

# Controlled Linear Perturbation

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joint work with

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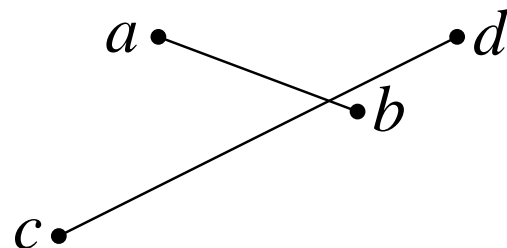
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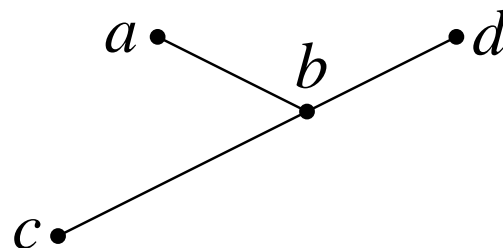
# Robustness Problem

- Algorithms are expressed in real RAM model.
- Input is assumed in general position.
- Implementations must use computer arithmetic.
- Implementations must handle degenerate input.
- Implementations must be fast and accurate.

# Geometric Predicates



unsafe



degenerate

Main interface with real RAM model (also constructions).

- Predicate  $P(x)$  is true when polynomial  $f(x)$  is positive.
- Unsafe predicate:  $|f(x)|$  near the rounding unit.
- Degenerate predicate:  $f(x) = 0$ .
- Example:  $b$  above  $cd$  if  $(d - c) \times (b - c) > 0$ ;  
 $f(b_x, b_y, c_x, c_y, d_x, d_y) = (d_x - c_x)(b_y - c_y) - (d_y - c_y)(b_x - c_x)$ .

# Exact Computational Geometry

Implement predicates exactly using algebra.

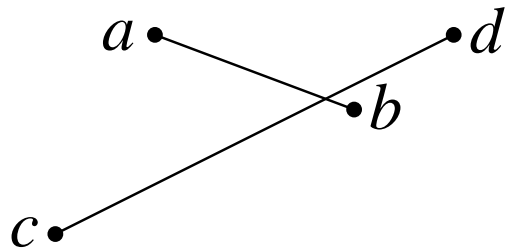
- Technical problems
  - Running time grows rapidly with algebraic degree.
  - Bit complexity grows rapidly.
  - Degeneracy requires separate, complex algorithm.
- Conceptual problem
  - Scientific computing is approximate because exact solutions are impractical and unnecessary.
  - Gold standard is fast algorithms with error bounds.
  - Why should computational geometry be exact?

# Approximate Computational Geometry

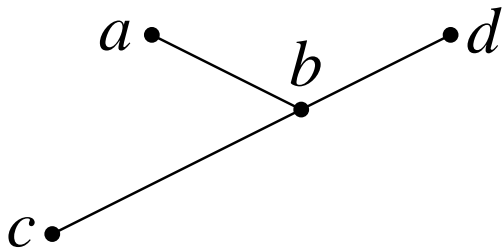
Implement predicates approximately using floating point arithmetic and numerical solvers.

- Advantages:
  - Running time grows modestly with degree.
  - Constant bit complexity.
  - Small constant factors.
- Challenge: generate consistent output.

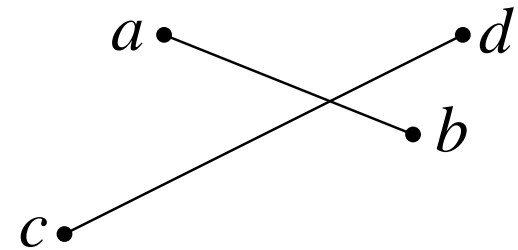
# Consistency



unsafe  $i$



degenerate  $i$



consistent  $p$

- An algorithm is consistent when for every input,  $i$ , there exists a perturbed input,  $p$ , such that the computed predicates are correct for  $p$ .
- The output error is the distance from  $i$  to  $p$ ,  $\|p - i\|$ .
- Inconsistent algorithms can crash or output garbage.

# Perturbation Strategy

1. Derive a safety threshold,  $e$ , such that  $|f(x)| > e$  in floating point implies safety.
2. Every time a predicate polynomial is evaluated, check its threshold.
3. If the check fails, perturb the input.

# CP versus CLP

- Controlled perturbation (CP)
  - Perturb randomly and restart.
  - Error exponential in polynomial degree.
  - No equality constraints or parameter definitions.
- Controlled linear perturbation (CLP)
  - Perturb carefully and continue.
  - No error on safe polynomials.
  - Error grows modestly with degree.
  - Equality constraints and parameter definitions.



# CLP Strategy

*Given:* polynomial  $f(x)$  with input  $x = a$ .

1. If  $|f(a)| > e$ , return its sign.
2. Compute  $p$  such that  $|f(p)| > e$  and likewise for previous polynomials.
3. Return the sign of  $f(p)$ .

# CLP Algorithm

- Write  $p = a + \delta v$  with  $\delta \geq 0$  the perturbation size and  $v$  the perturbation direction.
- Linearize  $f(p) \approx f(a) + \delta \nabla f \cdot v$  with  $\nabla f$  the gradient.
- Linearization error is negligible because  $\delta$  is tiny.
- Initialize  $\delta = 0, v = 0$  and update for each unsafe  $f$ .
- Best  $v$  for sign  $s$  is  $s \nabla f$  ignoring prior unsafe  $f_i$ .
- Define  $u$  by subtracting  $\nabla f_i$  from  $\nabla f$  and unitizing.
- Update  $v$  to  $v + su$ ; pick  $s = \pm 1$  with smaller  $\delta = (2se - f(a)) / (s \nabla f \cdot v)$ ; update  $\delta$ .
- Prior  $f_i$  are unaffected by change in  $v$ ; become safer due to increase in  $\delta$ .
- Verify signs of  $f(p)$  for final  $p$ .

# Sorting Example

- Sort  $x = (0, 0, 0, 1)$  in increasing order.
- Predicate  $x_i < x_j$  has polynomial  $x_j - x_i$  with  $e = 2\mu$ .
- Degenerate for  $i, j < 4$ ; safe otherwise.

1) Evaluate  $x_2 - x_1$  with  $v = (0, 0, 0, 0)$  and  $orth = \emptyset$ .

- $\nabla f = (-1, 1, 0, 0)$ , so  $u_1 = \sqrt{0.5}(-1, 1, 0, 0)$ .
- For  $s = 1$ ,  $\delta = \frac{2se - f(a)}{s\nabla f \cdot v} = \frac{4\mu}{u_1 \cdot \nabla f}$ .
- For  $s = -1$ ,  $\delta = \frac{-4\mu}{-u_1 \cdot \nabla f}$ .
- CLP picks  $s = 1$ ,  $\delta \approx 2.8\mu$ , and  $x_1 < x_2$ .

# Sorting Example Continued

2) Evaluate  $x_3 - x_1$  with  $v = u_1$  and  $orth = \{u_1\}$ .

- $\nabla f = (-1, 0, 1, 0)$ , so  $u_2 = \sqrt{1/6}(-1, -1, 2, 0)$ .

- For  $s = 1$ ,  $\delta < 2.8\mu$ , so CLP picks it and  $x_1 < x_3$ .

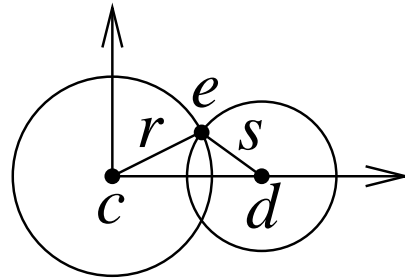
3) Evaluate  $x_3 - x_2$  with  $v = u_1 + u_2 \approx (-1.1, 0.3, 0.8, 0)$  and  $orth = \{u_1, u_2\}$ .

- $\nabla f = (0, -1, 1, 0)$ , so  $u_3 = (0, 0, 0, 0)$ .

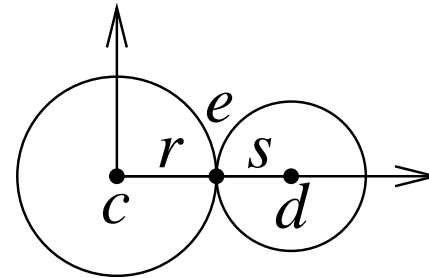
- Only choice is  $s = 1$  with  $\delta \approx \frac{4\mu}{-0.3+0.8} \approx 7.7\mu$  and  $x_1 < x_2$ .

- Final order,  $x_1 < x_2 < x_3$ , derives from  $v$ .

# Parameter Definitions



full rank



rank deficient

Define new parameters,  $y = b$ , with equations  $g(x, y) = 0$ .

- Enforce linearized equations by adding to *orth*.
- Extend  $v$  to  $y$  by solving  $g_x v + g_y w = 0$ .
- **Example:**  $e = (y_1, y_2)$ ,  $b = (3.6, -1.8)$ , equations  $g(x, y)$   
 $(y_1 - x_1)^2 + (y_2 - x_2)^2 - x_3^2 = 0$   
 $(y_1 - x_4)^2 + (y_2 - x_5)^2 - x_6^2 = 0$ .
- Rank deficient case requires special handling.

# Singular Predicate Polynomials

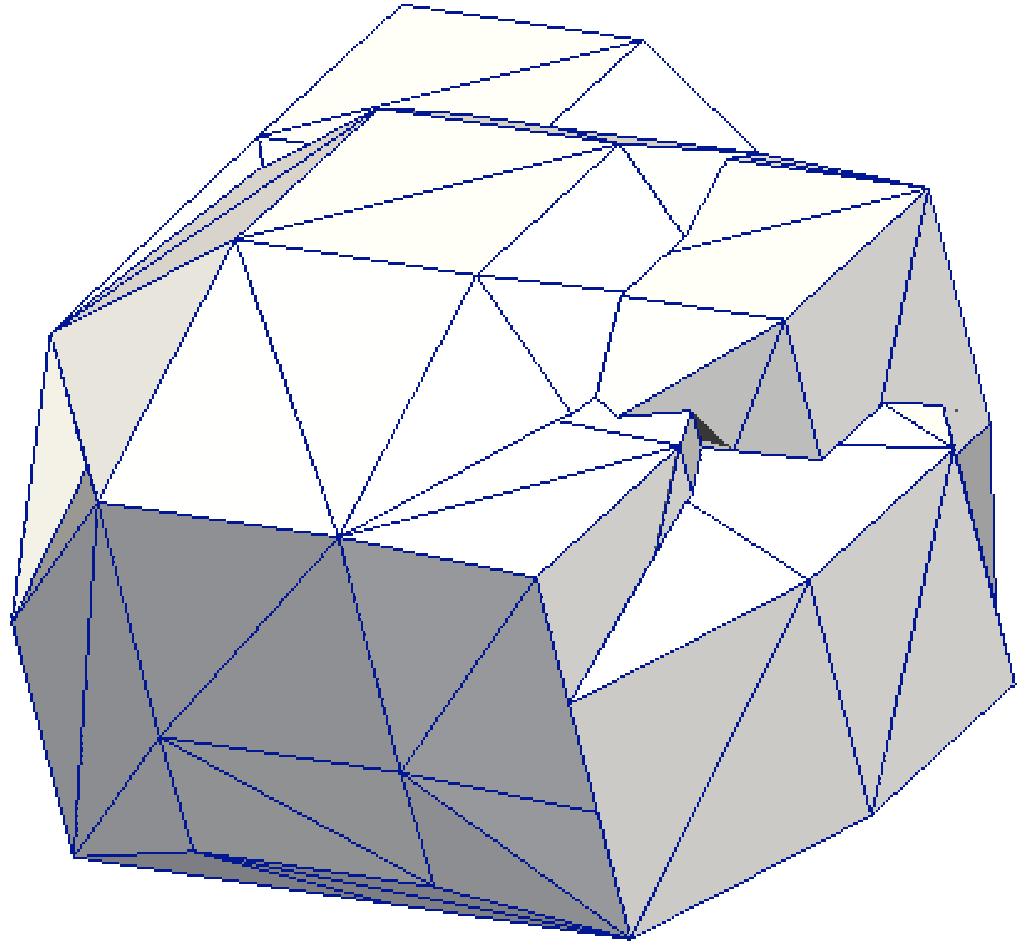
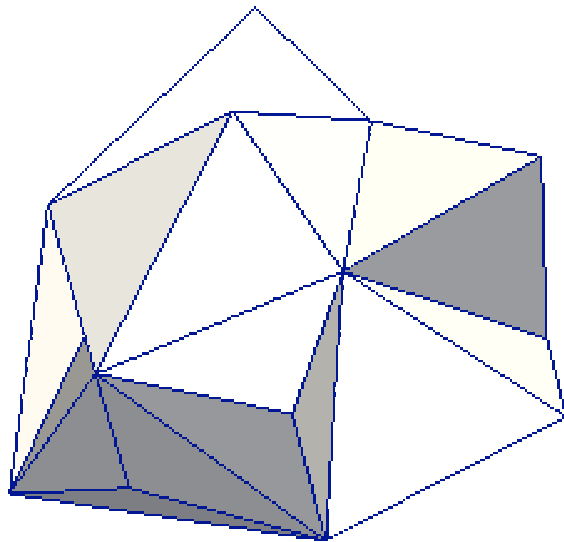
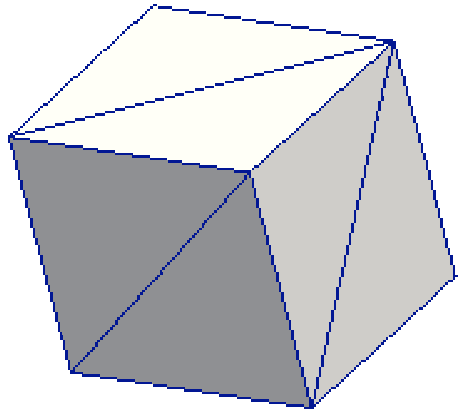
- Polynomial  $f$  is singular when  $\nabla f = 0$ .
- Core CLP fails on near singular unsafe polynomials.
- We avoid near singularity by predicate reformulation using judicious parameter definitions.
- Example: point  $b$  above line  $cd$  with  $b = c = d$ .
- Define unit vector,  $u = (d - c) / \|d - c\|$ , with equations  $u \cdot u - 1 = 0$  and  $u \times (d - c) = 0$ .
- Reformulation:  $u \times (b - c) = u_x(b_y - c_y) - u_y(b_x - c_x)$
- Gradient is large:  $(-u_y, u_x, u_y, -u_x, b_y - c_y, c_x - b_x)$ .

# Minkowski Sums

Minkowski sum of point sets  $A$  and  $B$  is the point set  $A \oplus B = \{a + b \mid a \in A, b \in B\}$ .

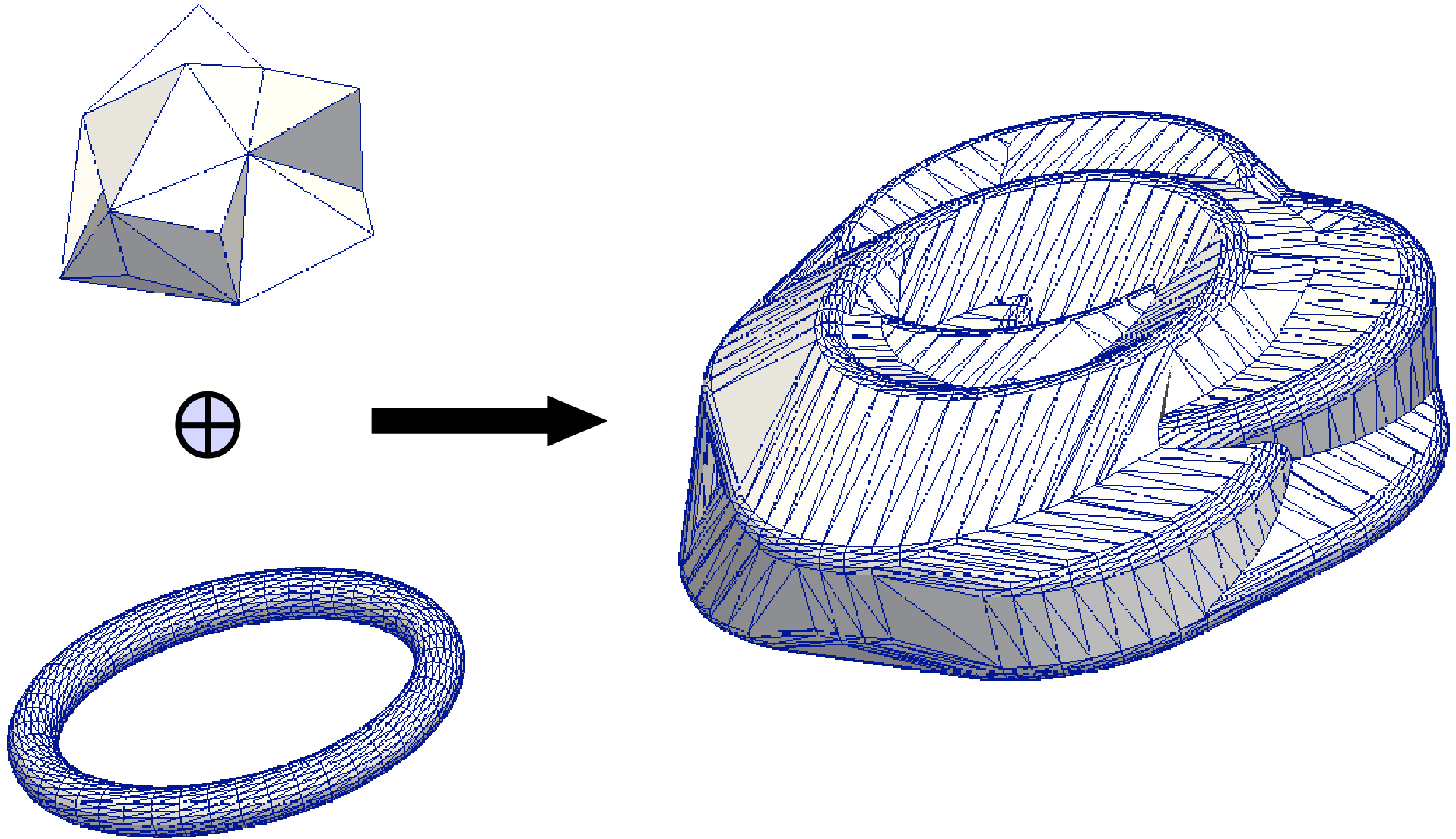
- Minkowski sums of polyhedra have many applications: packing, path planning, assembly, graphics, solid modeling, mechanics, simulation.
- Prior implementations decompose polyhedra into convex pieces.
- Complexity is  $\Omega(n^4)$  for input size  $n$ ; prohibitive.
- Approximate algorithms are tricky and slow.
- Efficient output sensitive algorithm known for 30 years.
- We use CLP to obtain the first robust implementation.

# Cube + Polyhedron

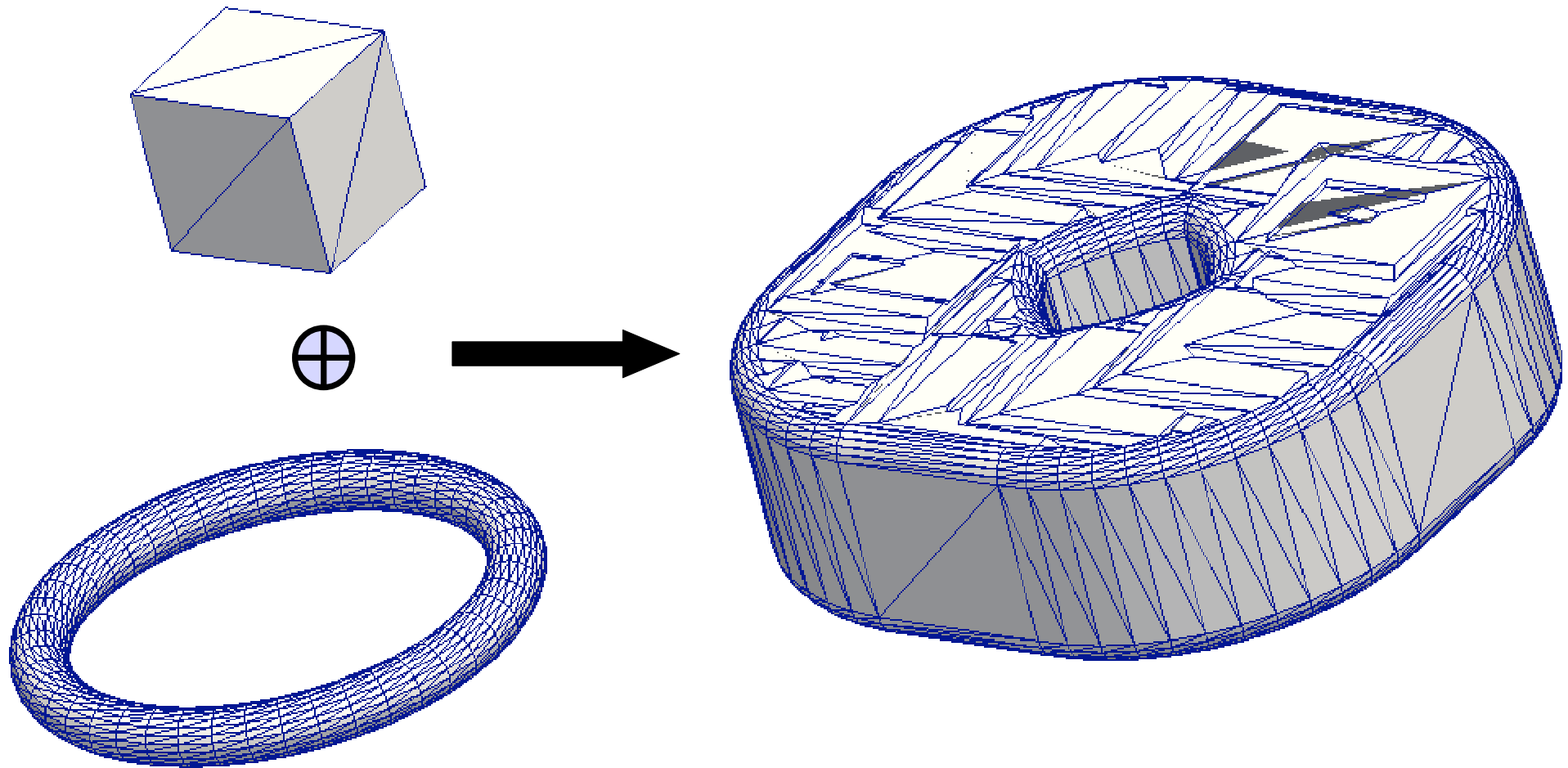




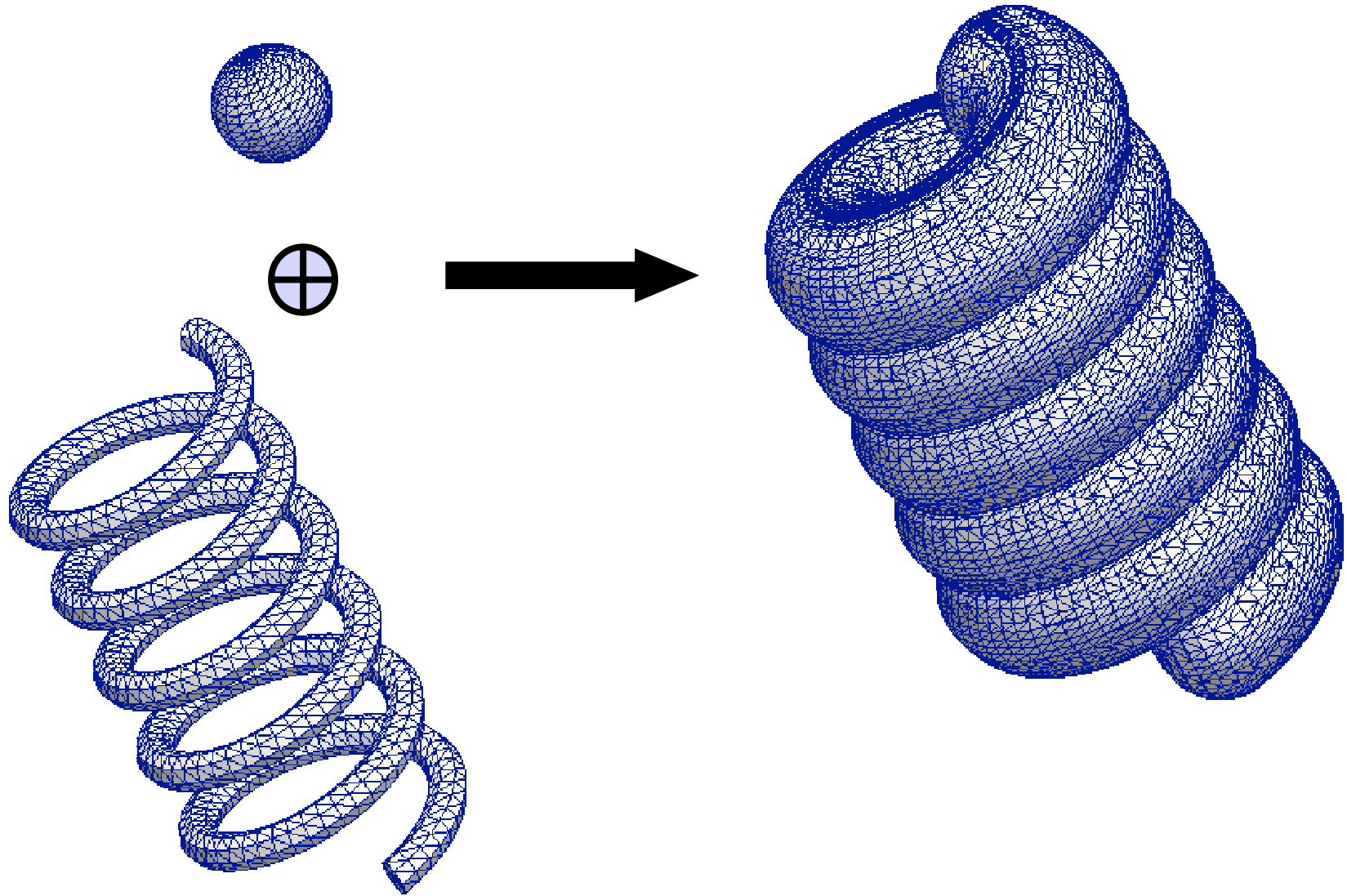
# Torus + Polyhedron



# Cube + Torus



# Sphere + Helix



# Results

$A$ ,  $B$ , and  $conv$  the number of triangles in part  $A$ , part  $B$ , and the convolution,  $time$  the running time in seconds,  $safe$  and  $unsafe$  the number of safe and unsafe predicate polynomials, and  $\delta$  the final perturbation size.

	$A$	$B$	$conv$	$time$	$safe$	$unsafe$	$\delta$
a	12	32	130	0.1	4e5	5,393	3e-12
b	32	2068	4336	5	2.2e6	13,145	8e-10
c	12	2068	2946	4.3	1.1e6	15,991	2e-10
d	760	4012	40,212	49	27e7	43,752	1e-10

# Future Work

- Research
  - Automated handling of near singular polynomials.
  - Output simplification.
- Education
  - Computational geometry curriculum organized around robustness.
  - Computational geometry textbook organized around robustness.
- Applications
  - Patent.
  - Software library.
  - Robust applications software.