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ManipulaPy: A GPU-Accelerated Python Framework for Robotic Manipulation, Perception, and Control

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Summary

ManipulaPy is an open-source Python toolbox that unifies the entire manipulation pipeline—from URDF parsing to GPU-accelerated dynamics, vision-based perception, planning and control—within a single API. Built on the Product-of-Exponentials (PoE) model (Lynch & Park, 2017), PyBullet (Coumans & Bai, 2019), CuPy (Okuta et al., 2017) and custom CUDA kernels (Liang et al., 2018), the library enables researchers to move from robot description to real-time control with up to 40× speedup over CPU implementations. DOF-agnostic GPU trajectory kernels accelerate 6-DOF and higher manipulators, while specialized inverse-dynamics prototypes achieve up to 3600× speedup for batch processing. Performance claims are reproducible via benchmarks in the repository.

Statement of Need

Modern manipulation research requires tight integration of geometry, dynamics, perception, planning, and control within a unified computational framework. However, existing open-source tools address only portions of this pipeline, forcing researchers to write substantial integration code:

Library	Core Strengths	Integration Challenges
MoveIt (Chitta et al., 2012)	Mature sampling-based planners	Custom ROS nodes for sensor integration, external plugins for real-time dynamics, no native GPU acceleration
Pinocchio (Carpentier et al., 2025)	High-performance PoE dynamics (C++)	CPU-only; perception & planning must be synchronized manually
CuRobo (Sundaralingam et al., 2023)	GPU collision checking & trajectory optimization	Planning-focused; lacks perception pipeline and closed-loop control
Python Robotics Toolbox (Corke & Haviland, 2021)	Educational algorithms, clear APIs	CPU-only; users build simulation/control/vision components separately

These integration challenges manifest as sensor-planner gaps, dynamics-control mismatches, GPU memory fragmentation, and synchronization complexity between components.

ManipulaPy eliminates these integration burdens through a unified Python API that maintains data consistency across the entire manipulation pipeline with GPU acceleration throughout.

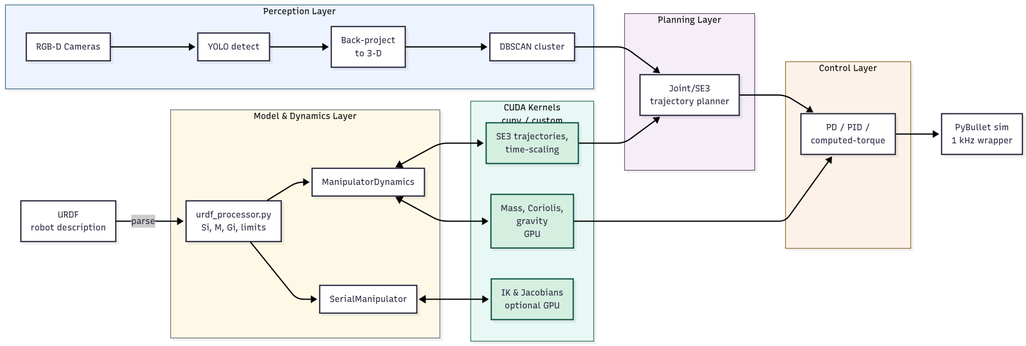

Figure 1: Figure 1: System architecture of ManipulaPy showing the unified manipulation pipeline. The framework integrates URDF processing, GPU-accelerated kinematics and dynamics, motion planning with collision avoidance, multiple control strategies, and PyBullet simulation within a single API. Data flows consistently between components without manual synchronization, while GPU acceleration provides 40× speedup for trajectory generation and real-time dynamics computation.

Library Architecture

ManipulaPy implements a unified manipulation pipeline with coherent data flow where each component builds upon shared representations:

Robot Model Processing converts URDF descriptions into PoE representations, extracting screw axes, mass properties, and joint constraints through PyBullet integration. This creates fundamental `SerialManipulator` and `ManipulatorDynamics` objects used throughout the system.

Kinematics and Dynamics provide vectorized FK/IK, Jacobians, and GPU-accelerated trajectory time-scaling that is DOF-agnostic. GPU dynamics kernels are shape-agnostic but simplified (per-joint/diagonalized), while fully coupled n-DOF spatial dynamics remain on the CPU path for exactness.

Motion Planning generates collision-free trajectories using GPU-accelerated time-scaling functions, supporting both joint-space and Cartesian-space planning with real-time obstacle avoidance.

Control Systems implement classical (PID, computed torque) and modern (adaptive, robust) control algorithms with automatic gain tuning, operating on the same dynamic model used in planning.

Simulation Framework provides PyBullet integration with synchronized camera rendering, physics simulation, and control execution.

Vision and Perception Pipeline

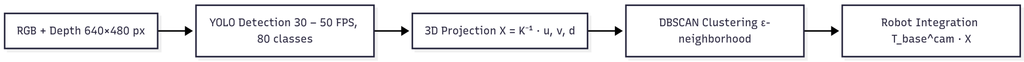

Figure 2: Figure 2: ManipulaPy vision and perception pipeline architecture. The five-stage pipeline processes raw sensor data from stereo cameras and RGB-D sensors through object detection using YOLO v8, transforms 2D detections to 3D world coordinates, applies DBSCAN clustering for object segmentation, and maintains multiple obstacle representations (point clouds, geometric primitives, SDFs) for robot integration at 5-15 Hz refresh rates during trajectory execution.

ManipulaPy's perception system converts raw sensor data into actionable robot knowledge through a five-stage pipeline:

Sensor Fusion handles stereo cameras (RGB+depth via OpenCV rectification), RGB-D sensors, and point cloud input with temporal alignment across sensor types.

Object Detection integrates YOLO v8 (Jocher et al., 2023) for real-time 2D bounding box detection and supports custom detectors for domain-specific models.

3D Integration transforms pixel coordinates to 3D world positions using camera intrinsics, performs multi-frame fusion to reduce noise, and applies calibrated transforms to register sensor data to robot coordinates.

Spatial Clustering applies DBSCAN clustering (Chu et al., 2021) to group 3D points using ε-neighborhoods for object segmentation and generates hierarchical representations.

Robot Integration maintains multiple obstacle representations simultaneously (geometric primitives, point clouds, SDFs) with 5–15 Hz refresh rates during trajectory execution.

Theory and Implementation

Product-of-Exponentials Kinematics

Like Pinocchio (Carpentier et al., 2025), ManipulaPy adopts the PoE formulation for robot kinematics, but provides GPU acceleration across the entire manipulation pipeline:

$$T(\theta) = e^{S_1\theta_1} \cdots e^{S_n\theta_n} M$$

where each screw axis $S_i \in \mathbb{R}^6$ encodes joint motion and $M \in SE(3)$ represents the home configuration. The space-frame Jacobian becomes:

$$J(\theta) = \left[\mathrm{Ad}_{T_1} S_1, \dots, S_n\right]$$

GPU-Accelerated Dynamics

Custom CUDA kernels parallelize computation for the fundamental dynamics equation:

$$\tau = M(\theta)\ddot{\theta} + C(\theta, \dot{\theta}) + G(\theta)$$

The mass matrix computation $M(\theta) = \sum_{i=1}^{n} \mathrm{Ad}_{T_i}^T \, G_i \, \mathrm{Ad}_{T_i}$ is optimized for 256-thread blocks.

ManipulaPy: GPU-Accelerated Trajectory with Visible Spline (side_view)

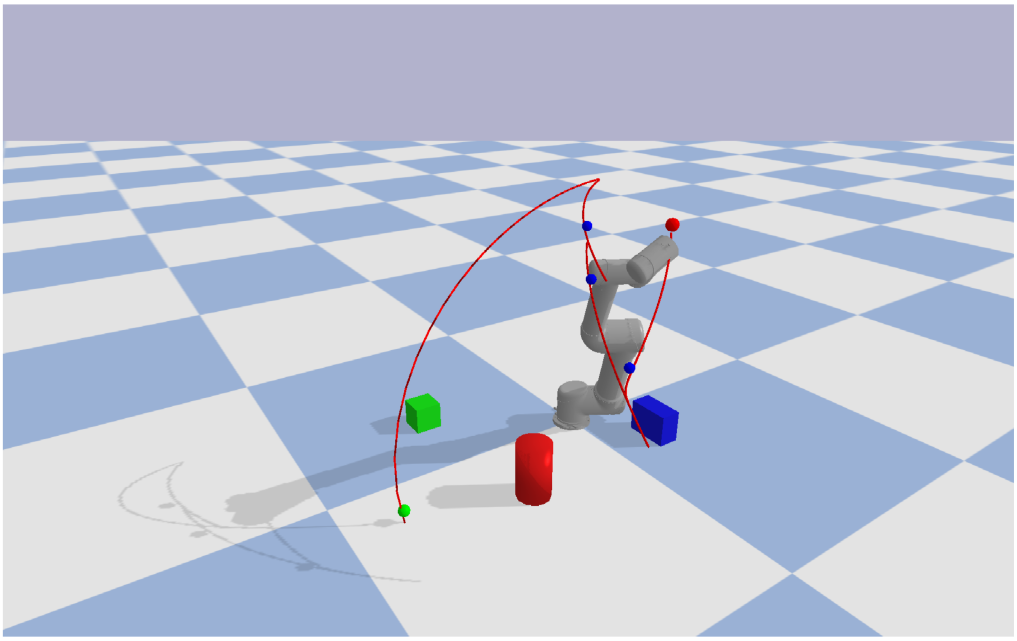

Figure 3: Figure 3: GPU-accelerated trajectory execution demonstration in PyBullet simulation. A 6-DOF robotic manipulator executes a complex trajectory while avoiding dynamic obstacles in real-time. The trajectory planning utilizes GPU acceleration for 40× speedup over CPU implementation, enabling 1 kHz control rates with real-time collision avoidance through potential field methods integrated with CUDA kernels.

CPU vs GPU Module Requirements

ManipulaPy provides tiered functionality that gracefully scales from CPU-only to GPU-accelerated operation:

CPU-Only Features

Core robotics modules include URDF processing, forward/inverse kinematics, Jacobian analysis, small trajectory planning ($N < 1000$ points), basic control, and simulation setup. Performance characteristics include single trajectory generation (~10–50 ms for 6-DOF robots) and real-time control limited to ~100 Hz due to Python's Global Interpreter Lock.

GPU-Required Features

High-performance modules include large trajectory planning ($N > 1000$ points) with 40× speedup, batch processing, real-time inverse dynamics >1 kHz, workspace analysis with Monte Carlo sampling, and GPU-accelerated potential fields. Performance characteristics include large trajectory generation (~1–5 ms for 6-DOF robots) and real-time control at 1 kHz rates.

Vision Features

Additional dependencies include OpenCV for camera operations, graphics libraries for visualization, and YOLO models for object detection, supporting camera operations, object detection, and spatial clustering.

Limitations and Design Trade-offs

Performance Constraints: Consumer GPUs (8 GB) limit trajectory planning to ~50,000 points. GPU acceleration is only beneficial for N > 1000 trajectory points due to kernel launch overhead. Python's Global Interpreter Lock limits CPU-only real-time control to ~100 Hz.

Integration Scope: Framework operates independently of ROS middleware, requiring manual integration with ROS-based systems. Vision features require system graphics libraries that may be missing in containerized environments.

Algorithmic Focus: Current implementation focuses on potential field methods and polynomial interpolation. Framework is designed for serial kinematic chains; parallel mechanisms require architectural modifications.

Development Focus: Optimized for research and education rather than industrial deployment, lacking safety certifications and formal verification mechanisms available in production systems.

Future Development

Planned enhancements include native ROS2 integration, advanced sampling-based planners, multi-robot support with GPU acceleration, direct hardware interfaces, safety monitoring with Control Barrier Functions (Morton & Pavone, 2025), and enhanced GPU utilization techniques.

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