-axis 3D printing
Deforming into a **Self-Supporting Shape**

- In practice, engineers modify parts into **Self-Supported**
- How to automate this shape editing?
- We optimize shape by **volumetric** deformation


Problem Statement

- Given a printing direction $d_p$ and the self-supporting coefficient $\tau$ in according with the maximal self-supported angle $\alpha$ as $\tau = \sin(\alpha)$
- Face with normal $n$:
  - Risky face: $n \cdot d_p + \tau < 0$
  - Safe face: $n \cdot d_p + \tau \geq 0$
- For risky regions, a **minimal rotation** is determined
- An elasticity deformation is conducted to **blend** all such minimal rotations together
- By a local/global approach called **as-rigid-as-possible** (ARAP) deformation – converting risky regions into safe
Shape Optimization Approach

Dino

Fabricated by FDM

Fabricated by MIP-SLA

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Searching Best Direction for 3D Printing

- **Supporting structures** bring in many problems
- Especially **appearance**
- Two damaging outcomes:
  - Visual artifacts
  - Damage on small features
- **How to find an optimal printing direction?**
- **Challenging**: ‘Best’ in this problem involves perception

Metrics for ‘Optimal’ Printing Direction

- Goodness of a printing direction $d$:
  \[ F( M_1(d), M_2(d), M_3(d), M_4(d) ) \]

- What is the function $F(...)$?
  - How to determine weights for blending these four factors?
  - Linear or nonlinear?
Perceptual Model – Training Data

- Training-and-Learning
  - Amazon Mechanical Turk
  - 22k valid choices
- How to score? Hard
- 2-Alternative Forced Choice

Pairs for comparison in Amazon study

Ten models used in the AMT training – including both natural and man-made objects
Learning – DL-ELM
Perceptual Model in Closed-Form

- A training set of 22k pairs input – results obtained in 9.6 min
- 10.5M pairs of samples are employed in the regression of 2\textsuperscript{nd} layer
- Directly applied using the coefficients of our perceptual model

\[
f(x) = \sum_{i=1}^{L} \beta_i \phi(a_i, b_i, x)
\]
\[
\phi(a_i, b_i, x) = \frac{1}{1 + e^{-(a_i \cdot x + b_i)}}
\]

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<th>(\beta_i)</th>
<th>(a_i)</th>
<th>(b_i)</th>
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‘Best’ Direction

- May not have a highest score (due to variations in personal preferences)
- Our solution
  - Local maximum
  - User selection

Three local maximums

(a) $F = 0.9437$
(b) $F = 0.9971$
(c) $F = 0.9792$
Verification of DL-ELM

- Our results is **consistent** with **votes** given by Turkers in AMT
- **Higher score ~ More votes**
More Results

- Tests on **new models** not in the training set
- Compared with using single factor of area (e.g., MeshMixer)
- Contradictions occur between factors – i.e., ours is better
Fabricated Models

Sculpture Objects

Man-made Models
Outline – Battles

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Discrete Rotation by Decomposition

- **Methodology:**
  - Decomposing a given *model* into *multiple regions*
  - An *optimal printing direction* can be computed for each region
  - Boundary surface *self-supported* and all materials can be accumulated *collision-freely*
Algorithm Overview

- **Phase I:** Shape-analysis-based coarse decomposition
- **Phase II:** Sequence planning
- **Phase III:** Fine tuning with manufacturing constraints
Constrained Fine Tuning

- Manufacturability Constraints:
  - No intersection between separation planes (collision-free)
  - All separation planes need to face up (easier for fabrication)

- Steps for fine-tuning:
  - Plane Perturbation
  - Region Merging
  - Fine Decomposition
Problem of Layered Manufacturing

- **Planar-layer-based material accumulation**
  - *Simplify* the algorithms of motion-planning
  - Limited the shape of models that can be support-free fabricated – i.e., support-structures in many cases
  - Relatively *weak mechanical* property between layer – especially at the regions with *thin* and *small features*
Multi-Axis Additive Manufacturing

- Using multi-axis platform for spatial motion in AM
- More DOFs to fabricate curved regions / layers
- Challenges:
  - Volume-to-path decomposition
  - Collision-free tool path generation
  - Configurations in joint-angle space
Curved Support-Free Volume Printing

- Tool-path generation problem is **challenging**:
  - Too many possibility of accumulating materials in a **volume**
  - How to plan **collision-free** motions for AM

- **Problems** of existing multi-axis AM approaches:
  - Only too simple shapes (i.e., from manufacturing community)
  - Build collision-detection into the loop of process planning (e.g., a sequence of 462k voxels – **FCL** takes \(~3.4\text{h}\) in a fixed order)
  - When different orders are tested, much more time is needed
5DOF Support-Free 3D Printing

- **Our solution:** field-based method to decompose a solid $M$ into a sequence of collision-free working surfaces as curved layers, and then generate spatial tool-paths.

- **Constraints for decomposition:**
  - Volume-to-Surface – uniform, accessible & self-supported
  - Surface-to-Curve – uniform and continuous in position, orientation & pose
Voxel-rep is used to compute a material growing field

- Support-free is ensured by only accumulate new voxels around voxels already solidified (added)
- A conservative shape – convex polyhedron is adopted to ensure the accessibility of material accumulation
Greedy Convex-front Advancing

- Starting from root, advancing a convex-front by trying to add as-many-as-possible voxels that:
  1. Next to already added voxels (for support-free)
  2. Not inside the convex-front front (for accessibility)

- Problem: shadowed voxels will be generated

- A voxel is defined as shadowed if it is unprocessed but inside the convex-hull of all already accumulated voxels
Growing with Shadow Avoidance

- **Incremental** search: Adding new voxels into the next front one by one by checking if it will lead to shadow
- **Recursive** search: Given a set of candidate voxels
  - Subdividing the set by splitting the longest axis of PCA
  - Applying shadow check on two sub-sets separately
  - Recursively apply the subdivision until reach a shadow-free subset or a single voxel
  - Adding shadow-free sets

Recursive search can achieve **17.9x speedup** on the Armadillo (with 540k voxels)

10,752 voxels missed  Only 3 voxels missed
Heuristic by Inverse Peeling

- A heuristic strongly reduces the need for shadow-check
- Motivation: considering material accumulation as inverse process of material removal in CNC

Basic idea:
1. A peeling field remove voxels on the convex-front together
2. Using the inverse peeling field to guide growing

Inverse peeling field controls the “speed” of material growing

This strongly reduces the chance of forming shadowed regions

e.g., computing time of Armadillo reduced from 304 min. to 61 min.
Different Growing Schemes

- Study the effectiveness of shadow avoidance (SP-GCFA), inverse peeling heuristic (PG-SP-GCFA)

Time: 32.5 sec.  
Missed Voxel: 10.8k

Time: 17,965.1 sec.  
Missed Voxel: null

Time: 3,605.0 sec.  
Missed Voxel: null
Different Growing Schemes (cont.)

- Study the effectiveness of shadow avoidance (SP-GCFA), inverse peeling heuristic (PG-SP-GCFA)
- Works very well on most examples
Curved Layer Extraction

- Extract iso-surface from material growing field
  - Dual Contouring (DC) [Ju et al. 2002] or
  - Marching Cube (MC) [Lorensen and Cline 1987]
- Trimming the iso-surface by the input model
  - Boolean operation [Zhou et al. 2016]
  - To ensure an effective trimming, the conservative voxelization is applied
Curved Layer Extraction

- Video of surface extraction
Tool-Path Planning for Fabrication

- Working principle is similar to FDM – **Position** continuity
- **Solution** – Fermat Spiral generation on mesh surface:
  - Exact geodesic by Fast-Wavefront-Propagation [Xu et al., 2015]
  - Generate iso-contours on the mesh surface
  - Convert iso-contours into spiral tool-path [Zhao et al., 2016]
- **To ensure smoothness of material accumulation** – **Orientation** cont. by a) closest pnt + b) low-pass filtering
To avoid poor dynamic behavior – **Pose** continuity

- One waypoint on the tool-path => multiple IK solutions
- A graph-based optimization
- Pose-to-pose collision-check
- Edge cost: pose variation
  - Evaluated by the $L^1$-norm
- Optim. by Dijkstra’s algo.
Video of Robotic 3D Printing

Discussion: Sources of Errors

- Voxel-rep – Variation of layer thickness

- Hardware – UR5 6DOF
  - Repeatability: 0.1 mm
  - Position Err: 1 mm
  - 3-Axis vs. 5-Axis
    - Different quality
    - See right

- Tool-path & Motion

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Limitation: Some Failure Cases

SP-GCFA scheme
Time: 2,093 sec.
Missed Voxels: 1,376

PG-SP-GCFA scheme
Time: 142 sec. (x14.7)
Missed Voxels: 511
Conclusion Remarks

- Optimize the **shape** of a designed model into a ‘**self-supported**’ state for additive manufacturing
  - A **closed-form** solution for *minimal rotation* to drive the optimization
  - Global shape of a model is preserved by minimizing the energy of rigidity (**ARAP**) 

- A perceptual model for finding preferable printing directions using a **training-and-learning** approach
  - A study to determine relative importance of **factors** affecting appearance of 3D printed models after removing support
  - A **double-layered extreme learning machine** (DL-ELM) to train the perceptual models from **2-alternative forced choice** (2AFC) experiment
Conclusion Remarks (cont.)

- **Recent work** towards computing **sequence** for spatial AM

- A **region decomposition** based solution – each model is decomposed into a few components **each** can be printed along a specific direction in a **support-free** way
  - Skeleton-based decomposition
  - Fabrication-aware refinement

- A **convex-front advancing** method – each model is peeled into curved layers can be **collision-freely** fabricated
  - A novel strategy of adding materials **only** on convex polyhedra
  - **Growing** based scheme and **inverse-peeling-field** governed scheme
Thanks for Your Questions

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