Exploring Approaches for Rigid Body Dynamics with Uncertainty

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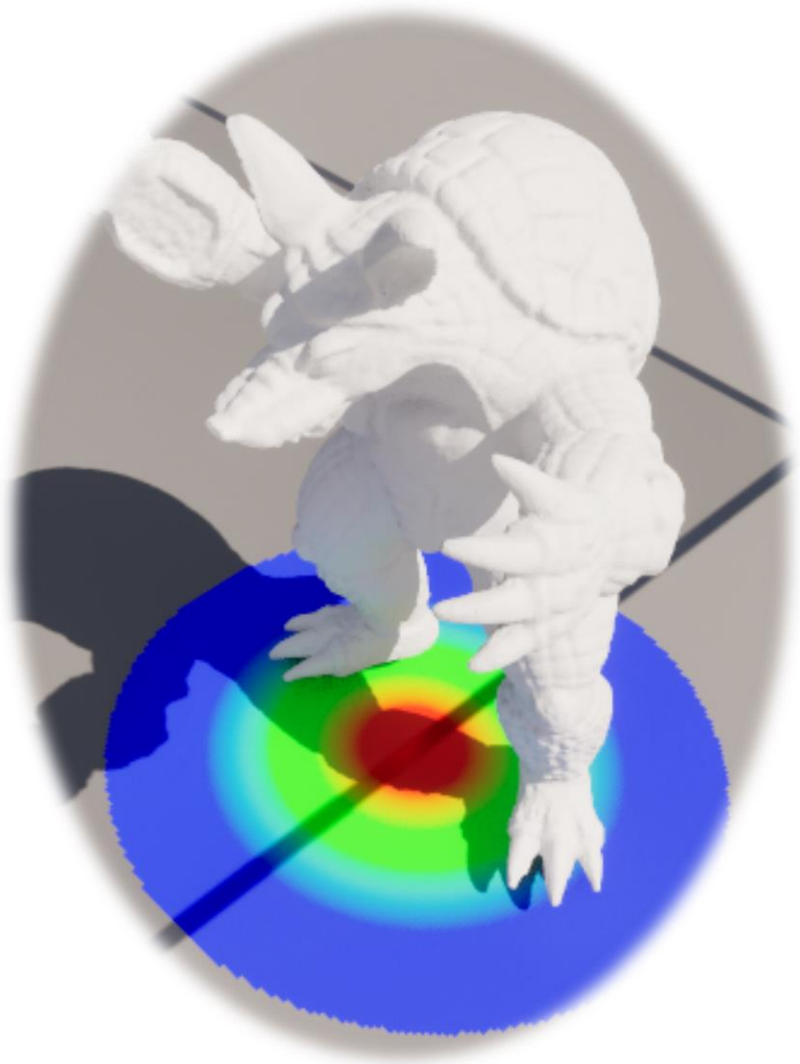

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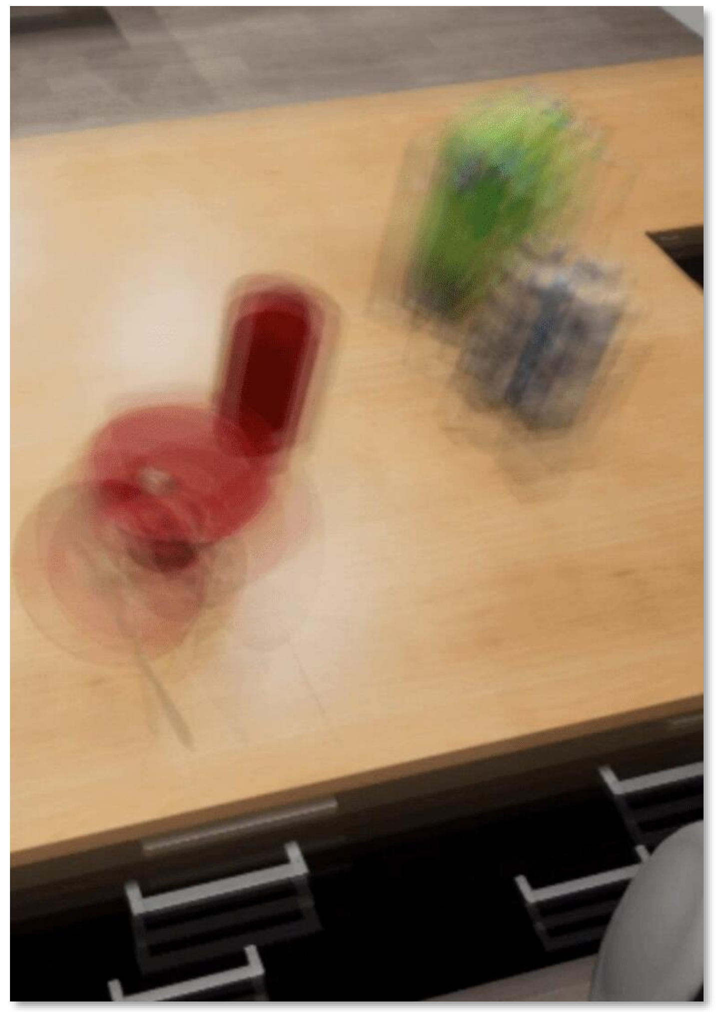
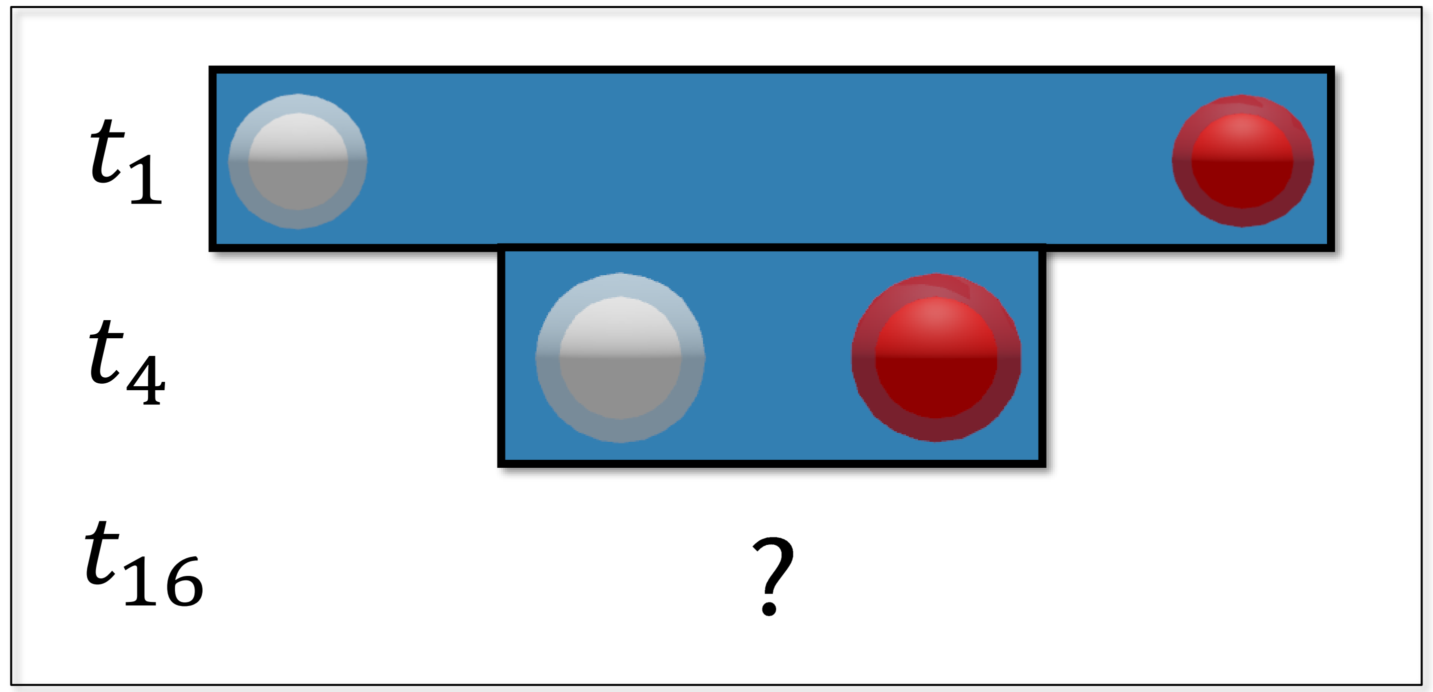
Motivation

- Real-world scenarios are often uncertain:
  - Sensor noise and incomplete models
- Why Simulation + Uncertainty?
  - Real-world inputs are uncertain: position, orientation, contact
  - Safety & reliability in real world for robotics
  - Current physics engines ignore variability, limiting robustness
  - Collisions can amplify uncertainty

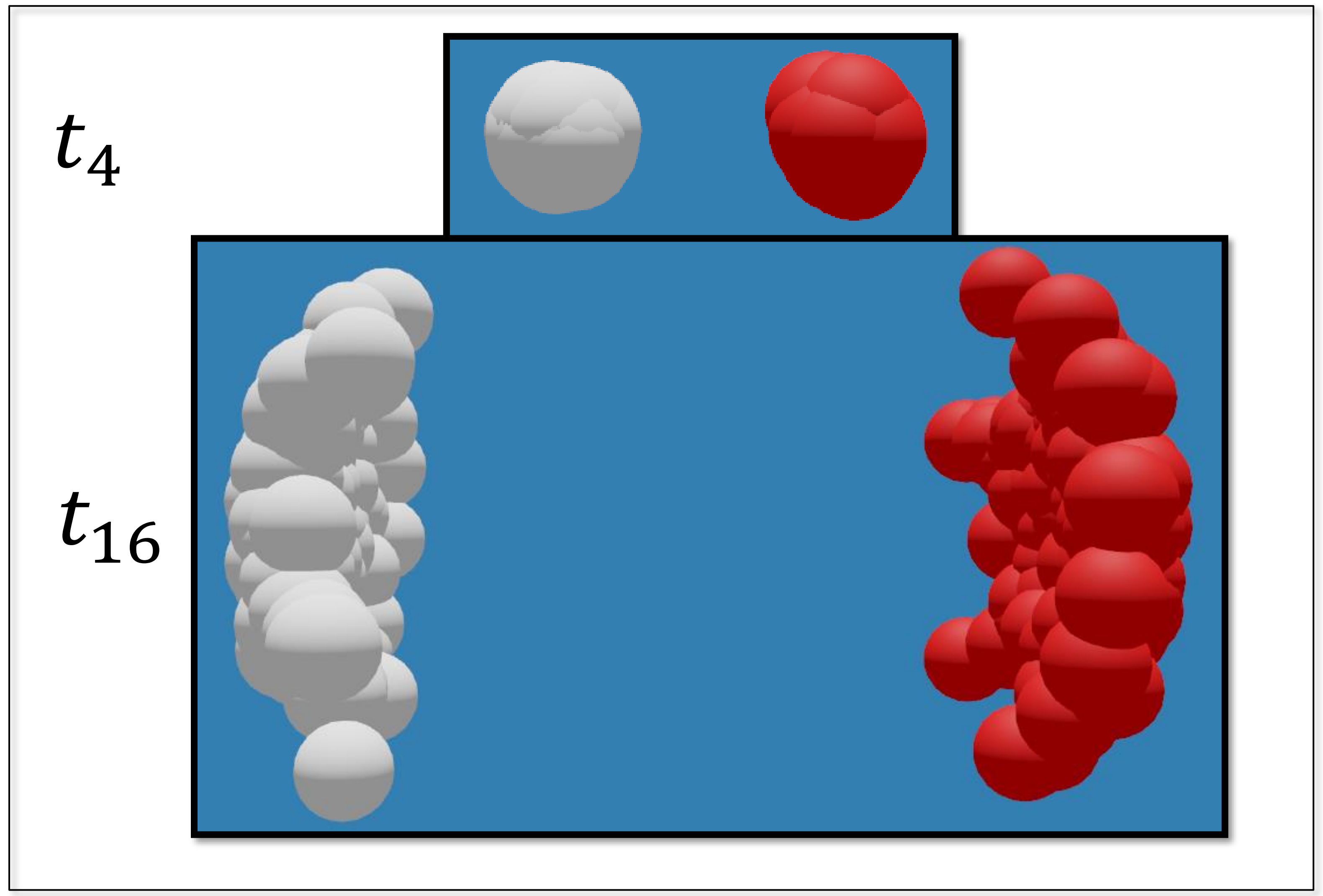


Motivation

- Standard approach: sample many initial states and simulate each case
- More samples improve fidelity
- But sampling is computationally expensive
- Challenge: efficient simulation while accounting for uncertainty



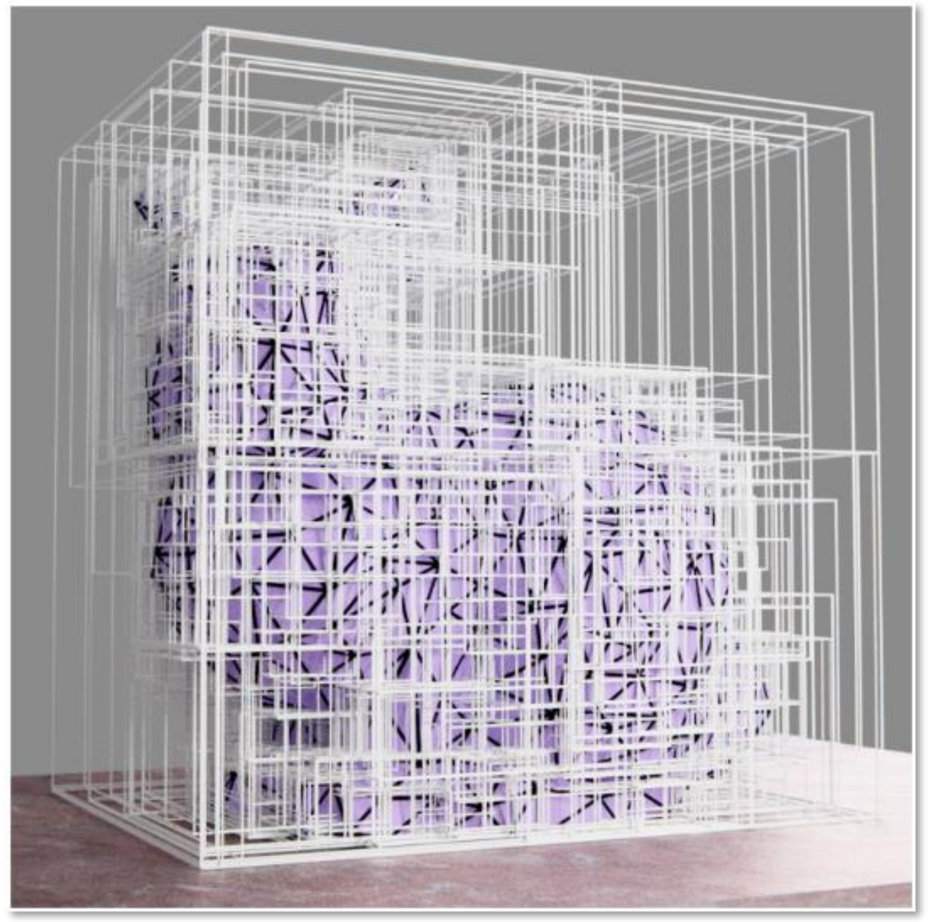
Problem example: Particles approaching with initial positional uncertainty



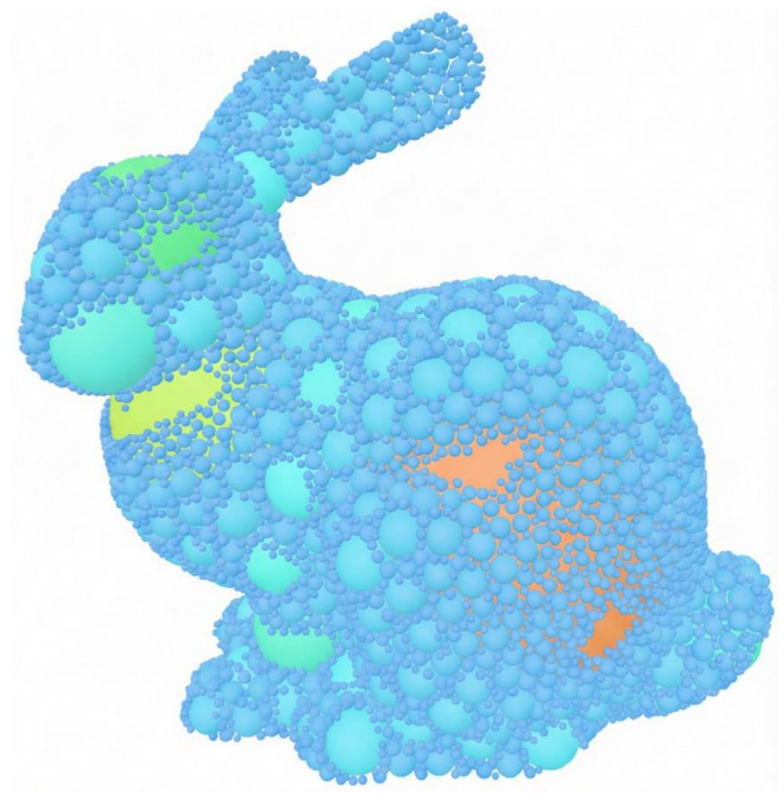
Baseline: Sample initial uncertainty and run *n* simulations

Related Work - Simulation

- Collision detection (CD)
  - Bounding Volume Hierarchies (BVH) [Zachmann98]
  - Grid-based methods [Teschner03]
  - Sphere packings [Weller10]
- Methods for physics-based animation:
  - Penalty [Terzopoulos87][Tang12]
  - Impulse [Mirtich96]
  - Constraint [Macklin16]
- Numerical integration:
  - Symplectic Euler, Runge-Kutta



BVH[Chitalu20]



Sphere Packing

Penalty[Jansson01]

Related Work - Uncertainty

- Error propagation rules
  - Analytic (Gaussian)
  - If non-linear function → approximating methods, non-Gaussian

Adding two 1D Gaussians

$$f = A + B$$ Mean values

$$\sigma_f^2 = \sigma_A^2 + \sigma_B^2 + 2\sigma_{AB}$$

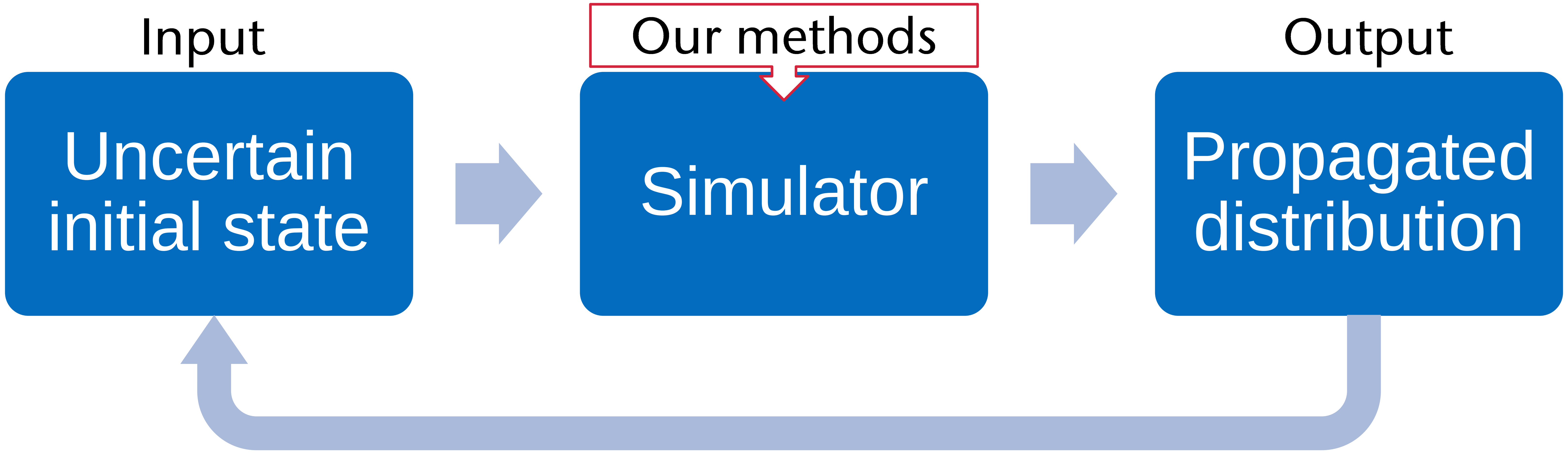
- Bayesian Filter
  - Kalman Filter [Kalman60]
  - Extended Kalman filter [Sorenson85]
  - Unscented transform (sigma points) [Julier97]
  - Particle filters [Gordon93] / Monte Carlo
- We got no measurement/correction

	Smooth Dynamics	Collision Dynamics
Deterministic	✔	✔
Uncertain	✔	Limited work

Our work is a first step

Overview

- Input: rigid bodies with Gaussian uncertainty in the state
- Simulator: penalty-based rigid-body dynamics
- Output: predicted distribution after simulation
- Formulate and compare four methods against Monte Carlo ground truth

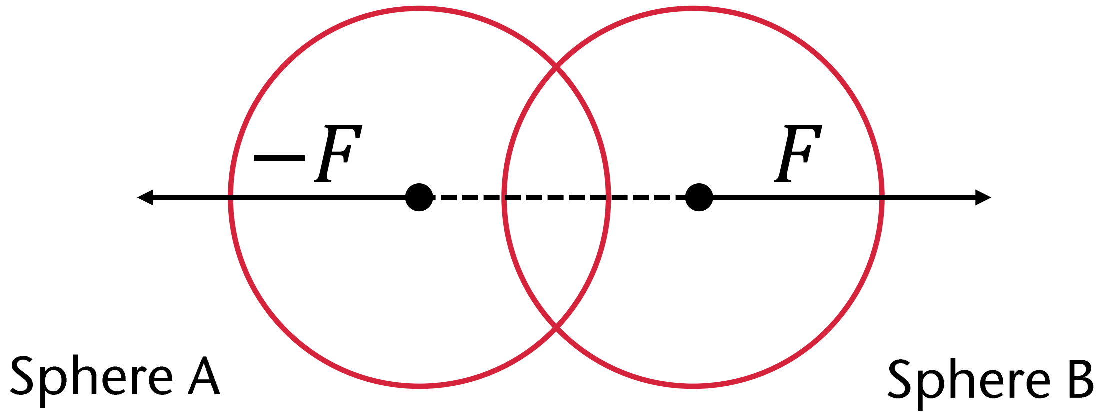


Overview

- State includes position, velocity, orientation, and angular velocity
- Position uncertainty is Gaussian in Euclidean space
- Rotation uncertainty is represented in the tangent space of $SO(3)$
- Collision detection uses non-uniform sphere packings
- Contact response uses penalty forces based on sphere overlaps

Sphere Packings & Test models

Penalty force F

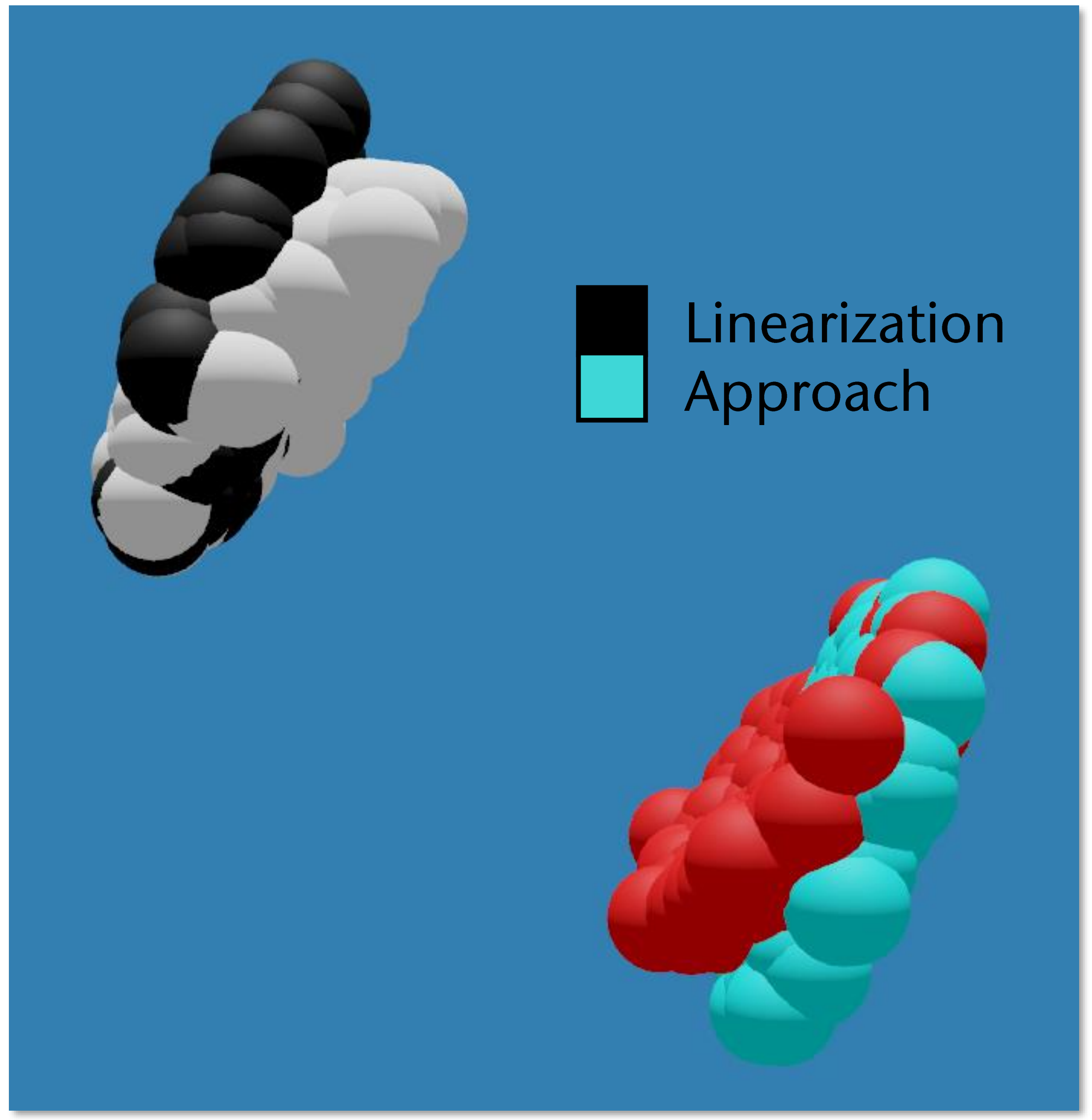


Handling Uncertainty: Linearization Approach

- Idea: Linearize the full simulator around the nominal state

$$\Sigma_{t+1} = J \Sigma_t J^\top$$

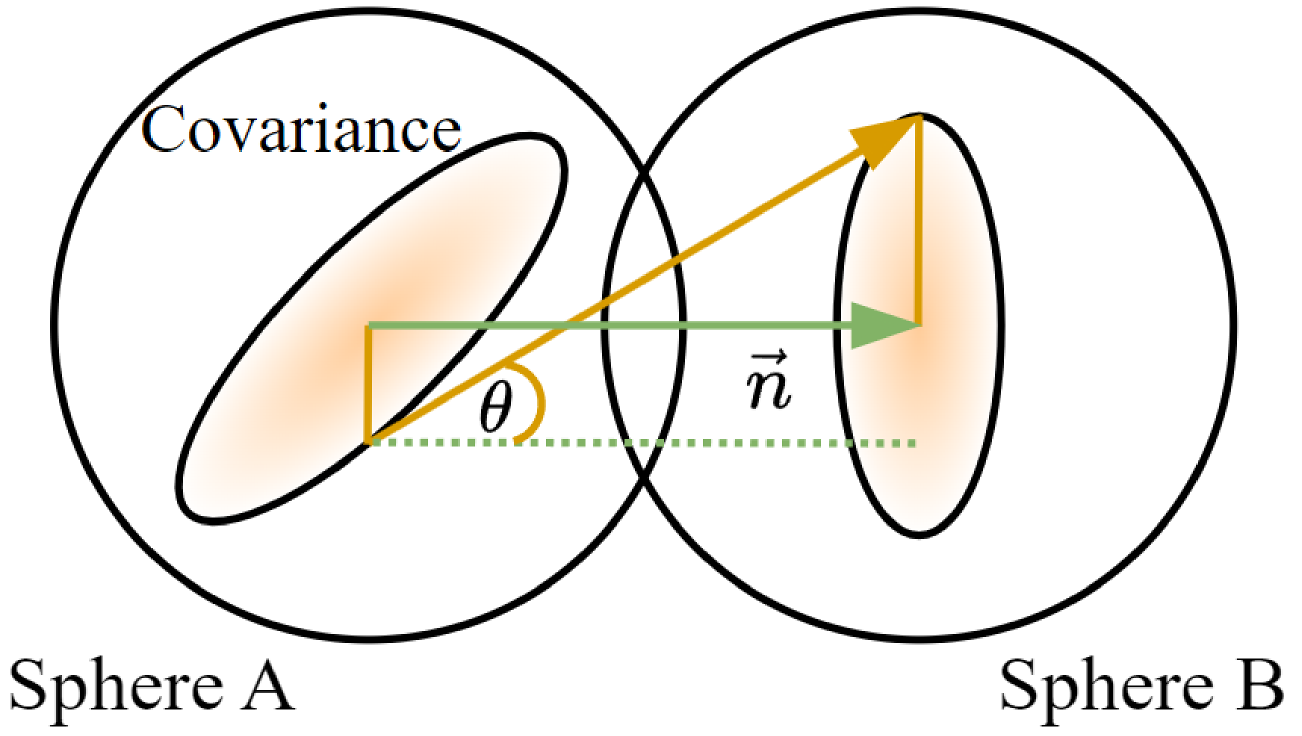
- Propagates the full covariance through a Jacobian
- Captures cross-body correlations
- Challenge: collisions make linearization unstable
- Uses a dominant-contact restriction to reduce covariance inflation

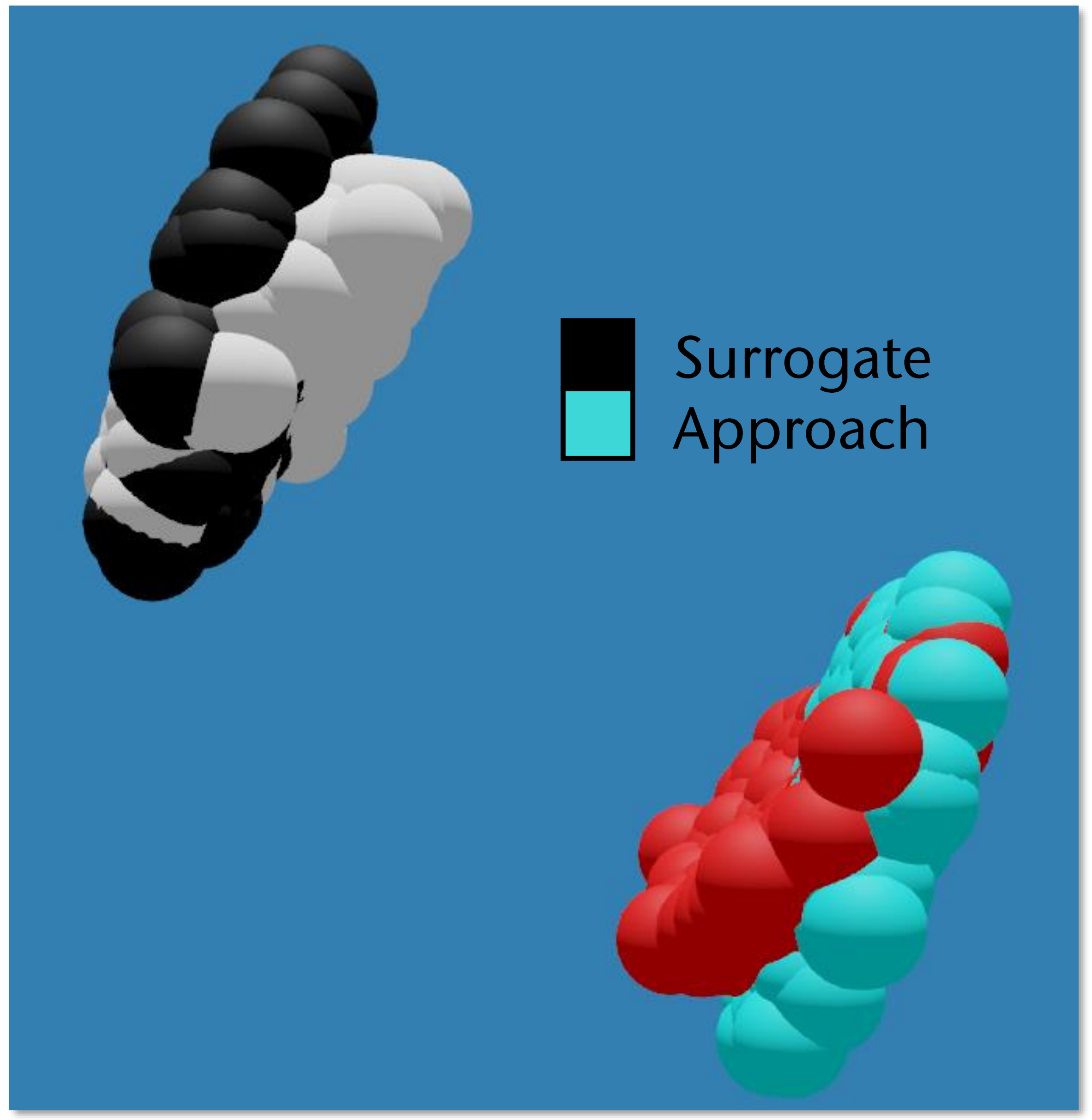


Handling Uncertainty: Surrogate Model

- Idea is to estimate contact normal uncertainty
  - Maximum cone angle
  - Converts this into tangential velocity and angular-velocity uncertainty
- Linearization for integration
- Designed as a fast, stable approximation
  - Uncertainty growth is bounded

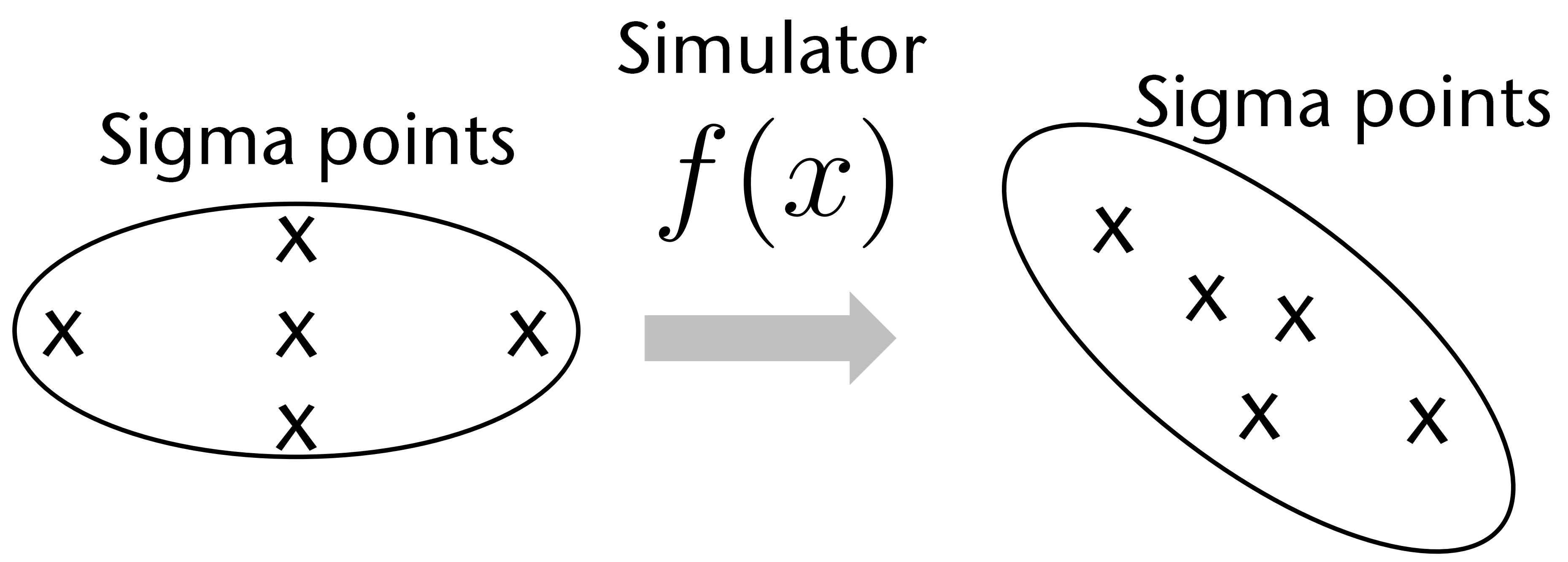
Uncertain contact -> many possible normal directions

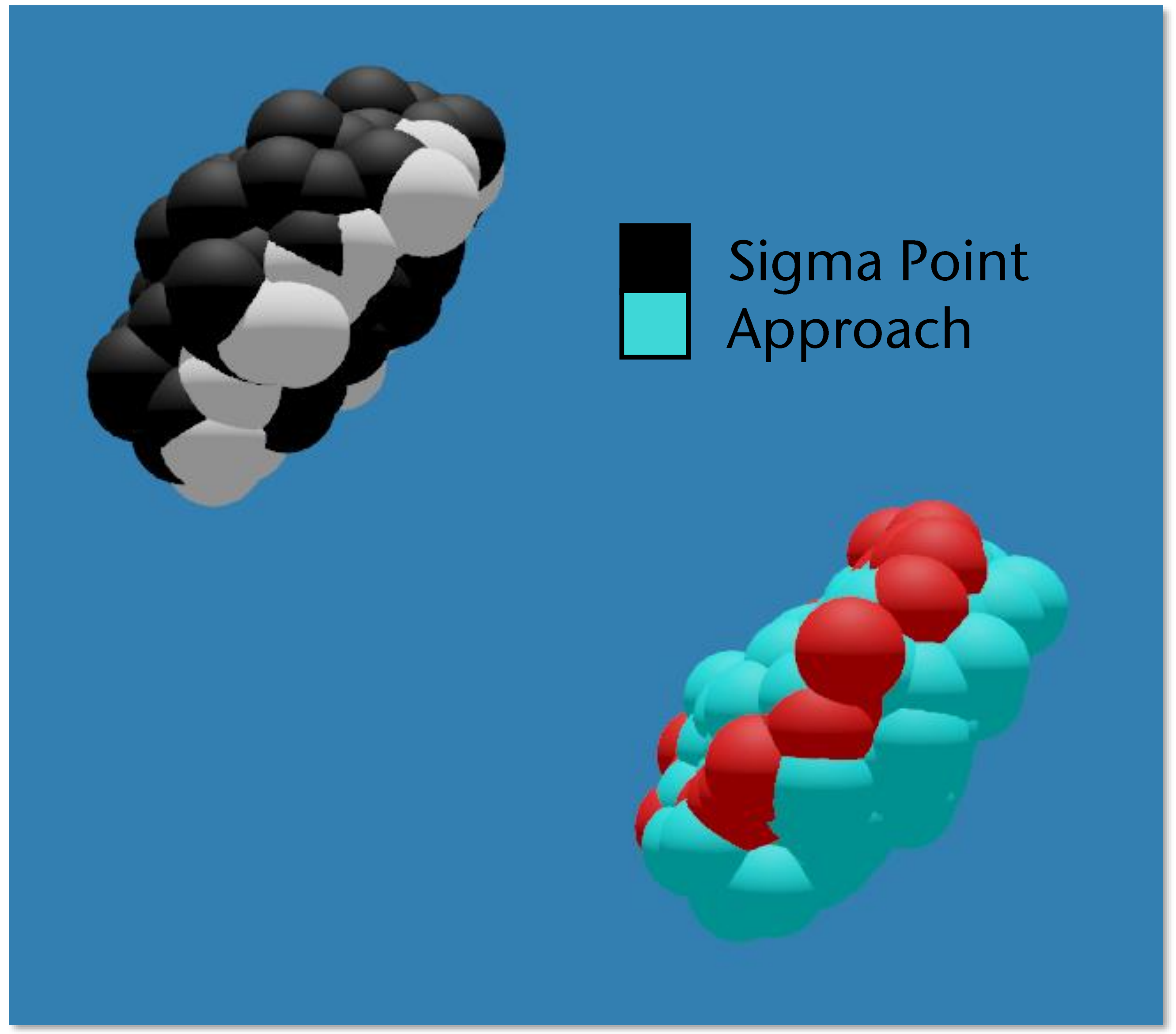




Handling Uncertainty: Persistent Sigma Points

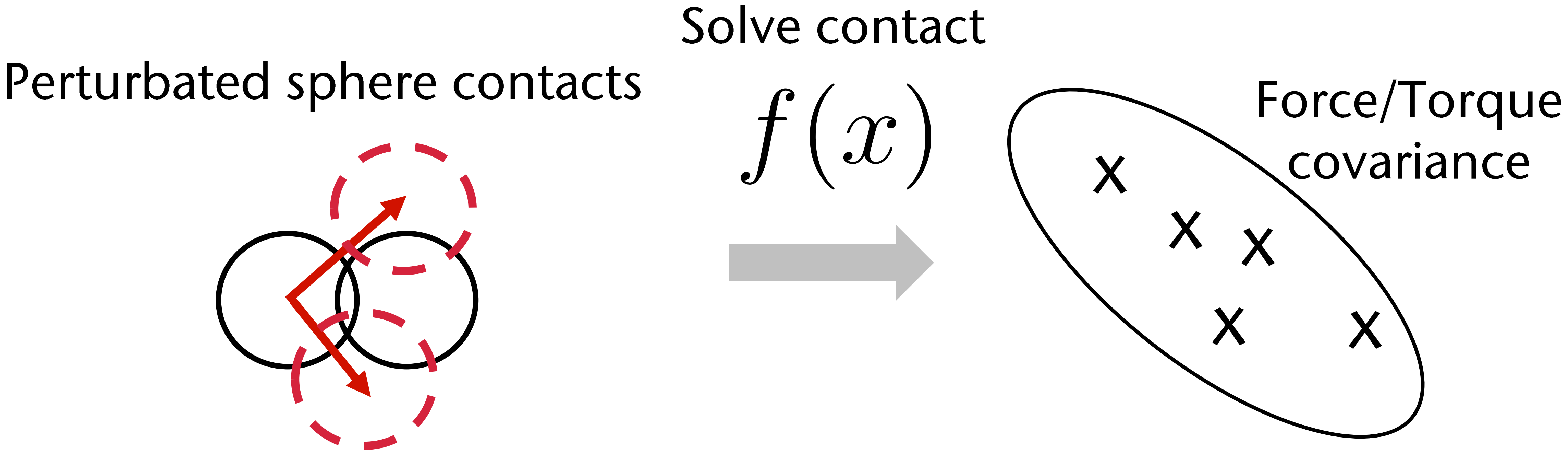
- Idea is to simulate representative states through time
- For two bodies: 49 sigma points
- Propagate them through the full simulator
- Challenge: unstable with collisions
  - Do not regenerate them every timestep

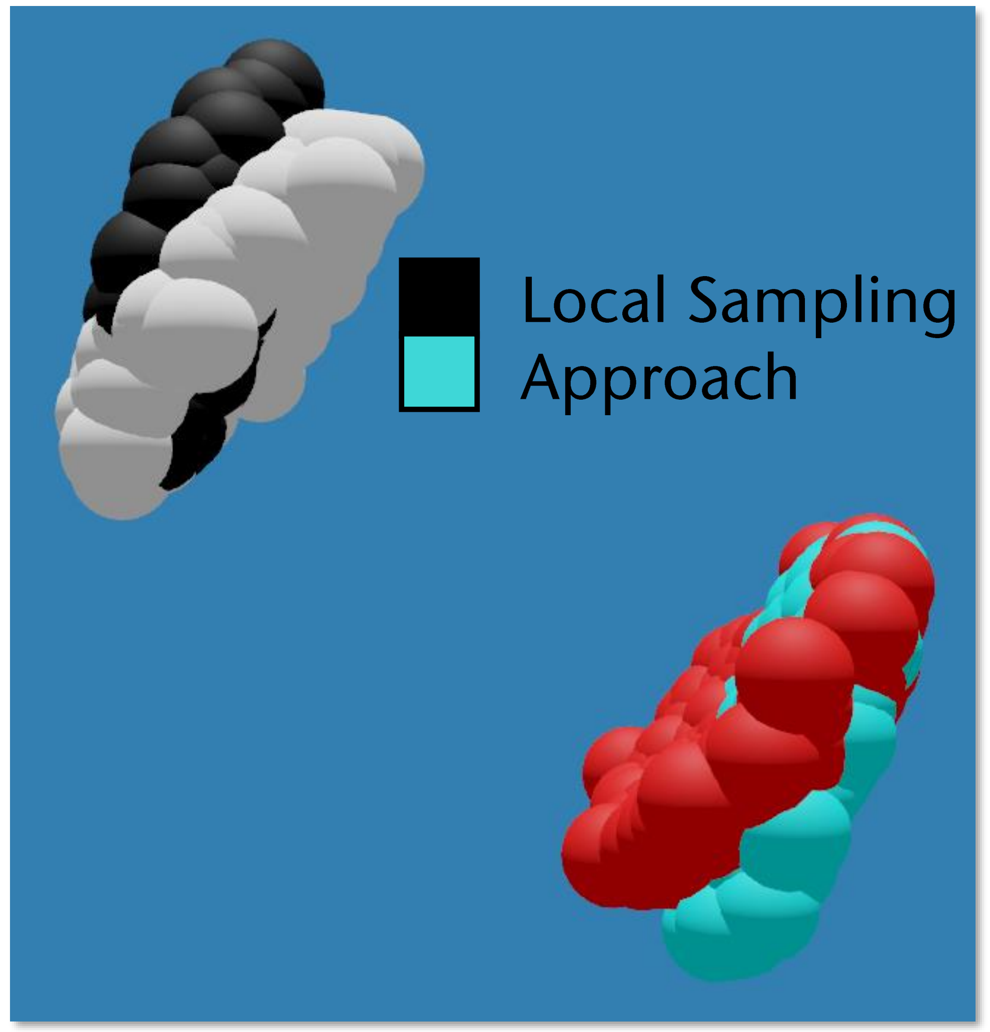




Handling Uncertainty: Local Sampling Approach

- Idea is to sample the uncertainty for contact solving function
- Generate x samples of state
  - Mean + perturbation
- Estimate covariance out of x-forces and torques
- Inject uncertainty into velocity and angular velocity

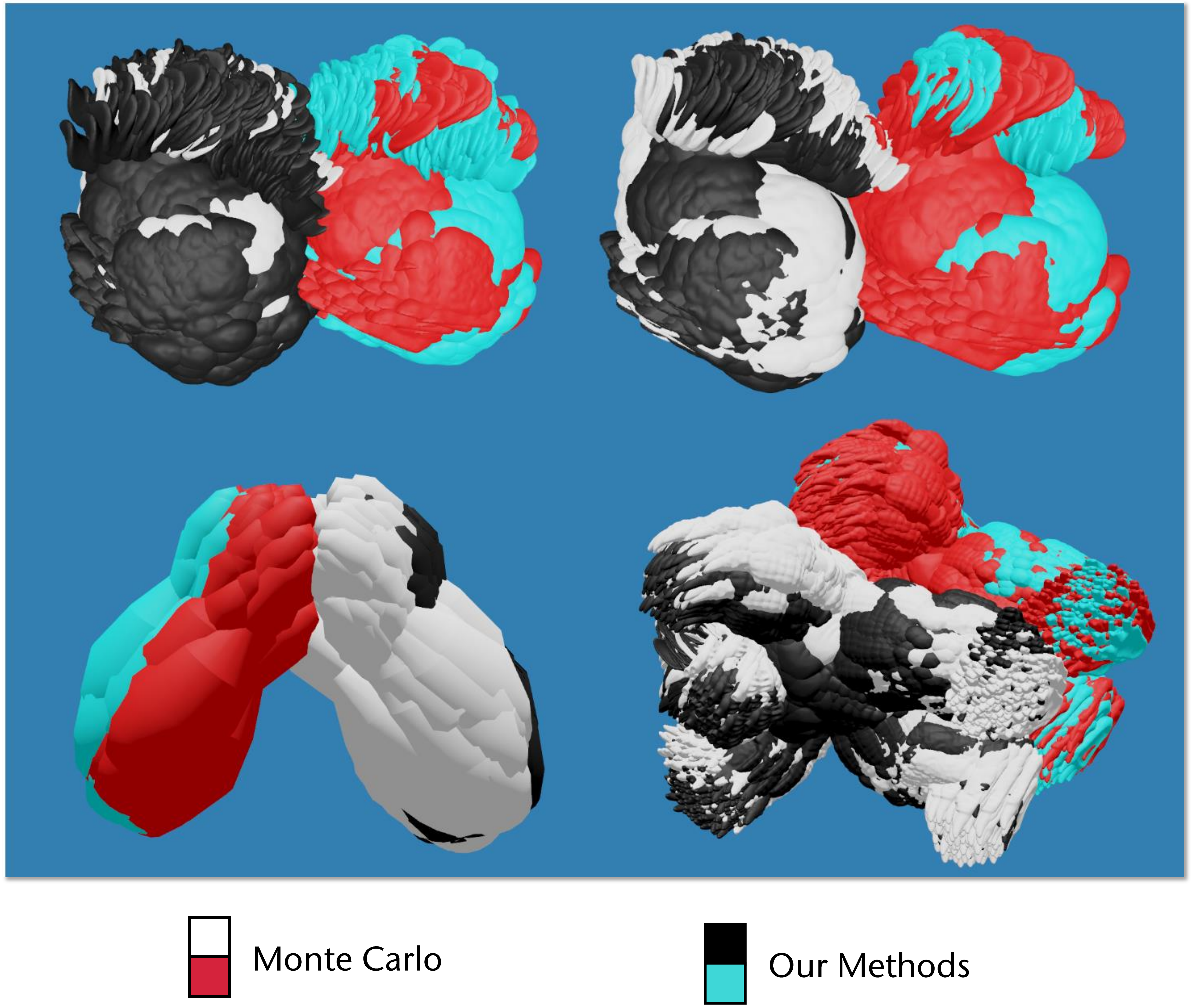




Evaluation Setup

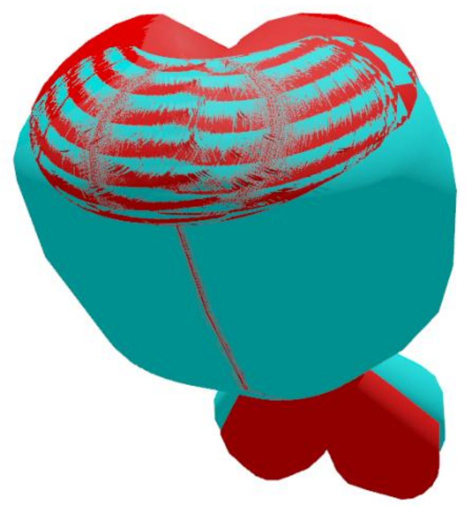
- Monte Carlo with 1000 samples as ground truth
- Metric: Wasserstein distance
- Collision-free and collision settings
- Test objects: Armadillo, Bunny, Pin
- With different initial conditions:
  - Sigma
  - Number of spheres
  - Method

Visual Comparison after Collision

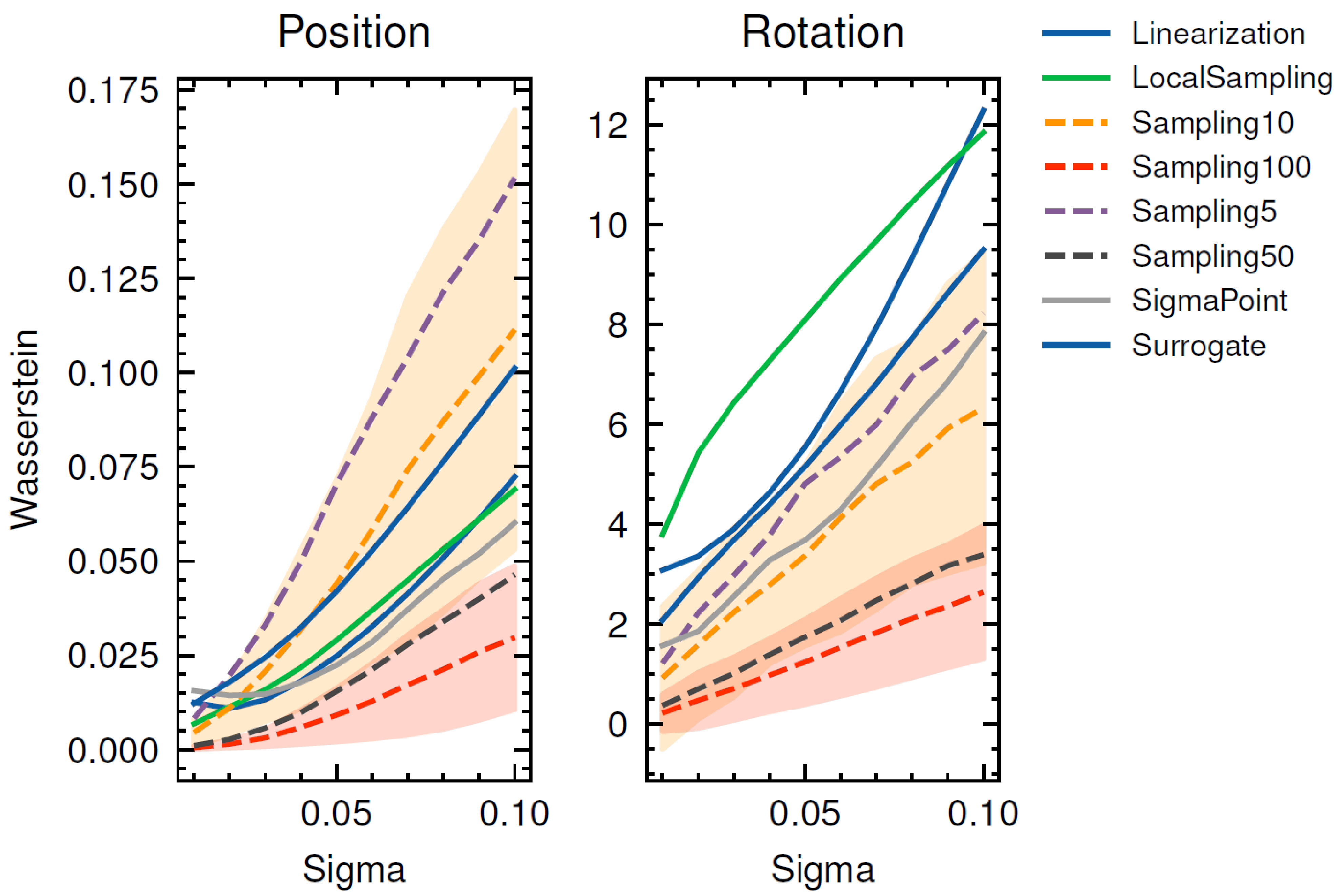


Results: Quality/Distance wrt. Uncertainty

- Collision-free experiments validate the implementation



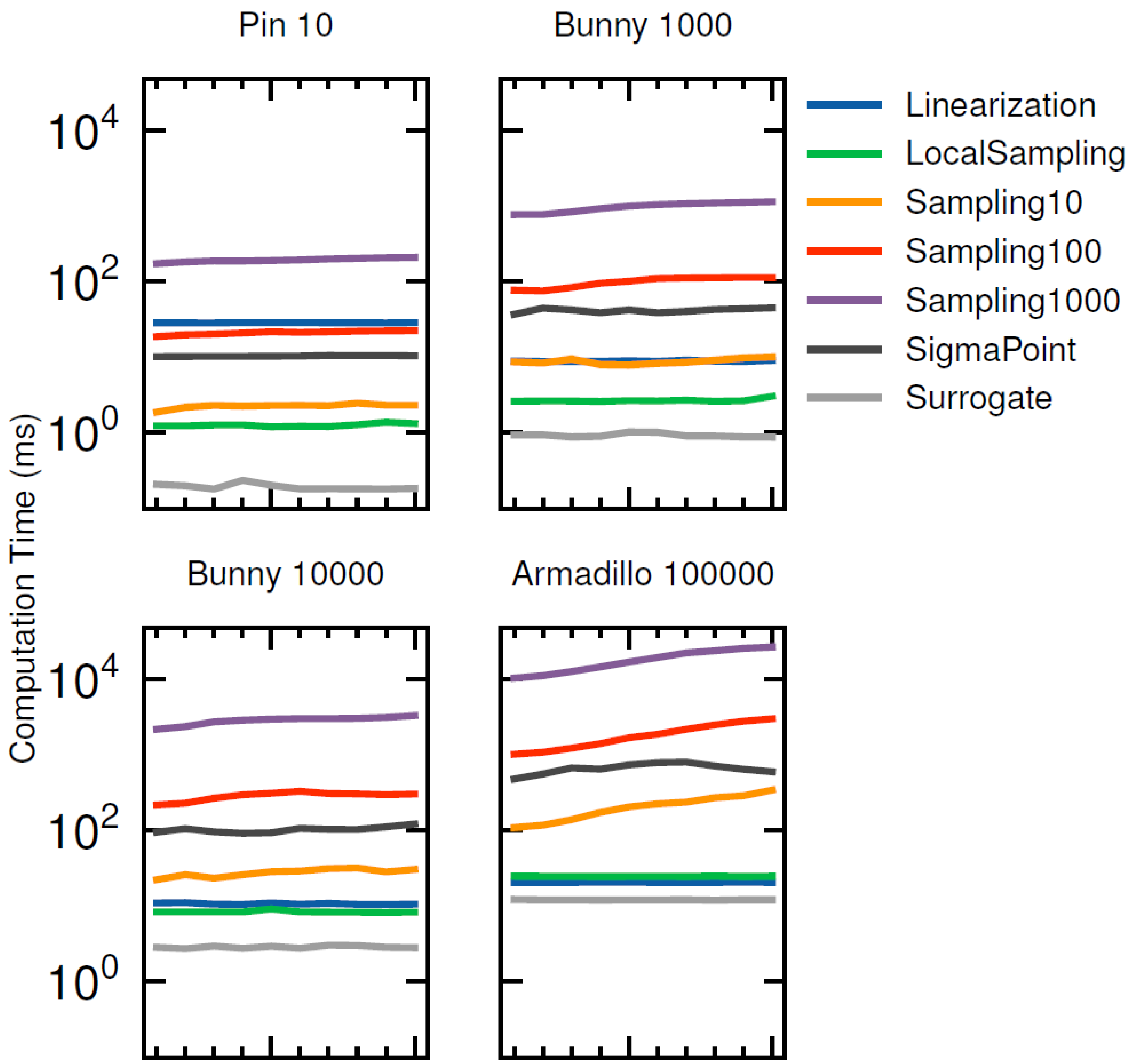
- In collision cases, error increases with larger uncertainty
- Persistent sigma points achieve the best overall position and rotation accuracy
- Linearization and local sampling perform well for position
- Rotation is more difficult than position

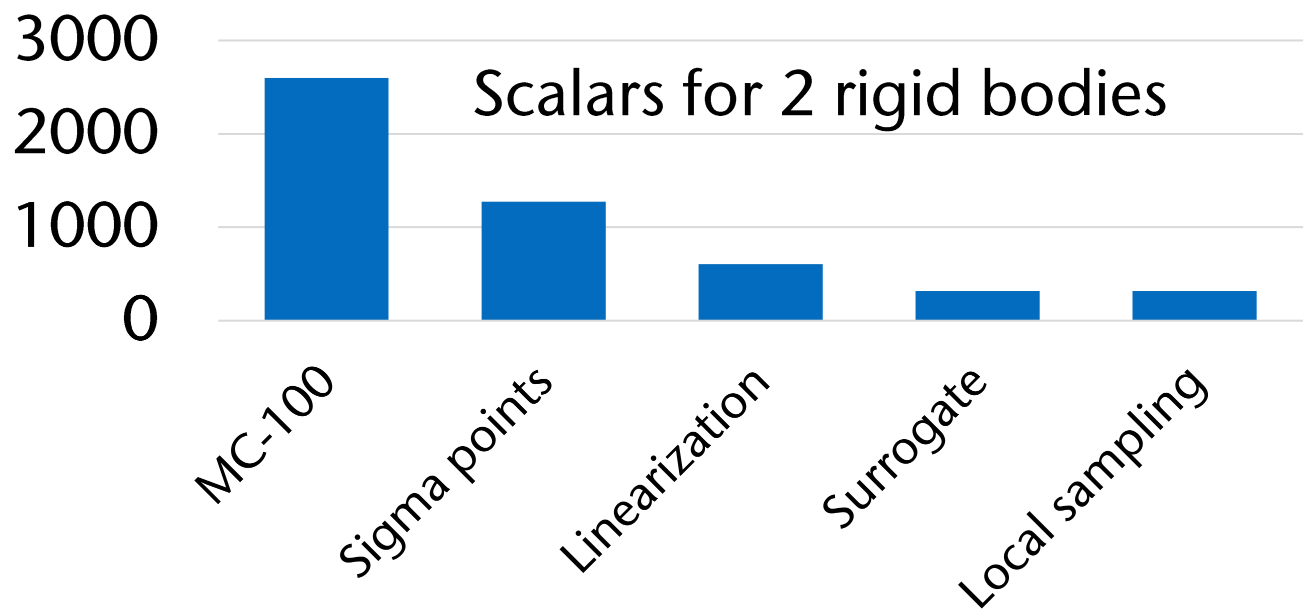


Results: Runtime Performance and Storage

- Proposed methods are significantly faster than sampling baselines
- Surrogate model is fastest
- Sigma points are costliest among proposed approaches, but still much faster than high-sample MC

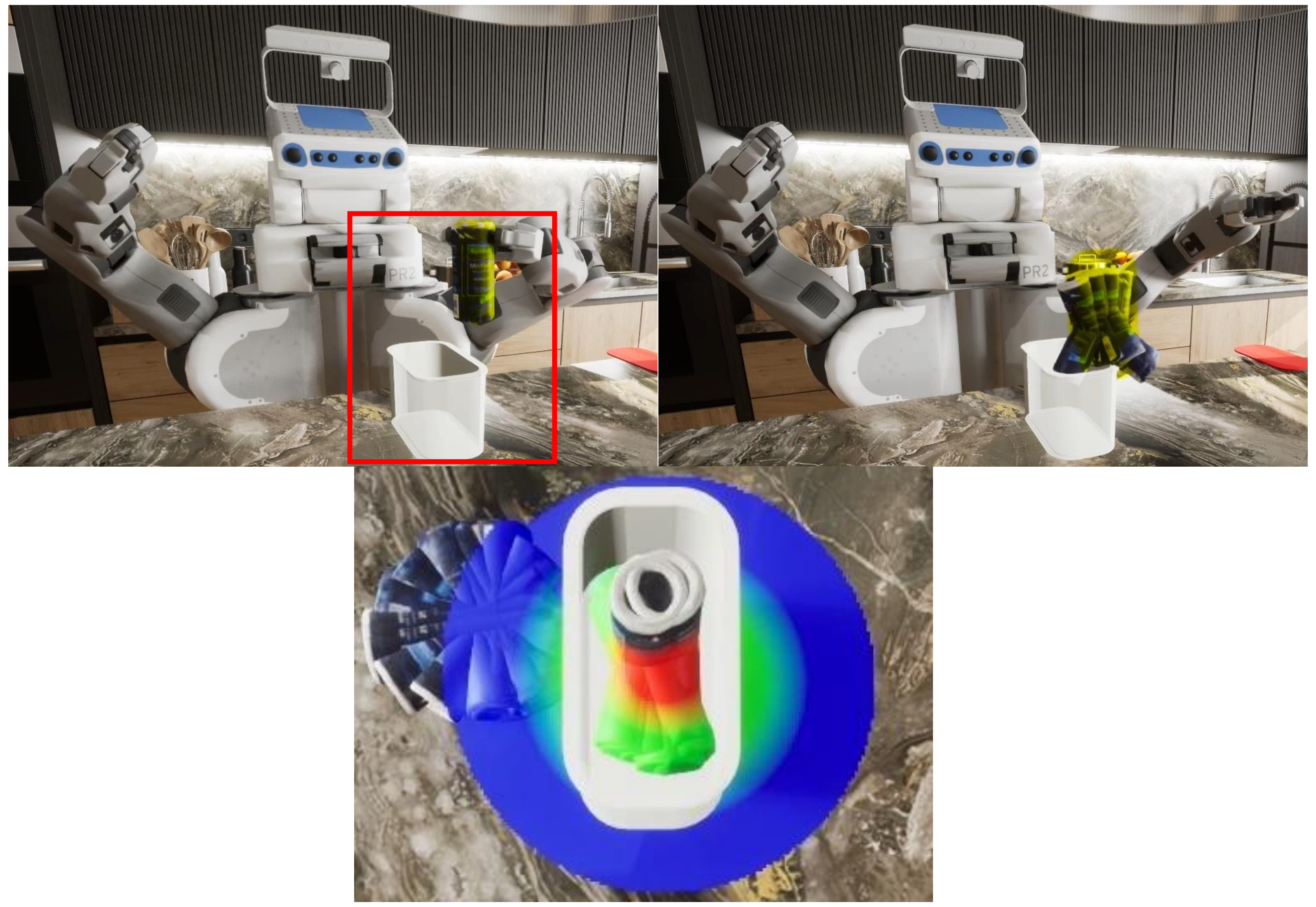
- Storage is lower than high-sample MC
- Per-body methods scale better in storage





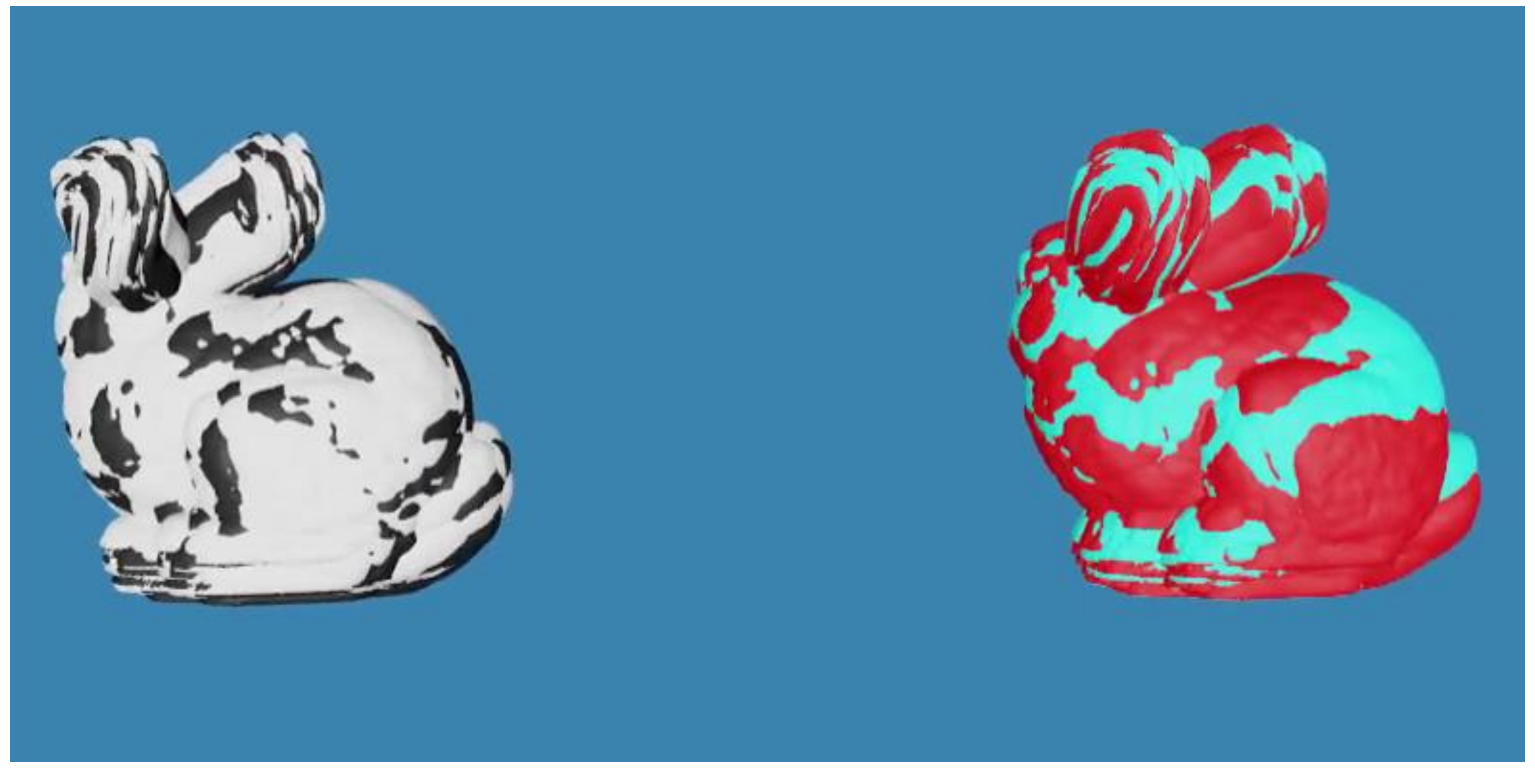
Conclusion and Future Work

- Up to 1-1.5 orders of magnitude faster
- Competitive accuracy with Monte Carlo
- Use cases: prediction, physical reasoning



- Future Work
  - Test more complex scenes beyond controlled two-body collisions
  - We plan to experiment with multi-modal distributions
  - Neural network to approximate uncertainty

Thank You for Your Attention!



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