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Machining force co-simulation for self-aware machine tools

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Industrial Need and Relevance

- Machining amounts to more that 15% of the value of all manufactured products in all industrialized countries [1]
- Annual labor and overhead costs are estimated to be $300BN/year in the US
  (not including materials and tools) [1]
- Industrial machining practice is "open-loop"
- Code is sent to the machine and operators watch the machine's behavior
- Machine tools are not aware of:
  - Forces experienced by the tool
  - **Dynamic stability**
    (Tony Schmitz Talk – Chatter Avoidance in Machining)
  - Tool wear
  - Opportunities to optimize their own performance
- Roombas have more intelligence

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[1] Trent, Edward Moor, and Paul K. Wright. *Metal cutting*. Butterworth-Heinemann, 2000.

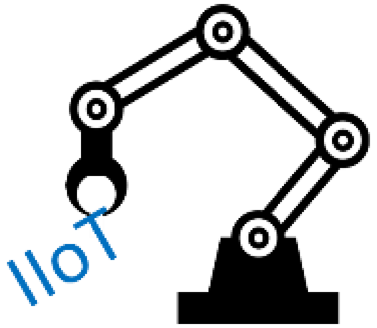
Project Objective

- Explore how volumetric (digital) vs surface representations of parts enable advanced machine tool awareness, tool path automation, force analysis and machining dynamics during machining.
- Related Objective: Explore how digital data generated by 3D scanning can be used to generate tool paths for machining castings and weldments with form variations.

Machine tool was not aware that it was on fire.

https://www.mmsonline.com/articles/the-case-for-supplementary-fire-suppression

Approach/Methodology

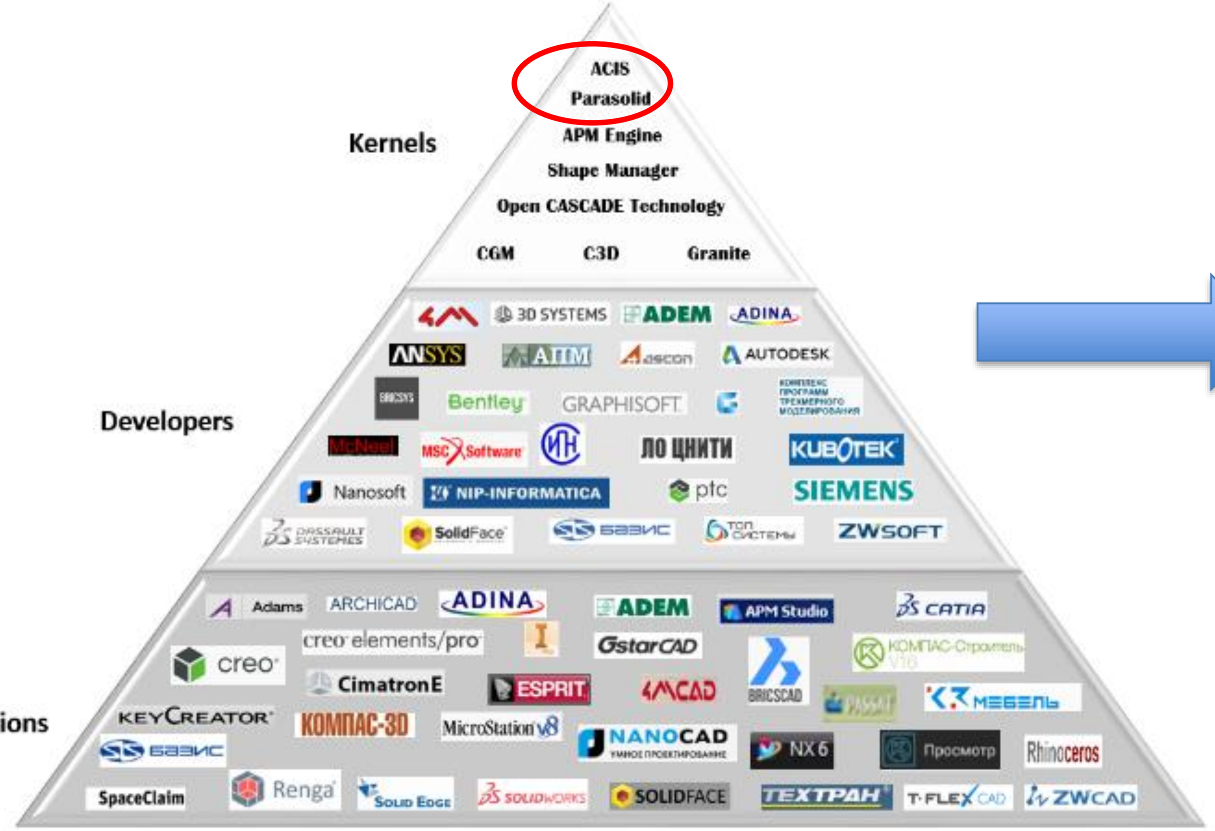


	1D Data Revolution	2D Data Revolution Pixels
Analog		
		
Digital		

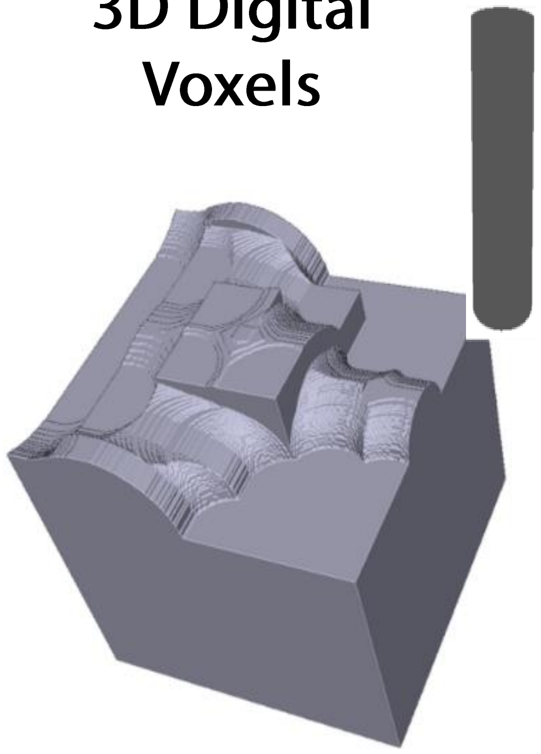
Pixels = Picture Elements

3D Data Revolution

Analog?



3D Digital Voxels



Voxels = Volume Elements

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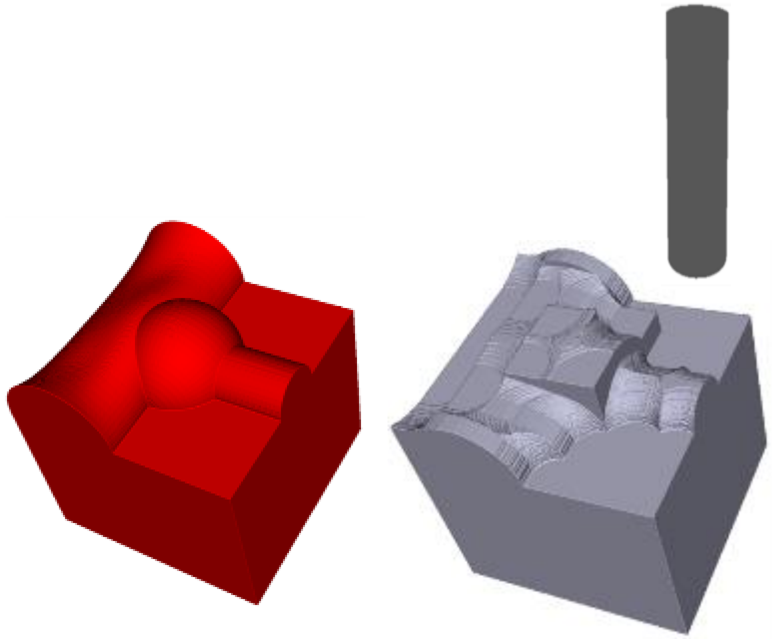
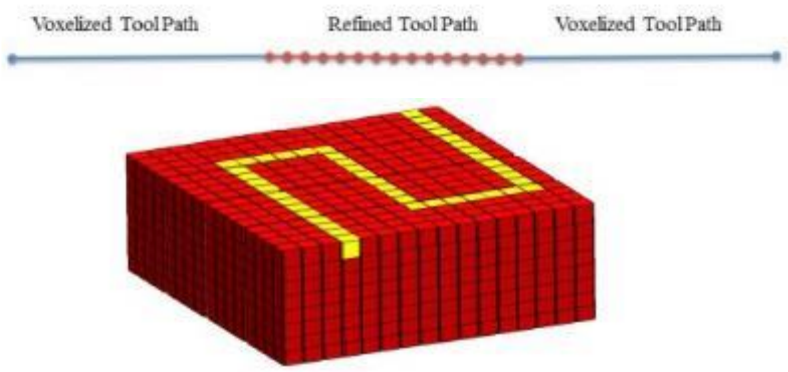
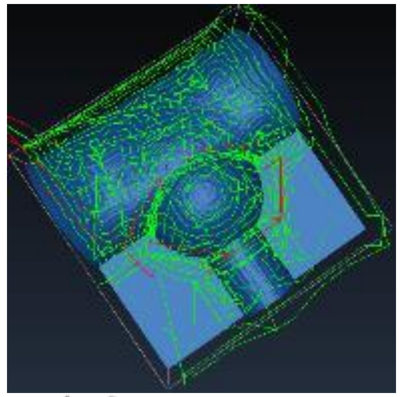
Approach/Methodology

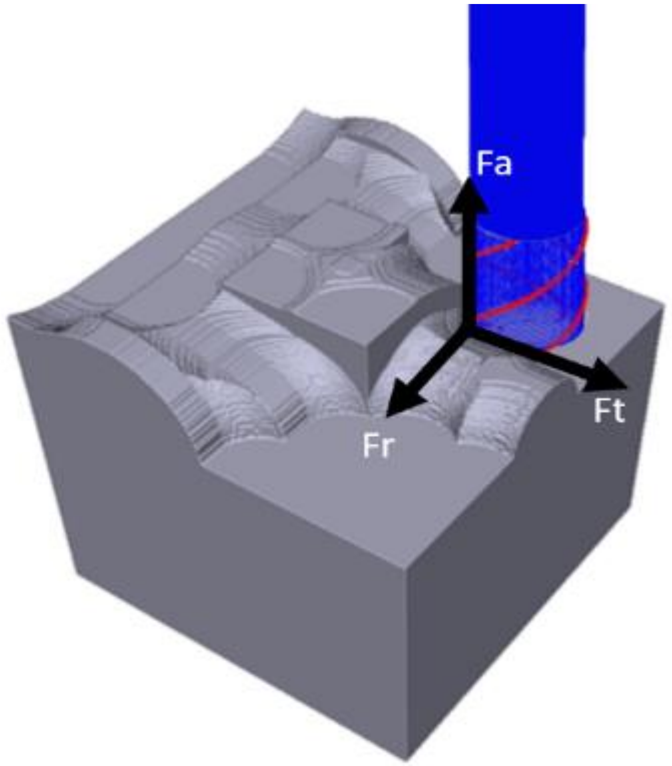


Voxelize the work-piece, tool and stock

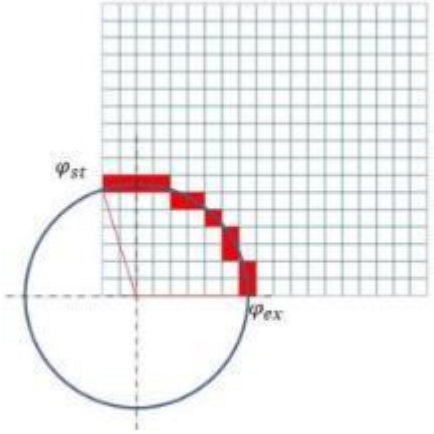


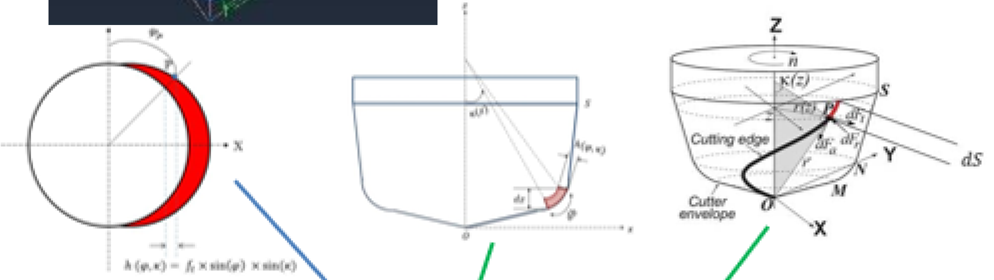


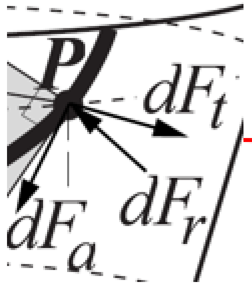
Refine the tool-path



Detect the engagement of tool and work-piece





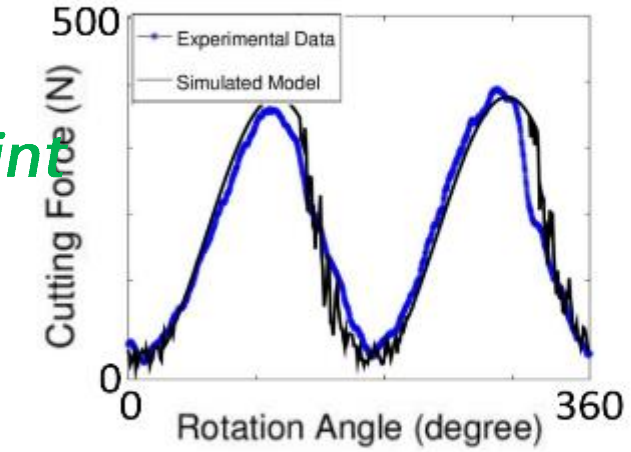


$$\begin{cases} dF_t = K_{tc}\, h(\varphi,\kappa)\, db + K_{te}\, dS \\ dF_r = K_{rc}\, h(\varphi,\kappa)\, db + K_{re}\, dS \\ dF_a = K_{ac}\, h(\varphi,\kappa)\, db + K_{ae}\, dS \end{cases}$$

Shearing cutting force coefficients

Edge constants

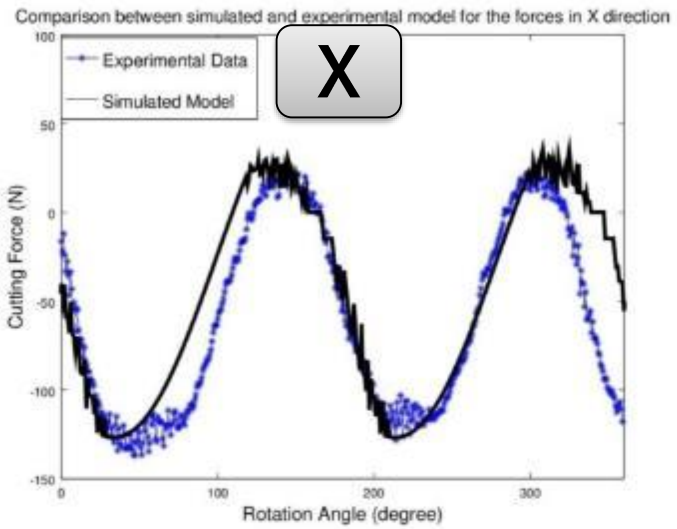
Calculate point by point Cutting forces

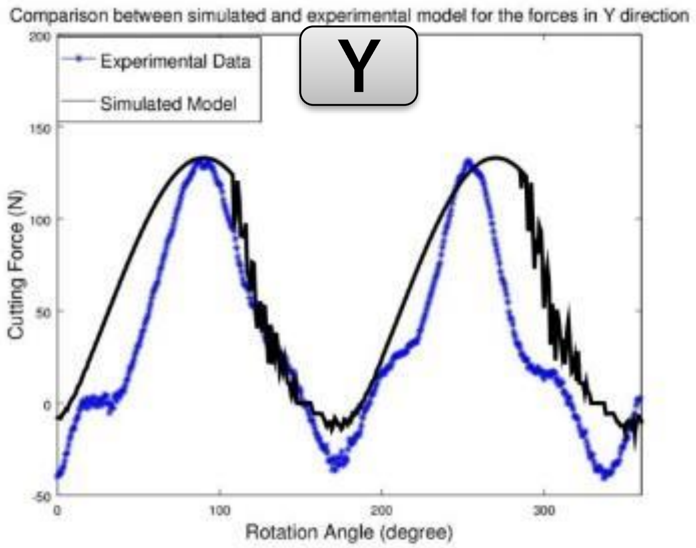


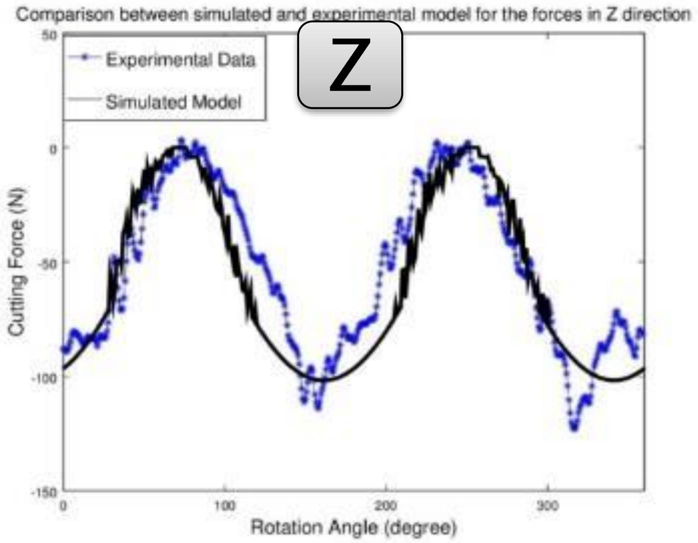
Results

Cutting Tools

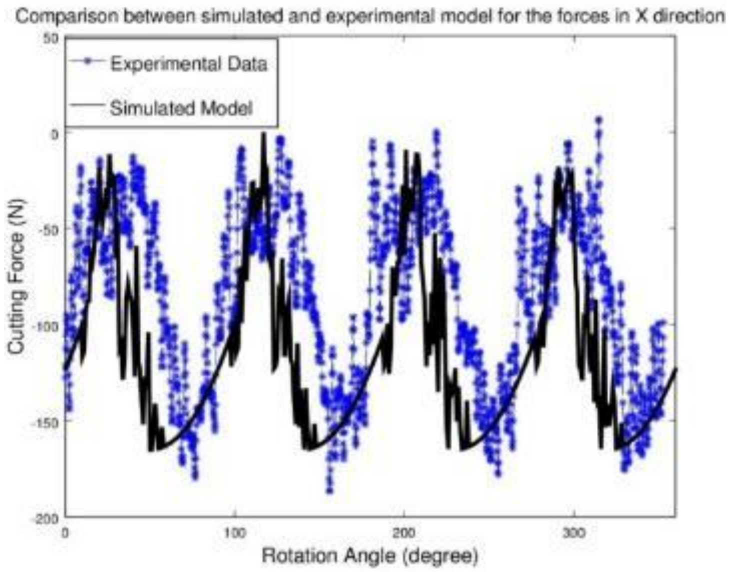
Two flute Flat-end mill

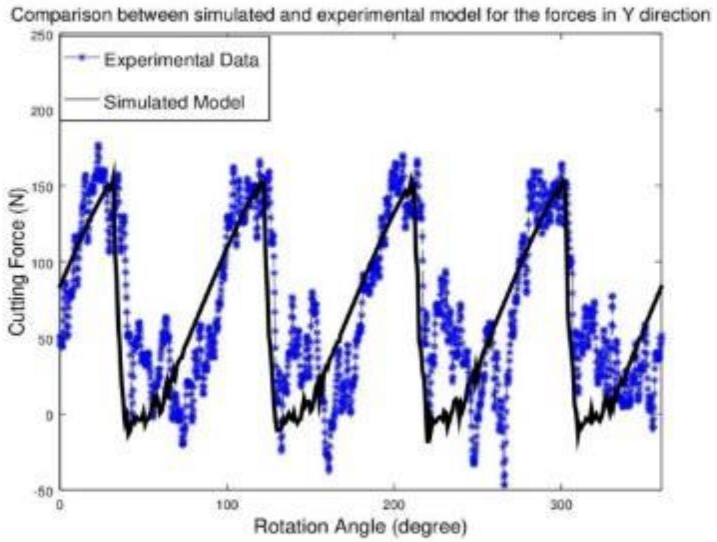


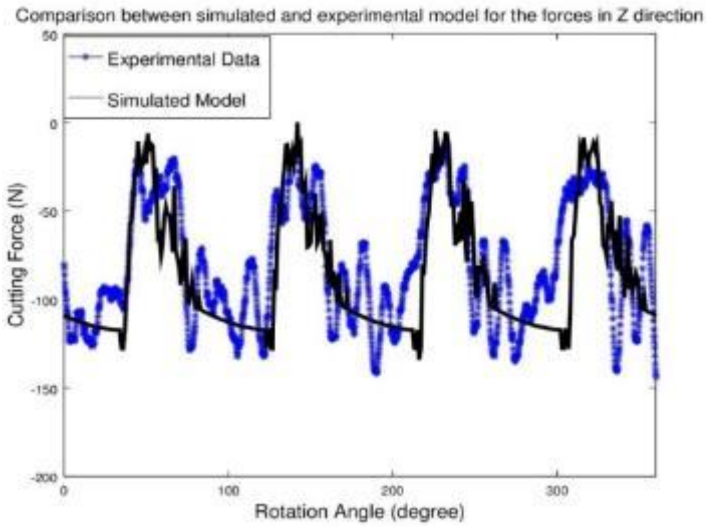




Four flute ball-end mill







Work-piece Material

304 Stainless Steel

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Results

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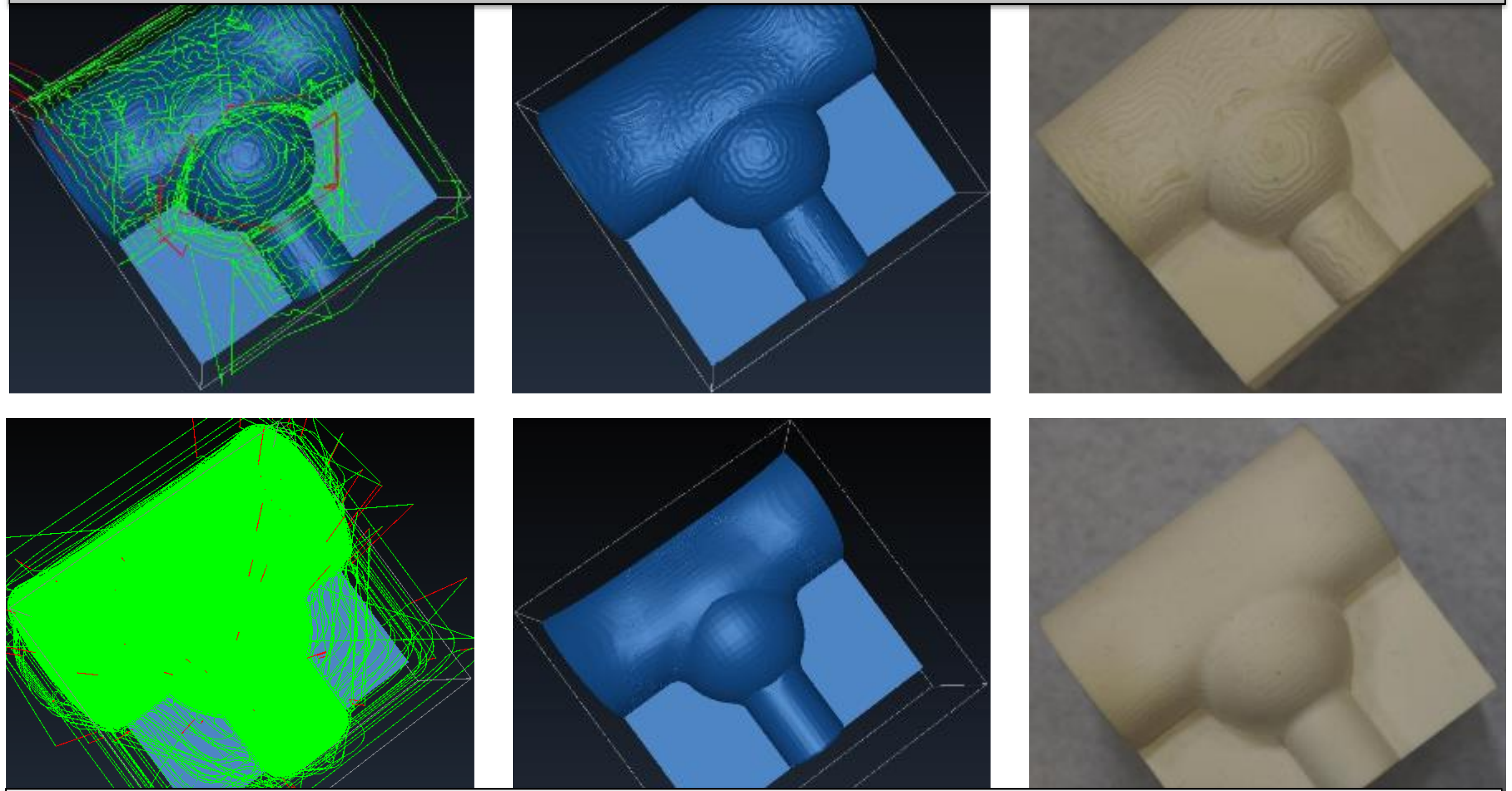
Automatically Generated Tool Path

Voxel-Based Tool Path



Total machining time is about 6 min

Simple CAM tool path using ESPRIT

Surface-Based Tool Path

Total machining time is 18 min

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Next Steps

Explore how machine learning and artificial intelligence can be combined with digital machining to enable machine self-awareness and increase productivity.

1. Use the digital machining force model to simulate a healthy or "expected" tool path.
2. Use the force model to simulate unhealthy or "unexpected" tool path problems that the machine is unaware of - such as edge and flank wear, chatter, edge breaking, a chipped or sheared tool and related surface quality to train a machine learning/AI model.
3. Instrument the machine to relate measured parameters to healthy simulated tool path.
4. While machining, **co-simulate expected machining forces** and relate these expected forces to variables that can be measured during machining.
5. Make the machine aware of **online** differences between expected forces from a healthy co-simulation and measured parameters during machining.