

SPARK: A Modular Benchmark for Humanoid Robot Safety

Yifan Sun¹, Rui Chen¹, Kai S. Yun¹, Yikuan Fang¹, Sebin Jung¹
 Feihan Li¹, Bowei Li¹, Weiye Zhao¹, and Changliu Liu¹

Robotics Institute, Carnegie Mellon University

{yifansu2, ruic3, sirkhooy, yikuanf, sebinj, feiharl, boweili, weiyezha, cliu6}@andrew.cmu.edu

<https://intelligent-control-lab.github.io/spark/>

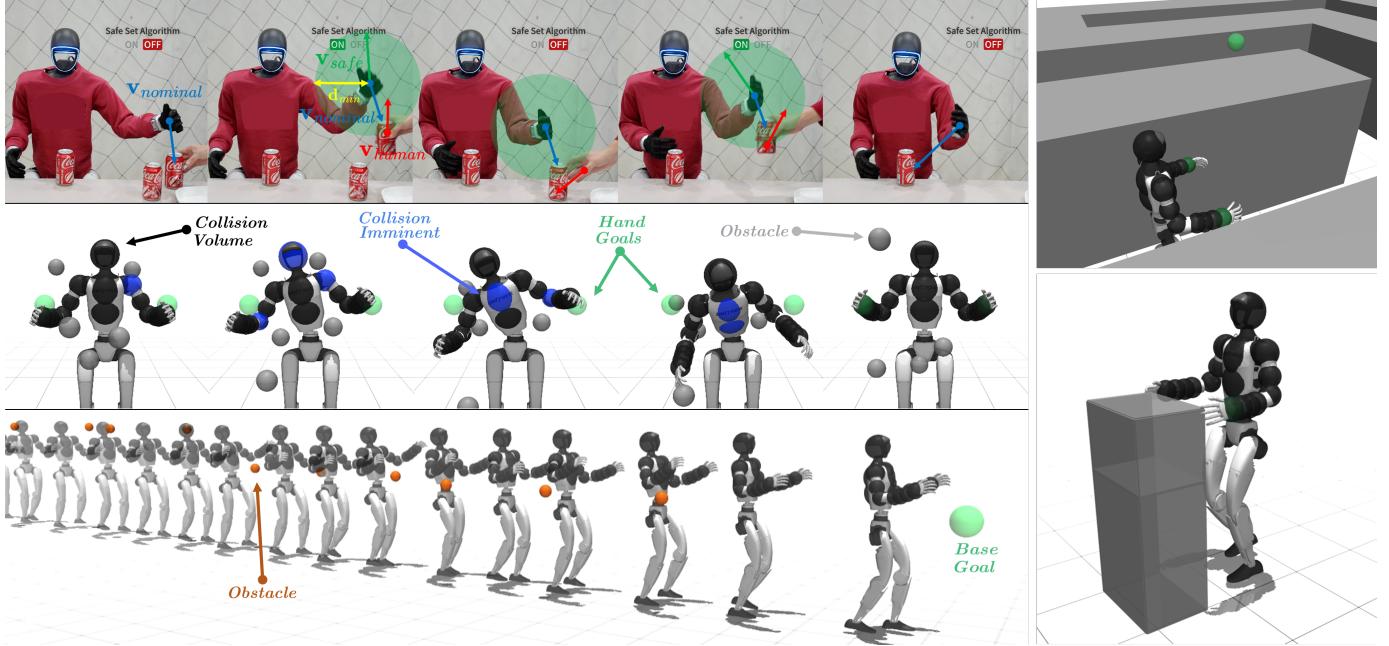


Figure 1: Scenarios of safe humanoid control achieved with **SPARK**. **Left top figure:** A real Unitree G1 humanoid robot avoiding human hands to ensure safe human-robot interaction. **Left middle figure:** A fixed-base humanoid robot safely reaching a target hand position in a crowded environment. **Left bottom figure:** A simulated humanoid robot navigating to a target position while avoiding obstacles. **Right top figure:** An example of a user-defined scenario for safe robot navigation in a maze. **Right bottom figure:** A daily-life scenario where a humanoid robot, under teleoperation, picks up objects from a cabinet in simulation.

Abstract—This paper introduces the Safe Protective and Assistive Robot Kit (**SPARK**), a comprehensive benchmark designed to ensure safety in humanoid autonomy and teleoperation. Humanoid robots pose significant safety risks due to their physical capabilities of interacting with complex environments. The physical structures of humanoid robots further add complexity to the design of general safety solutions. To facilitate safe deployment of complex robot system, **SPARK** can be used as a toolbox that comes with state-of-the-art safe control algorithms in a modular and composable robot control framework. Users can easily configure safety criteria and sensitivity levels to optimize the balance between safety and performance. To accelerate humanoid safety research and development, **SPARK** provides simulation benchmark that compare safety approaches in a variety of environments, tasks, and robot models. Furthermore, **SPARK** allows quick deployment of synthesized safe controller on real robots. For hardware deployment, **SPARK** supports Apple Vision

Pro (AVP) or a Motion Capture System as external sensors, while offering interfaces for seamless integration with alternative hardware setups at the same time. This paper demonstrates **SPARK**'s capability with both simulation experiments and case studies with a Unitree G1 humanoid robot. Leveraging these advantages of **SPARK**, users and researchers can significantly improve the safety of their humanoid systems as well as accelerate relevant research. The open source code is available at <https://github.com/intelligent-control-lab/spark>.

I. INTRODUCTION

Safety is an essential element for robotic systems not only in industrial settings but also in everyday life. From an algorithmic perspective, safe control ensures a system operates within user-specified safety constraints to minimize risks and harm while achieving objectives. Recognizing the

vital importance of maintaining these constraints, numerous safe control approaches have been developed and successfully applied to a wide range of robotic systems.

Among these approaches, the general pathway is to formulate the safe control problem as a constrained optimization problem, where the objective is to accomplish a given task while satisfying the safety constraints imposed on the robot. Analytical methods can transform this optimization problem into a quadratic programming (QP) formulation, which can then be solved efficiently by existing solvers. Alternatively, data-driven methods leverage black-box policies to generate control solutions directly. However, regardless of the success of the approaches, the fundamental challenge remains: *how to allow non-experts to efficiently synthesize and deploy safe controllers in diverse applications?* The efficient synthesis and deployment require easy specification of both the objective and constraints that ensure safety while fulfilling task requirements, informed selection of the best safe control approaches, and tuning-free deployment on the real hardware.

As model-free data-driven approaches have not been successful in safety assurance in high-dimensional systems, and the formal verification of these methods still requires the system model [1], this paper focuses on efficient synthesis and deployment of model-based approaches.

Synthesizing a model-based safe controller for simple scenarios is relatively straightforward. Consider a differential-drive 2D autonomous vehicle tracking a trajectory with an upperbound velocity constraint for safety. It is not difficult to design an appropriate energy-like function that ensures the vehicle does not go over this speed limit. However, as the scenario grows more complex (e.g., more complex constraints and objectives, more complex robot dynamics, or more complex environments), synthesizing model-based safe controllers for each case becomes increasingly challenging and requires significantly more time and resources.

Now, consider replacing the differential-drive vehicle with a humanoid robot delivering a package with the same upper-bound velocity constraint. Due to the different dynamics of a humanoid robot, such as its joint limits, the safe controller previously synthesized for the vehicle may no longer be valid. Furthermore, once the humanoid robot successfully arrives at the package dropoff destination, e.g., a loading truck, the task transitions from navigation to upper body manipulation, requiring the robot to load the box onto the truck while avoiding collisions. The humanoid dynamic can no longer be treated as a mobile robot and the upper body needs to be incorporated into the safety constraint. Even for the same loading task, changing the control mode from autonomous operation to teleoperation or language-vision-based commands introduces new challenges for safe control.

Finally, even for similar safety constraints, the safe controller may need re-synthesis when the environment changes. For instance, consider a warehouse where a humanoid robot operates alongside human workers who are loading boxes. In this setting, the robot must avoid both static obstacles, e.g., a parked truck, and dynamic human participants. Safe

controller synthesis in this scenario must also ensure robust human safety, potentially achieved by integrating a human motion prediction model into the control stack.

Hence, synthesizing a safe controller from scratch on a case-by-case basis can quickly become time-consuming and inefficient, as each change in *robot*, *task*, or *environment* requires re-synthesis by experts. At the same time, designing a single, universal safe controller capable of handling every possible scenario - varying tasks, diverse robot dynamics, ever-changing environments, and arbitrary safety constraints - is highly challenging, if not impossible. This inherent inefficiency hinders the practical development and deployment of safe controllers across real-world robotic applications.

To lower the barrier and increase the efficiency of safe controller synthesis and deployment, a plug-and-play modular framework is essential. To this end, we present the **Safe Protective and Assistive Robot Kit (SPARK)**, as a modular safe control framework. With SPARK, users can efficiently design, verify, and benchmark safe controllers for complex robot systems without starting from scratch. This approach reduces the effort of synthesis while promoting scalability and generalization of safe control methods across diverse robot configurations and task scenarios. Guided by these principles, we designed SPARK to be

Composable:

- Provides a set of modular components that users can assemble to create safe robotic control scenarios with custom task goals and safety requirements as shown in Figure 1.
- Offers predefined module options to facilitate large-scale benchmark scenario generation for evaluating safe control approaches.
- Enables users to switch between similar scenarios by simply replacing the corresponding module.

Extensible:

- Allows users to customize each module, such as developing their own safe controllers or modifying robot dynamics, using provided templates.
- Supports the integration of additional user-defined modules, including external sensors and task planners.
- Provides a general wrapper to seamlessly bridge SPARK with other existing benchmarks.

Deployable:

- Enables users to deploy synthesized safe control algorithms on real robotic hardware by wrapping the hardware SDK (Software Development Kit) with the SPARK interface.
- Ensures compatibility with real-time middleware such as ROS (Robot Operating System) and DDS (Data Distribution Service).
- Maintains robustness across diverse real-world task settings, including human-robot interaction and teleoperation through Apple Vision Pro.

Ultimately, we hope SPARK alleviates many of the challenges in safe controller synthesis and benchmarking, empow-

ering robots to operate safely and reliably in diverse real-world scenarios.

II. RELATED WORK

In this section, we briefly survey previous work closely tied to our objective of enabling efficient, modular safe controller synthesis and benchmarking for robotic systems. We mainly focus on safe control for humanoids as humanoids are one of the most complex platforms in robotics.

a) Modular Safe Control Toolboxes: Safe control toolboxes aim to provide modular and general safe control algorithms that can be integrated into various robotic systems. The Benchmark of Interactive Safety (BIS) [2] implements a set of energy-function-based safe control algorithms, such as the Potential Field Method (PFM) [3]. Similarly, [4] introduces a toolbox focused specifically on Control Barrier Functions (CBF). However, these toolboxes do not offer the modularity required for seamless compatibility with other frameworks and lack tasks tailored for complex robotic systems.

When it comes to complex robotic systems such as humanoids, specialized safe control methods have been proposed to address their high-dimensional dynamics. In particular, CBFs are widely used to ensure locomotion safety of bipedal robots [5, 6], safe humanoid navigation [7], self-collision avoidance for humanoids [8, 9], and humanoid whole-body task space safety [10]. Moreover, ARMOR [11] employs a novel egocentric perception system to learn data-driven safe motion planning policies for humanoid robots. Despite these advancements, no existing benchmark provides standardized tasks for comparing current methods or supports the development of new safe control approaches in a consistent and modular way.

b) Benchmark Platforms for Safety-critical Tasks: As safe reinforcement learning (RL) has emerged as a powerful framework for learning safe control policies from data, such as Constrained Policy Optimization (CPO) [12] and State-wise CPO (SCPO) [13], many of the existing benchmark platforms for safety-critical tasks are tailored for safe RL. For instance, GUARD [14] offers a comprehensive set of environments featuring safe RL tasks alongside state-of-the-art safe RL algorithms. Similarly, Safety-Gymnasium [15] integrates a wide range of safe RL environments into a unified benchmark. Safe Control Gym [16] provides a collection of safe control environments to facilitate model-free safe control policy learning. However, these platforms do not cater to tasks that involve high-dimensional robotic systems, such as humanoid robots. In addition, they place limited emphasis on model-based methods, which remain essential for addressing safe control challenges due to their analytical rigor, compositability, and interpretability.

c) Benchmark Platforms for Humanoid Robots: Humanoid robots are among the most complex robotic systems, posing significant challenges [17] in control. Learning-based methods have shown impressive results in humanoid control, and various open-source humanoid benchmarks have been

developed. H2O [18] and OmniH2O [19] develop RL-based whole-body humanoid teleoperation, with H2O using an RGB camera and OmniH2O extending to multimodal control and autonomy. [20] enables humanoids to learn motion and autonomous skills from human data via RL and behavior cloning. ExBody [21] and ExBody2 [22] develop RL-based whole-body control for humanoid robots, with ExBody enabling expressive motion and ExBody2 enhancing generalization and fidelity via a privileged teacher policy. Both [23] and [24] employed pure reinforcement learning methods to achieve humanoid robot locomotion. HOVER [25] unifies diverse humanoid control tasks via multi-mode policy distillation, enabling seamless transitions without retraining. HumanoidBench [26] provides a benchmark for humanoid RL on whole-body tasks, while Humanoid-Gym [27] enables zero-shot sim-to-real humanoid locomotion training. Mimicking-Bench [28] establishes a benchmark for humanoid-scene interaction learning using large-scale human animation data, while MS-HAB [29] accelerates in-home manipulation research with a GPU-optimized benchmark and scalable demonstration filtering. BiGym [30] is a benchmark for bi-manual robotic manipulation with diverse tasks, human demonstrations, and multi-modal observations. Nevertheless, none of these benchmarks specifically focus on testing the safety of humanoid robots. Achieving safety for humanoids requires not only model-free [31, 32] approaches but also model-based methods [33, 34], which offer valuable analytical insights and interpretability in addition to their control capabilities.

III. SPARK'S FRAMEWORK FOR TESTING, BENCHMARKING, DEVELOPMENT AND DEPLOYMENT

In this section, we begin by outlining the various components that form safety-critical robotic scenarios. Next, we introduce SPARK's modular framework. Finally, we show how the framework of SPARK aligns with the principles outlined in Section I.

A. Components of a Safety-Critical Robotic Scenario

To fully appreciate the design of the SPARK framework, we must first define the system-level components that constitute a safety-critical robotic scenario. The intricate interdependencies among these components directly influenced the design choices for the SPARK framework, discussed in Section III-B. By understanding how these components interact, we crafted a solution that streamlines the synthesis of safe controllers, ensuring that the framework is both composable and extensible. This approach not only simplifies the process of safe controller synthesis for users but also guarantees that the framework can be seamlessly deployed across a variety of safety-critical robot scenarios. Below, we introduce our definitions for *system state*, *system dynamics*, *system objectives*, *system measurements*, and *system controller*. While some of these definitions echo conventional control theory, others have been adapted to more precisely capture the nuances of safe controller synthesis procedure.

a) **System State**: includes the robot's internal state, such as a humanoid's joint positions and locomotion velocity, as well as the external state, which encompasses information about obstacles and human participants. The *system state* can be obtained from either a simulated environment or the real physical world.

b) **System Dynamics**: encompass both the robot's internal dynamics and the external dynamics that influence its operation. It is important to note that the *system dynamics* defined here are user-defined models rather than the true dynamics of the real world. In practice, capturing the complete complexity of real-world dynamics is infeasible. These models, whether formulated analytically or derived from data, approximate the real world and are tailored for use by the *system controller*, though they may differ from the actual dynamics.¹

c) **System Objectives**: encompass both task-specific targets, such as following a trajectory or reaching a designated point, and safety constraints, such as ensuring obstacle avoidance. These *system objectives* can be derived from pre-coded autonomy programs and user-defined safety criteria. Additionally, they may originate from user inputs, such as teleoperator gestures, or be generated by a Large Language Model (LLM)-based task planner.

d) **System Measurements**: provide the information about the system state to the controller. By interfacing with external sensors, *system measurements* capture details such as obstacle shape, number, and location, along with the goal positions.

e) **System Controller**: encompasses robot algorithms that optimize the control inputs for the robot based on the *system dynamics*, *system objectives*, and the *system measurements*. It ensures that the robot operates efficiently while maintaining safety and achieving task-specific goals.

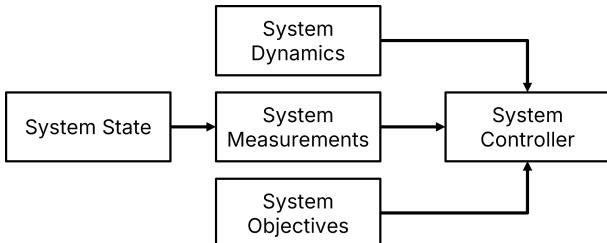


Figure 2: System components of a safety-critical robotic scenario and their interdependencies. $A \rightarrow B$ translates to “ B depends on A ”.

Designing safe controllers for specific robot scenarios can be challenging due to the complex interdependencies among the system components as described above and shown in Figure 2. *System controller* heavily depends on the *system measurements* to estimate the *system state*, *system objectives* to inform its optimization process, and *system dynamics* to model the effect of its control actions. *System measurements*

¹This distinction is crucial to avoid confusion with the traditional control theory interpretation, where “system dynamics” typically refer to the system’s true behavior.

are intrinsically dependent on the *system state*, aiming to approximate it through sensor data. By contrast, *system state*, *system objectives*, and *system dynamics* are relatively self-contained and do not depend on other components.

Recognizing these differences suggests a structured approach to reduce complexity. Considering these interdependencies, we designed the SPARK framework to be easily composable and extensible, thereby facilitating uniform, modular safe controller synthesis across different robotic scenarios.

B. Framework of SPARK

To facilitate the decomposition and integration of the components discussed in Section III-A, we present the SPARK framework, as shown in Figure 3, offering users a collection of modular Python class templates designed to streamline the synthesis, testing, benchmarking, development, and deployment of safe controllers for robotic systems.

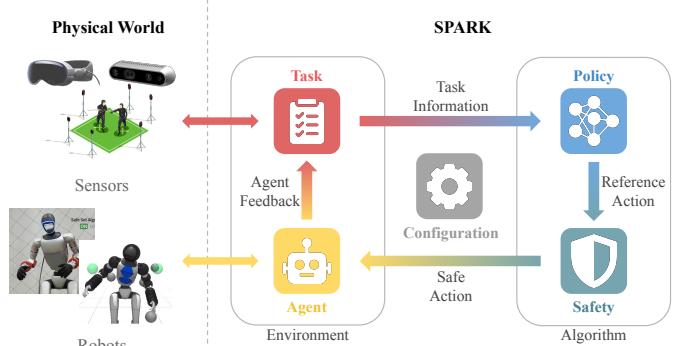


Figure 3: SPARK system framework.

The SPARK framework is structured around the decomposition of system components into distinct modules that allow efficient handling of system states, measurements, objectives, dynamics, and controllers. This modularity, inspired by the relationships established in Section III-A, enables composable, extensible, and deployable safe controller design.

We first introduce the **Configuration** module which supports all other modules.

a) **Configuration Module**: houses *system dynamics*, encapsulating robot-specific configurations such as degrees of freedom, motor interfaces, and system models. It provides essential context for other modules and enables the incorporation of robot-specific details, making it essential for defining and customizing dynamics within SPARK.

Environment, composed of **Agent** and **Task** modules, is the “front-end” of SPARK, responsible for obtaining the *system measurements* and modifying the *system state*, in the context of *system objectives*.

b) **Agent Module**: interacts with the physical robot or its simulation. It receives control commands from the system controller and manipulates the robot's state by applying these commands to the robot's actuators or simulated system. Consequently, the **Agent** module's primary role is to influence and modify the robot's *system state*, reflecting its position in the overall framework as an executor of system control.

Agent module houses the interfaces for both simulated and real robots, allowing SPARK to be deployable for various tasks.

c) **Task Module**: represents a key link in the SPARK framework, responsible for providing system measurements and objectives to downstream modules. *System objectives* are naturally incorporated into this module, where they serve as task-specific goals, e.g., goal points, obstacle avoidance. Additionally, the *system measurements* module is integrated here, bridging the robot's current state (via the **Agent** module) and information about the surrounding environment (e.g., obstacles, goal points). By providing system measurements along with the objectives, the **Task** module ensures that both system status and intended mission goals are captured and made available for policy decision-making in the subsequent module. This approach of combining measurements with objectives allows SPARK to construct a comprehensive picture of the robot's state in context with its task, ensuring efficient task execution and safe control under evolving conditions.

We now turn to the “back-end” of the framework, encompassed by **Algorithm**, which unifies the **Policy** and **Safety** modules. The *system controller* is incorporated here, divided into these two modules.

d) **Policy Module**: processes the **Task** information to generate reference control actions that aim to achieve performance-oriented objectives, such as reaching a goal location, without considering safety constraints.

e) **Safety Module**: refines the control actions given by the **Policy** module to ensure compliance with the safety constraints while attempting to follow the original reference control actions as closely as possible.

Both **Policy** and **Safety** modules allow users to incorporate either model-based or data-driven controllers, preserving SPARK’s core principles of composability and extensibility.

C. Why decomposing system components into the SPARK framework is valuable

As described in Section I, the SPARK framework is grounded in three core principles: *composability*, *extensibility*, and *deployability*. By decomposing the system components into distinct, modular units, SPARK maximizes flexibility and scalability for various robotic platforms and tasks. This design fosters the following advantages.

- **Composability**: Users can rapidly mix and match built-in or custom modules to create safe robotic control scenarios. Predefined module options enable large-scale benchmarking, while module swapping allows easy scenario variation without re-engineering the entire synthesis process.
- **Extensibility**: Each module can be independently customized or replaced, such as implementing novel safe control algorithms in the **Safety** module, integrating additional sensors in the **Task** module, testing new reinforcement learning algorithms in the **Policy** module, and incorporating latest humanoid robot in the **Configuration** module. This flexibility supports rapid development,

wide-ranging experimental setups, and seamless adoption of new research innovations.

- **Deployability**: The unified interface within the **Agent** module bridges simulation and physical hardware, simplifying the transition from prototyping to real-world experiments. By supporting middleware like ROS and DDS in the **Agent** module, SPARK ensures robust real-time performance, whether in controlled lab settings or complex human-robot interactions.

This clear separation of responsibilities across SPARK’s modules not only accelerates testing and benchmarking of safe control methods but also streamlines development and real-world deployment. Researchers can quickly iterate on scenarios and algorithms, and then confidently transfer their solutions to hardware platforms with minimal friction, all within one coherent framework.

IV. SPARK SUITE OPTIONS

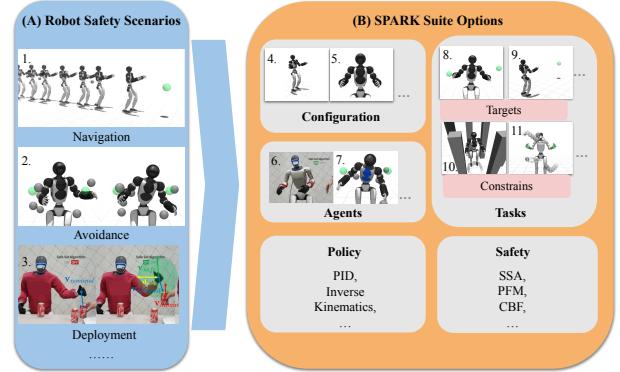


Figure 4: SPARK Suite Options.

In addition to the safe control library, SPARK offers users a comprehensive testing option suite to evaluate the performance of various safe controllers, which is shown in Figure 4. In this use case, we leverage SPARK’s composability to extract two types of Unitree G1 configurations from the Configuration Module and retrieve the simulation agent from the Agent Module. In the Task Module, we combine different goals and constraints to generate benchmarks. The Policy Module is then used for control, followed by an analysis of the performance of different algorithms within the Safety Module.

A. Configuration Options

As the humanoid robot represents a highly nonlinear and complex system, SPARK provides users with predefined robot configurations based on the Unitree G1 humanoid robot. The simulations define the robots using MuJoCo XML files.

The testing suite includes 2 types of robot configurations in the benchmark environments:

G1FixedBase: As shown in Figure 4 (4), this robot configuration consists of 17 Degrees of Freedom (DoFs), including 7 DoFs for each arm and 3 DoFs for the waist. The pelvis of the robot is fixed relative to the world frame. The setup is designed to help users analyze the performance of safe controllers specifically for the robot manipulators.

G1WholeBody: Figure 4 (5) illustrate the robot configuration which includes **20** Degrees of Freedom (DoFs), comprising 17 DoFs for the upper body and an additional 3 DoFs for base motion. The base motion is modeled as a floating base in the world frame, with the 3 DoFs representing x-axis velocity, y-axis velocity, and yaw rotational velocity relative to the robot's base frame. This setup is designed to help users evaluate the capabilities of safe controllers for a humanoid robot with both locomotion and manipulation DoFs. The floating base configuration decouples the upper body's movement from lower body locomotion, enabling the analysis of whole-body safety without interference from locomotion perturbations.

The definitions of the robot configurations are listed in Section XII-B

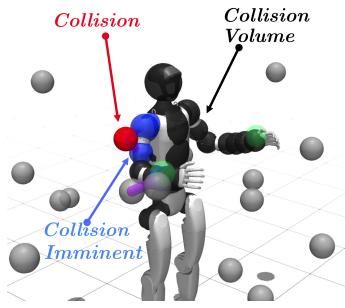


Figure 5: SPARK whole body task environment.

B. Agent Options

Our testing suite includes two types of agents: a simulation agent and a real robot agent, both of which support the configurations specified in the configuration options. We used a Unitree G1 humanoid robot, for which SPARK provides an interface in the agent module. G1 humanoid physically features 29 DOFs, but we modeled it as a 20 DOF mobile dual-manipulator system by simplifying the locomotion. For the upper body dynamics, each arm was treated as a general manipulator with seven DOFs, while the waist was equipped with three rotational joints (roll, pitch, yaw). Regarding locomotion, three DOFs were considered: longitudinal, lateral, and rotational in the humanoid's body frame. Table 3 in the Appendix shows the detailed configuration for the G1 humanoid.

1) **Simulation Agent:** As shown in Figure 4 (7). The simulation agent is implemented based on MuJoCo and serves as a benchmark tool for evaluating algorithm performance. Within the simulation environment, users can access the agent's position, joint positions, and other relevant states, facilitating the implementation of various control algorithms.

2) **Real Robot Agent:** As shown in Figure 4 (6). In the real robot agent, users can access low-level interfaces to read the robot's joint position data. Within the testing suite, we utilize Unitree's high-level control API to achieve raw pitch and yaw movements on a 2D plane.

C. Task Options

The testing suite of SPARK provides predesigned tasks to generate reference controls, enabling the evaluation of safe controllers under various scenarios.

1) **Task Objectives Options:** To simulate manipulation and navigation tasks, SPARK provides test suites with **two** types of goal configurations:

Arm Goal: As shown in Figure 4 (8). This goal is used to simulate the manipulation scenario in simulation. The task requires the robot to reach designated static 3D target positions with each hand while ensuring precise and safe movement.

Base Goal: As shown in Figure 4 (9). This goal is used to simulate the navigation scenario in simulation. The task requires the robot to autonomously navigate to a specified 2D goal position while ensuring safe movement and avoiding obstacles in the environment.

In addition to the above two types of goals, users can also configure **Goal Motion**, which includes static and dynamic options. The goals for the arms and the robot base are marked in green spheres in Figure 5.

2) **Task Constraints Options:** To represent collision volumes and evaluate safety performance, SPARK provides test suites with **three** simple yet general constraint configurations:

Obstacle Shape: Various obstacle shapes are provided, including circles and rectangles. Circular obstacles can be used to represent key points of certain objects, while rectangular obstacles are suitable for depicting tables or other square-shaped objects.

Obstacle Motion: Obstacles can be either static or dynamic. Both types are represented as floating spheres that the robot must avoid. Trespassing incurs penalties. Static obstacles remain fixed, while dynamic obstacles move based on predefined patterns, such as Brownian motion.

Obstacle Number: Users have the flexibility to control the number of obstacles within a task. For example, in our experiments, configuration v1 represents a scenario with 10 obstacles, whereas v0 corresponds to a denser environment with 50 obstacles.

The collision volumes of the robot and the environment obstacles are marked in Figure 5. Section XII-F reports the configuration of the robot collision volumes.

3) **Task Interface Options:** Different agents can utilize distinct interfaces. For the Simulation Agent, users can control the position of obstacles using a keyboard, allowing for flexible and interactive environment adjustments within the simulation. In contrast, the Real Robot Agent leverages Apple Vision Pro to track human hand positions in real time, treating them as dynamic obstacles. This enables the real robot to perceive and react to obstacles in its environment, enhancing its ability to perform collision avoidance in real-world scenarios.

D. Policy Options:

We achieve humanoid locomotion tasks using PID control and implement manipulation tasks through a combination of PID control and inverse kinematics (IK). However, the choice of policy is not limited, as SPARK supports user-defined

policies, including data-driven approaches. Additionally, users can replace the standalone safety module with an end-to-end safe reinforcement learning policy, further demonstrating the extensibility of SPARK. Since the model based safe controllers are the primary focus of SPARK, we leave the integration of more complex control policies for future work.

E. Safety Options:

The safe controller of SPARK is aimed at achieving both efficient and safe interaction with the environment by solving the following safe control problem:

$$\begin{aligned} \min_{\mathbf{u}} \quad & \|\mathbf{u} - \mathbf{u}_{\text{ref}}\|_{\mathbf{Q}_u}^2 \\ \text{s.t. } & \dot{\mathbf{x}} = \mathbf{f}(\mathbf{x}) + \mathbf{g}(\mathbf{x})\mathbf{u} \\ & \mathbf{x} \in \mathbf{X}_s \end{aligned} \quad (1)$$

where $\mathbf{x} \in \mathcal{X} \subseteq \mathbb{R}^{N_x}$ represents the system state, and $\mathbf{u} \in \mathcal{U} \subseteq \mathbb{R}^{N_u}$ is the control variable corresponding to the N_u degrees of freedom. \mathbf{Q}_u represents the cost matrix corresponding to \mathbf{u} . $\dot{\mathbf{x}} = \mathbf{f}(\mathbf{x}) + \mathbf{g}(\mathbf{x})\mathbf{u}$ denotes the system dynamics, and \mathbf{X}_s is the set of safe system states. At each timestep, the objective of the control problem is to track the reference control \mathbf{u}_{ref} given by a nominal controller while satisfying both the system dynamic constraints and the safety constraints.

The safe control of humanoid robots faces two major challenges: complex dynamics and dexterous safety. Humanoids integrate mobile robotics and dual-arm manipulation, resulting in a high-dimensional, nonlinear system where the coupling of uncertain legged locomotion and high-DOF arm movements significantly increases control complexity. While some degrees of freedom (DOFs) operate independently, others—such as those affecting localization—impact the entire system, making precise tracking and safe motion in Cartesian space difficult. Beyond dynamic constraints, safety considerations further complicate control. Humanoids must navigate confined spaces, carefully adjusting their poses to avoid collisions with obstacles and themselves. Modeling at a limb level rather than a whole-body level is essential, but this introduces combinatorial safety constraints, creating a highly nonconvex safe state space that challenges real-time safety assurance.

To address these challenges, SPARK provides five different safety algorithms to ensure safe control.

1) *Safe Set Algorithm*: Proposed by [35], Safe Set Algorithm (SSA) introduces a continuous, piecewise smooth energy function $\phi := \mathcal{X} \mapsto \mathbb{R}$, or safety index, to quantify safety while considering the system dynamics. An n^{th} ($n \geq 0$) order safety index ϕ_n has the following general form:

$$\phi_n = (1 + a_1 s)(1 + a_2 s) \dots (1 + a_n s) \phi_0, \quad (2)$$

where s is the differentiation operator. (2) can also be expanded as

$$\phi_n := \phi_0 + \sum_{i=1}^n k_i \phi_0^{(i)}. \quad (3)$$

where $\phi_0^{(i)}$ is the i^{th} time derivative of ϕ_0 . ϕ_n should satisfy that (a) the characteristic equation $\prod_{i=1}^n (1 + a_i s) = 0$ only

has negative real roots to prevent overshooting of ϕ_0 and (b) $\phi_0^{(n)}$ has relative degree one to the control input \mathbf{u} .

Ensuring humanoid safety involves solving optimal control problems with multiple safety constraints due to the limb-level modeling of the robot. To address this challenge, SPARK extends the single-constraint safe control problem described in [35] to handle multi-constraint cases by allowing the safe set of system states, \mathbf{X}_s , to be defined by $M \geq 1$ energy functions ϕ . Formally, the safe set is defined as:

$$\mathbf{X}_s := \{\mathbf{x} \in \mathcal{X} \mid \phi[i](\mathbf{x}) \leq 0, \forall i \in [M]\}. \quad (4)$$

Replacing the original safety constraint $\mathbf{x} \in \mathbf{X}_s$ in (1), the generalized safe control problem solved by SPARK is written as:

$$\begin{aligned} \min_{\mathbf{u}} \quad & \|\mathbf{u} - \mathbf{u}_{\text{ref}}\|_{\mathbf{Q}_u}^2 \\ \text{s.t. } & \dot{\mathbf{x}} = \mathbf{f}(\mathbf{x}) + \mathbf{g}(\mathbf{x})\mathbf{u}, \\ & \forall i \in [M], \dot{\phi}[i](\mathbf{x}, \mathbf{u}) \leq -\eta \quad \text{if } \phi[i](\mathbf{x}) \geq 0. \end{aligned} \quad (5)$$

Where η is a positive constant. It can be shown that under the control constraints in (5), a safe set $\mathbf{X}_{\text{safe}} \subseteq \mathbf{X}_s$ can still be identified. Within this set, both the forward invariance and the finite-time convergence properties are satisfied, ensuring theoretical safety guarantees [36].

2) *Control Barrier Function*: The Control Barrier Function (CBF) method [37] enforces safety constraints continuously by ensuring that $\dot{\phi} < -\alpha(\phi)$, where $\alpha : \mathbb{R} \rightarrow \mathbb{R}$ is a strictly increasing function with $\alpha(0) = 0$.

In its simplest form, α can be chosen as a positive constant λ , leading to a straightforward implementation. When considering multiple safety constraints, the safe control problem solved using CBF can be formulated as:

$$\begin{aligned} \min_{\mathbf{u}} \quad & \|\mathbf{u} - \mathbf{u}_{\text{ref}}\|_{\mathbf{Q}_u}^2 \\ \text{s.t. } & \dot{\mathbf{x}} = \mathbf{f}(\mathbf{x}) + \mathbf{g}(\mathbf{x})\mathbf{u}, \\ & \forall i \in [M], \dot{\phi}[i](\mathbf{x}, \mathbf{u}) \leq -\lambda \phi[i](\mathbf{x}). \end{aligned} \quad (6)$$

As a result, CBF may always deviate from the reference control input \mathbf{u}_{ref} , even when it is safe, i.e., $\phi[i] < 0$. In such cases, the control input may lead to an increase in the safety index $\phi[i]$, potentially reducing efficiency.

3) *Sublevel Safe Set Algorithm*: The Sublevel Safe Set (SSS) algorithm [2] combines the strengths of SSA and CBF to address their respective limitations. It solves the following safe control problem:

$$\begin{aligned} \min_{\mathbf{u}} \quad & \|\mathbf{u} - \mathbf{u}_{\text{ref}}\|_{\mathbf{Q}_u}^2 \\ \text{s.t. } & \dot{\mathbf{x}} = \mathbf{f}(\mathbf{x}) + \mathbf{g}(\mathbf{x})\mathbf{u}, \\ & \forall i \in [M], \dot{\phi}[i](\mathbf{x}, \mathbf{u}) \leq -\lambda \phi[i](\mathbf{x}) \quad \text{if } \phi[i](\mathbf{x}) \geq 0. \end{aligned} \quad (7)$$

In the SSS algorithm, the control correction is only applied when $\phi[i](\mathbf{x}) \geq 0$, allowing for a more efficient correction compared to CBF. Since the constraint is inactive when $\phi[i](\mathbf{x}) < 0$, the robot achieves better performance while tracking the reference control input \mathbf{u}_{ref} .

4) *Potential Field Method*: PFM [3] computes the control input \mathbf{u} indirectly by first deriving a Cartesian-space control input \mathbf{u}_c . By defining the function $\mathbf{c}_r = \mathbf{h}(\mathbf{x})$, which calculates the closest point on the robot to the obstacles, the Cartesian-space dynamics can be written as:

$$\dot{\mathbf{c}}_r = \mathbf{u}_c := \mathbf{u}_{c\text{-ref}} + \mathbf{u}_c^*, \quad (8)$$

where $\mathbf{u}_{c\text{-ref}}$ is the reference control in the Cartesian space transformed from \mathbf{u}_{ref} via:

$$\mathbf{u}_{c\text{-ref}} = \nabla \mathbf{h}(\mathbf{x}) \mathbf{f}(\mathbf{x}) + \nabla \mathbf{h}(\mathbf{x}) \mathbf{g}(\mathbf{x}) \mathbf{u}_{\text{ref}}. \quad (9)$$

The term \mathbf{u}_c^* represents a repulsive "force" added to the reference $\mathbf{u}_{c\text{-ref}}$ to push the robot away from the obstacles whenever the safety constraint is violated. Specifically:

$$\mathbf{u}_c = \begin{cases} \mathbf{u}_{c\text{-ref}} - c_1 \nabla \tilde{\phi} & \text{if } \tilde{\phi}(\mathbf{c}_r) \geq 0, \\ \mathbf{u}_{c\text{-ref}} & \text{otherwise,} \end{cases} \quad (10)$$

where $c_1 > 0$ is a tunable constant and $\tilde{\phi}(\mathbf{c}_r)$ is the energy function with respect to the Cartesian point \mathbf{c}_r . Finally, the equivalent control input \mathbf{u} in the configuration space is derived from \mathbf{u}_c .

5) *Sliding Mode Algorithm*: SMA [38] ensures safety by maintaining the system state around a sliding layer defined by $\phi = 0$ whenever the safety constraint is violated.

For a single safety index ϕ , its gradient can be decomposed as:

$$\begin{aligned} \dot{\phi}(\mathbf{x}) &= \nabla \phi^\top(\mathbf{x}) \dot{\mathbf{x}} \\ &= \nabla \phi^\top(\mathbf{x}) (\mathbf{f}(\mathbf{x}) + \mathbf{g}(\mathbf{x}) \mathbf{u}) \\ &= \underbrace{\nabla \phi^\top(\mathbf{x}) \mathbf{f}(\mathbf{x})}_{L_f \phi} + \underbrace{\nabla \phi^\top(\mathbf{x}) \mathbf{g}(\mathbf{x}) \mathbf{u}}_{L_g \phi}, \end{aligned} \quad (11)$$

where the term $L_g \phi$ represents the sensitivity of the safety index ϕ to the control input \mathbf{u} .

To handle multiple constraints, SPARK considers only the most unsafe safety index, denoted as ϕ_{\max} , and corrects the reference control input as follows:

$$\mathbf{u} = \begin{cases} \mathbf{u}_{\text{ref}} - c_2 L_g \phi_{\max}^\top & \text{if } \phi_{\max} \geq 0, \\ \mathbf{u}_{\text{ref}} & \text{otherwise,} \end{cases} \quad (12)$$

where the constant $c_2 > 0$ is set sufficiently large to ensure that:

$$\dot{\phi}_{\max} = L_f \phi_{\max} + L_g \phi_{\max} \mathbf{u} - c_2 \|L_g \phi_{\max}\|^2 < 0. \quad (13)$$

By doing so, SMA ensures that the system remains in a safe state while effectively handling multiple constraints.

F. Evaluation metrics

SPARK provides four metrics to assess the performance of various safe control methods across different benchmark scenarios, evaluating both their safety and efficiency:

- Step-wise average arm goal tracking score J_{arm} .
- Step-wise average base goal tracking score J_{base} .
- Step-wise average self safety score M_{self} .
- Step-wise average environment safety score M_{env} .

Formally,

$$J_{\text{arm}} = \frac{1}{T} \sum_{t=0}^T \mathcal{G}(\Delta d_{\text{arm}}, \sigma_{\text{arm}}), \Delta d_{\text{arm}} \geq 0 \quad (14)$$

$$J_{\text{base}} = \frac{1}{T} \sum_{t=0}^T \mathcal{G}(\Delta d_{\text{base}}, \sigma_{\text{base}}), \Delta d_{\text{base}} \geq 0 \quad (15)$$

$$M_{\text{self}} = \frac{1}{T} \sum_{t=0}^T \mathcal{G}(\Delta d_{\text{self}}, \sigma_{\text{self}}), \Delta d_{\text{self}} \leq 0 \quad (16)$$

$$M_{\text{env}} = \frac{1}{T} \sum_{t=0}^T \mathcal{G}(\Delta d_{\text{env}}, \sigma_{\text{env}}), \Delta d_{\text{env}} \leq 0 \quad (17)$$

where Δd_{arm} is the distance from the robot's hands to the corresponding goals, Δd_{base} is the distance from the robot's pelvis to the corresponding base goal, Δd_{env} is the violated distance between the robot and obstacles, and d_{self} is the violated distance between the robot's collision volumes.

\mathcal{G} is the goal tracking score function, which converts the distance into a score within the range $[0, 1]$. The closer the distance to 0, the higher the score.

The score function is defined as follows:

$$\mathcal{G}(\Delta d, \delta) = \exp \left[-\frac{\Delta d^2}{\sigma} \right] \quad (18)$$

To demonstrate the versatility of the SPARK framework, we deploy its safe control pipelines across various use cases. The agents range from a simulated humanoid robot to the real Unitree G1 humanoid robot, while the task inputs vary from autonomous target trajectories to teleoperation commands. Additionally, the environments span from static confined spaces to dynamic human-robot interaction scenarios. The various use cases are designed to serve multiple purposes, including benchmarking safe control algorithms V, deploying them on real robots VII, enabling safe teleoperation for human-robot interaction (HRI) scenarios VIII, and allowing users to teleoperate a simulated robot with visual feedback VI. The details of each use case, along with their corresponding sections, are outlined in Section XII-D

V. USE CASE 1: BENCHMARKING SAFE CONTROL ALGORITHMS

To demonstrate SPARK's capability as a benchmarking toolbox for safe control, we utilize it to systematically evaluate various algorithms under different constraints and objectives. By leveraging SPARK's suite options, we ensure fair comparisons and gain insights into algorithmic performance, safety-efficiency trade-offs, and task complexity effects. In our experiments, we aim to address the following questions:

Q1: What are the overall benchmark results?

Q2: How do various safe control algorithms balance the trade-off between safety and efficiency?

Q3: How do different types of constraints affect algorithm performance?

Table 1: Performance metrics for different tasks. The table presents the scores obtained by each algorithm using its optimal parameters. The final scores are computed based on these selections. **Bold**: The highest score among different algorithms for the same task and metric. **Blue**: The lowest score among different algorithms for the same task and metric.

Algorithm	Metric	G1WholeBody		G1WholeBody		G1FixedBase		G1FixedBase	
		WG_SO_v1	WG_SO_v0	WG_DO_v1	WG_DO_v0	AG_SO_v1	AG_SO_v0	AG_DO_v1	AG_DO_v0
SSA	J_{arm}	0.8691	0.8318	0.8536	0.6780	0.6202	0.7090	0.5810	0.5680
	J_{base}	0.5517	0.5805	0.5065	0.6221	NA	NA	NA	NA
	M_{self}	1.0000							
	M_{env}	0.9010	0.8784	0.8876	0.7222	0.7590	0.6815	0.3448	0.3745
PFM	J_{arm}	0.8535	0.6357	0.8482	0.6502	0.4019	0.3077	0.3143	0.3642
	J_{base}	0.5062	0.5584	0.4971	0.5839	NA	NA	NA	NA
	M_{self}	1.0000	1.0000	1.0000	0.9658	1.0000	1.0000	0.6328	1.0000
	M_{env}	0.8374	0.5390	0.5977	0.3364	0.4767	0.3649	0.2794	0.2299
CBF	J_{arm}	0.8761	0.8290	0.8662	0.7275	0.6742	0.5726	0.5538	0.5705
	J_{base}	0.5277	0.5910	0.5060	0.6193	NA	NA	NA	NA
	M_{self}	1.0000	1.0000	1.0000	0.9472	1.0000	1.0000	1.0000	1.0000
	M_{env}	0.9819	0.9596	0.3674	0.8995	0.8687	0.8631	0.2387	0.2512
SMA	J_{arm}	0.8808	0.8649	0.8816	0.8443	0.6276	0.7028	0.5720	0.5915
	J_{base}	0.5116	0.5268	0.4824	0.6059	NA	NA	NA	NA
	M_{self}	1.0000	1.0000	1.0000	0.6619	1.0000	1.0000	1.0000	1.0000
	M_{env}	0.8582	0.6254	0.4925	0.2863	0.6994	0.5876	0.5345	0.4155
SSS	J_{arm}	0.8761	0.8306	0.8732	0.7253	0.6752	0.7179	0.5839	0.5634
	J_{base}	0.5281	0.5907	0.4997	0.6170	NA	NA	NA	NA
	M_{self}	1.0000	1.0000	1.0000	0.9497	1.0000	1.0000	1.0000	1.0000
	M_{env}	0.9844	0.9685	0.9380	0.9026	0.8618	0.6728	0.3538	0.3749

Q4: How does task complexity influence algorithm performance?

Q5: How does the success rate of each algorithm compare?

A. Experimental Setup

a) *Experiment tasks*: By combining the robot, task, and constraint options introduced in Section IV, 8 benchmark tests are designed for the evaluation and comparison of algorithm performance. These predefined benchmark testing suites adhere to the standardized format: $\{\text{Robot}\}_{\{\text{Task}\}_{\{\text{Constraint}\}_{\{\text{Version}\}}}}$. The configuration of all experiment tasks is introduced in Section XII-E. In this format, **WG** represents *Whole Body Goal*, **AG** stands for *Arm Goal*, **SO** denotes *Static Obstacle*, and **DO** refers to *Dynamic Obstacle*. In particular, this benchmark does not provide WG as a standalone task; instead, WG indicates a combination of both *Arm Goal* and *Base Goal*. In addition to obstacles, self-collision is also taken into consideration. For more details, please refer to Section XII-C. In our experiments, we analyze and compare the performance of these algorithms using the metrics provided in Section IV-F. We use $\sigma_{arm} = 0.002$, $\sigma_{base} = 0.05$, and $\sigma_{env} = \sigma_{self} = 0.0002$ to scale the scores to fit the magnitude of the raw distance.

b) *Comparison Group*: To evaluate the performance of the SPARK safe control library, we define a comparison group consisting of various alternative approaches. The methods in this group include all the techniques available in the safe control library SPARK: (i) Safe Set Algorithm (SSA) [35], (ii) Control Barrier Function (CBF) [37], (iii) Sublevel Safe Set (SSS) [2], (iv) Potential Field Method (PFM) [3], and (v) Sliding Mode Algorithm (SMA) [38].

c) *Overall Benchmark Results*: Table 1 presents the overall benchmark performance results, evaluating different safety controllers in terms of safety and efficiency metrics. The experimental results indicate significant variations in the performance of different methods across various tasks and robotic setups. Specifically, in terms of motion accuracy and environmental safety, PFM exhibited the weakest overall performance, whereas optimization-based methods such as SSA, CBF, and SSS demonstrated a superior balance between safety and efficiency. Notably, despite not relying on optimization for safety control, SMA still managed to achieve a commendable trade-off between safety and efficiency.

PFM consistently showed low motion accuracy and environmental safety scores across all tasks, with particularly poor performance in fixed-base robotic tasks, where both its safety and execution efficiency were significantly lower than those of other methods. This suggests that PFM struggles to ensure feasibility in complex environments and is more susceptible to environmental constraints, leading to a higher risk of collisions. The primary issue with PFM is its reliance solely on repulsive forces in low-dimensional Cartesian space, making it ineffective in handling complex constraints in high-dimensional joint space, thereby limiting its safety control capabilities.

In contrast, SSA exhibited stable environmental safety across all tasks, demonstrating strong adaptability to external constraints. However, in fixed-base robotic tasks, SSA's motion accuracy was somewhat reduced, indicating that it may encounter challenges when dealing with scenarios where movement degrees of freedom are restricted.

CBF excelled in environmental safety, significantly outperforming PFM and showcasing its advantage in minimizing

environmental collisions. However, compared to SSA, CBF exhibited slightly lower motion accuracy, suggesting that in certain tasks, it may sacrifice some execution efficiency to achieve higher safety.

As an optimization-based method, SSS demonstrated stable safety and execution efficiency across multiple tasks. For example, in some mobile robot tasks, its motion accuracy was comparable to SSA and CBF, while its environmental safety performance exceeded that of other methods. Additionally, in fixed-base robotic tasks, SSS achieved higher motion accuracy than other optimization methods, indicating that its optimization strategy effectively adapts to task requirements.

Unlike optimization-based methods, SMA does not rely on optimization for safety control; instead, it refines control signals by decomposing the gradient of the safety index, thereby preserving effective task execution capabilities. The experimental results reveal that SMA generally achieved higher motion accuracy than other method in most tasks, while also maintaining high stability in environmental safety. This suggests that SMA can reduce environmental collision risks while ensuring smooth task execution.

d) Trade-off between Safety and Efficiency: Balancing performance between safety and efficiency is a key challenge for every safe controller. To explore this trade-off, we tuned the parameters of each safe control algorithm across various scales: from 0 to 1 in steps of 0.1, from 1 to 10 in steps of 1, from 10 to 100 in steps of 10, and from 100 to 1000 in steps of 10. These experiments were conducted under different tasks, enabling us to plot safety and efficiency performance on the same graph. By extracting the convex hull of the sampled parameters, We generated the trade-off curves and selected two representative scenarios, as shown in Figure 6, which illustrate how each controller balances safety and efficiency. The efficiency is defined as $\frac{J_{arm}+J_{base}}{2}$ and is plotted on the x-axis, while the average safety score ($\frac{M_{self}+M_{env}}{2}$) is plotted along the y-axis.

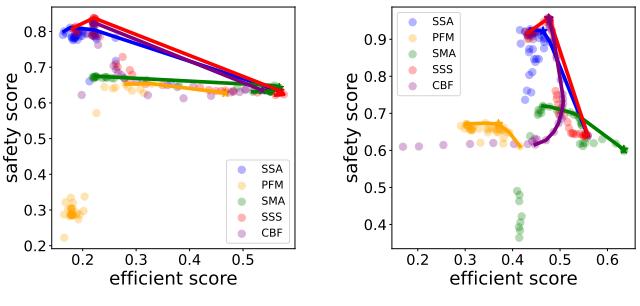


Figure 6: Comparison of trade-off curves between safety and efficiency for different robot configurations.

The results indicate that as parameters vary, safety and efficiency may adjust in opposition to each other. On average, SMA and PFM achieve better balance, while SSA, SSS and CBF excel at achieving higher safety scores without collisions. This behavior arises because, when their respective parameters

c_{sma} and c_{pfm} approach zero, SMA and PFM cease correcting the reference control and revert to nominal controllers. However, PFM exhibits a less favorable trade-off curve compared to SMA due to its incompatibility with high-dimensional robotic systems and environments with multiple constraints.

Optimization-based methods, on the contrary, require their parameters to remain positive scalars, which consistently introduce additional safety constraints into the control problem. These methods prioritize ensuring safety over minimizing control deviations from the reference control. Unlike other optimization-based methods, CBF simultaneously impacts both safety and efficiency. This is due to its control law, which enforces that $\dot{\phi}$ remains below an upper bound.

When the CBF parameter λ_{cbf} is too small, the robot may reduce the safety index unnecessarily even in safe environments, negatively impacting efficiency. Additionally, a small λ_{cbf} limits the safety constraints' ability to react rapidly in unsafe situations. Conversely, a large λ_{cbf} imposes overly strict safety constraints, even for minor safety violations, which can hinder efficiency.

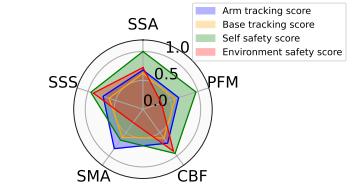
In the other comparison experiments, the parameter for each algorithm is picked to achieve the best trade-off balancing. The optimal parameters for each algorithm and task are marked in Figure 17 and Section XII-G reports the parameters used for the rest experiments.

e) Impacts of Constraint Types: As shown in Figure 7, obstacle motion and obstacle number both significantly impact algorithm performance. Dynamic obstacles introduce greater safety challenges compared to static ones. The radar charts illustrate that when obstacles are in motion, the corresponding **Arm Tracking Score** and **Environment Safety Score** tend to decrease. Furthermore, a comparison between v0 and v1 reveals that v1, which has fewer obstacles, achieves higher **Arm Tracking Score** and **Environment Safety Score**. This observation underscores the fact that a greater number of obstacles exerts a more pronounced negative impact on performance.

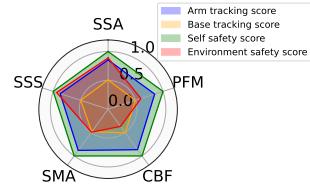
The other benchmark performance comparison is provided in Section XII-K and Table 1.

f) Influence of Task Difficulty: From Figure 6, it is evident that task difficulty significantly affects performance. For instance, when the robot is required to track both arm and base goals using whole-body movement, its performance is lower compared to tasks where a fixed base allows it to focus solely on arm goal tracking. This is because tracking the robot's base goal may require sacrificing arm goal tracking to avoid collisions and reach the base target.

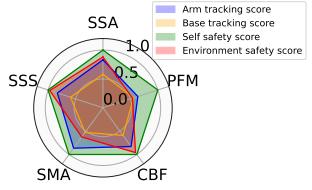
g) Success Rate across various Algorithms: In addition to evaluating average step-wise performance, it is crucial to assess whether the safe controllers can successfully complete tasks trajectory-wise. A trajectory is defined to be successful if the robot reaches the goal without collisions within a maximum number of steps. In this evaluation, 50 feasible environment settings were generated and each algorithm was tested under these settings. The maximum number of steps was set to 200. The success results of each algorithm are



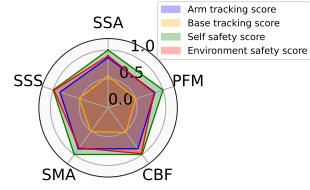
(a) G1WholeBody_WG_DO_v0



(b) G1WholeBody_WG_DO_v1



(c) G1WholeBody_WG_SO_v0



(d) G1WholeBody_WG_SO_v1

Figure 7: Performance comparison of the benchmark.

Table 2: Success rate for Different Tasks and Algorithms

Task Name	SSA	PFM	CBF	SMA	SSS
G1WholeBody_WG_SO_v1	0.9667	0.9500	1.0000	0.9667	1.0000
G1WholeBody_WG_SO_v0	0.9333	0.5667	0.9333	0.6333	0.9333
G1WholeBody_WG_DO_v1	0.9833	0.9500	0.8833	0.9833	1.0000
G1WholeBody_WG_DO_v0	0.7833	0.5667	0.8500	0.4667	0.8500
G1FixedBase_AG_SO_v1	1.0000	0.6667	1.0000	1.0000	1.0000
G1FixedBase_AG_SO_v0	0.8667	0.4167	0.7000	0.9500	0.9000
G1FixedBase_AG_DO_v1	0.8833	0.6333	0.5500	0.9500	0.9000
G1FixedBase_AG_DO_v0	0.8167	0.4167	0.4833	0.9500	0.8000

listed in Table 2, which shows the conditional success rate of the algorithms. Detailed results are provided in Section XII-I. From these results, it can be observed that SSS achieves the highest success rate for tasks involving whole-body motion. The second is CBF. For tasks with a fixed base, SMA attains the highest success rate, while SSS and SSA also perform well. This suggests that optimization-based methods, such as SSS and SSA, are better equipped to handle multiple constraints in complex environments. Conversely, SMA’s safe correction is more efficient for relatively simple tasks. Among all algorithms, PFM exhibits the lowest success rate.

Beyond individual success rates, it is also informative to examine the relative advantages between pairs of safe control algorithms. To do this, we define the conditional success rate $P(B|A)$ as:

$$P(B|A) = \frac{\#(A \cap B)}{\#A}, \quad (19)$$

where $\#(B \cap A)$ represents the number of environments successfully completed by both algorithm A and algorithm B , and $\#A$ represents the number of environments successfully completed only by algorithm A .

Figure 8 presents a heatmap of the conditional success rates for each task where the value of the cell (i, j) is calculated by $P(algo[j]|algo[i])$. The results indicate that optimization-based methods, such as SSA, SSS, and CBF,

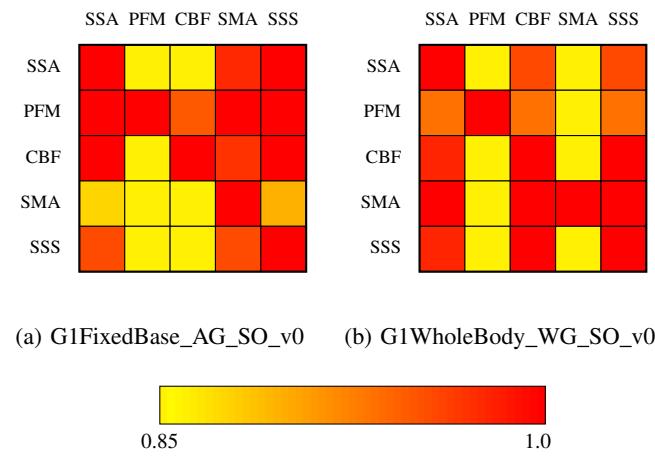


Figure 8: Conditional success plots for selected tasks.

significantly outperform PFM and SMA in success rates. Furthermore, the comparison of conditional success rates reveals that $P(SSA|CBF) > P(CBF|SSA)$ in five out of eight tasks, indicating that SSA successfully completes most of the trajectories that CBF can achieve in these cases. In contrast, CBF does not achieve the same success rate. Detailed conditional success rates are reported in Section XII-J and Section XII-M.

In conclusion, using SPARK as a safe control benchmark highlights its composability by enabling the convenient generation of large-scale testing configurations. As a benchmarking framework, it also provides users with a structured parameter-tuning process and a comprehensive understanding of the implemented safe control algorithms, aiding in the synthesis of the most suitable safe controller for each task. The results indicate that there is still significant room for improvement in safe controller design to achieve a fully guaranteed 100% safety assurance, presenting further challenges for future research.

VI. USE CASE 2: SAFE TELEOPERATION WITH SIMULATED ROBOT

This section presents a user scenario in which teleoperation is performed within a simulation environment to collect human data in the absence of available hardware [39, 40, 41].

To meet this requirement, we configure the robot with G1fixedBase while selecting the simulation agent in SPARK. By designing a **Task** module where a cabinet acts as an obstacle and the human teleoperation serves as the task goal—while taking human input through an external Apple Vision Pro block—we can retain the same **Policy** and **Safety** modules as in the previous use case (Section VIII).

From the first two figures in Figure 9, we observe that the robot’s hands can maneuver into a confined cabinet under user teleoperation. In the fourth figure, we see that when the green spheres—representing the teleoperation target positions for the hands—move outside the cabinet, the robot’s hands remain inside to ensure safety, demonstrating the effectiveness of the safe controller.

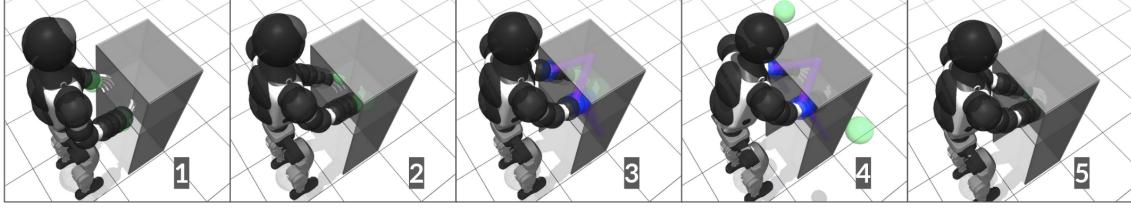


Figure 9: VI The first two illustrate how the robot’s hands successfully reach into a confined cabinet under user teleoperation. In the fourth figure, even when the green spheres—representing the target positions for teleoperation—move outside the cabinet, the robot’s hands stay within the safe region. This demonstrates the controller’s ability to enforce safety constraints while following user commands.

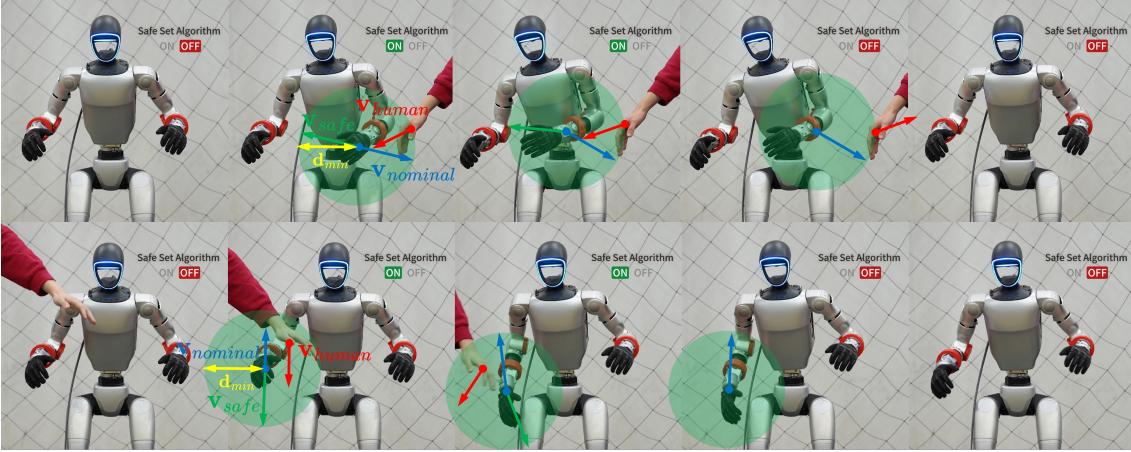


Figure 10: VII Limb-level collision avoidance with static humanoid reference pose: the robot moves away when the human hand gets closer than d_{\min} and resumes its target position once the hand retreats and the environment is safe.

This scenario highlights the flexibility of SPARK in integrating human input with simulated robots. It not only guarantees absolute safety for algorithm verification but also provides users with richer visual feedback that cannot be directly obtained from real robot teleoperation, such as the spatial relationship between the robot’s hands and obstacles. Moreover, it offers an intuitive and efficient way to collect human demonstration data without relying on real robot hardware.

VII. USE CASE 3: SAFE AUTONOMY ON REAL ROBOT

To showcase the practical applicability of the SPARK framework, we deployed its safe control pipelines on a real robot. For our experiments, we utilized the Unitree G1 humanoid robot, which features 29 degrees of freedom (DOFs). The perception module incorporated an Apple Vision Pro to capture human gestures and determine the robot’s position. The robot’s dynamic system was modeled as a mobile dual-manipulator system.

Building on the benchmark use case introduced in Section V, we only need to replace the agent module with the real G1 SDK and integrate the Apple Vision Pro interface into the task module. With these modifications, the control algorithms validated in the benchmark can be directly deployed on the real robot.

We begin with the simplest task, in which the robot remains in a fixed position while avoiding potential collisions with the human user. As shown in Figure 10, when the user attempts

to approach the robot arm from various angles, the robot reacts by moving away from the human hand if the minimum distance between them becomes smaller than d_{\min} . Once the robot detects that the human hand has moved away and the surrounding environment is safe, it resumes following the nominal controller’s inputs, which commands it to remain in the target static position.

We further evaluate the performance of the SPARK safe controller in tracking a dynamic target position by designing a dynamic limb-level collision avoidance test case. Unlike the static test, where the nominal controller simply tracks a fixed target, the nominal controller in the dynamic test is tasked with following a dynamic target $\mathbf{x}_{\text{target}}^R$. Specifically, the nominal controller tracks a circular trajectory for the right hand. In this case, the robot must track the target trajectory while simultaneously avoiding collisions with the human user using the same safety index ϕ as previously defined.

From Figure 12, we observe that when the human hand remains outside the d_{\min} region, the robot follows the reference trajectory and moves along the circular path. If a human hand gets too close to the robot’s hands, the humanoid will use both its waist and arm movements to avoid a collision, regardless of the target’s motion. In other words, the safety constraint takes precedence over the normal control input, ensuring the humanoid remains safe. Once the human hand moves away, the robot returns to the reference trajectory while remaining prepared for potential collision avoidance.

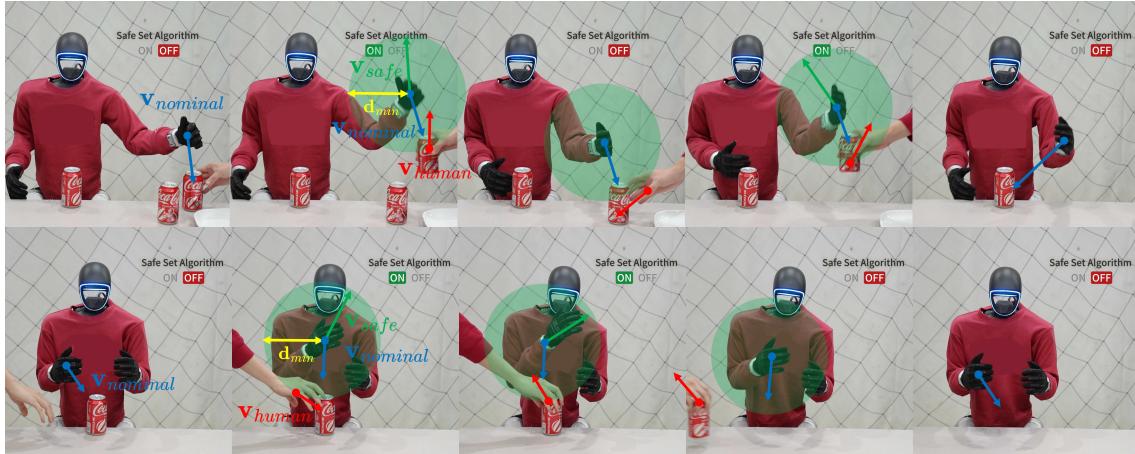


Figure 11: VIII Limb-level collision avoidance with teleoperation commands: if the human user reaches for the same object as the robot, the safe controller is triggered, prioritizing collision avoidance over teleoperation commands to ensure safe interaction and prevent hazards from limited remote perception.

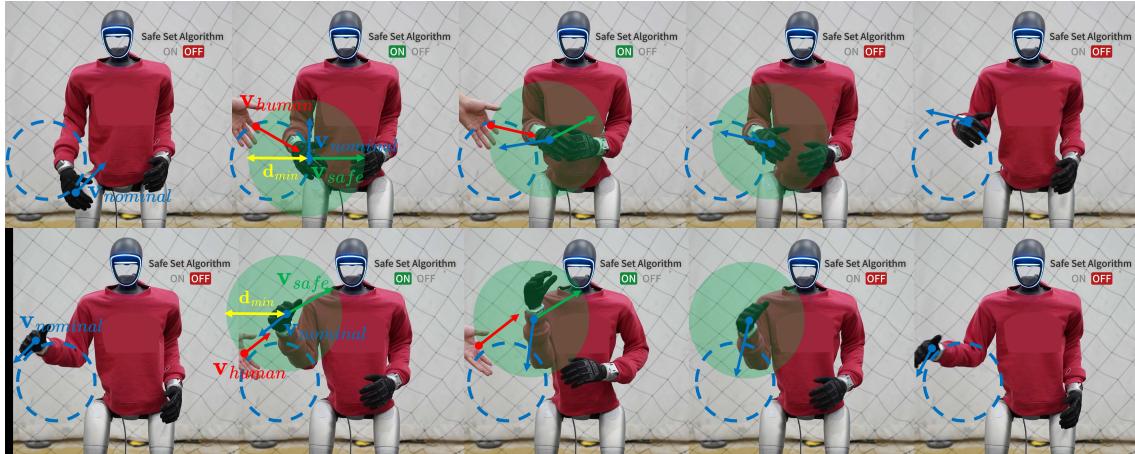


Figure 12: VII Limb-level collision avoidance with dynamic humanoid reference poses: when the human hand stays outside d_{\min} , the robot follows the reference trajectory. If it gets too close, the humanoid adjusts its waist and arms to avoid collision, prioritizing safety. Once the hand moves away, the robot resumes its trajectory while remaining prepared.

VIII. USE CASE 4: SAFE TELEOPERATION WITH REAL ROBOT

As teleoperation becomes more widely used to control humanoid robots [42, 43], it is paramount to ensure safety in this operating mode. Thus, this section assesses the safe controller’s performance in more general scenarios, in which the humanoid robot is tasked with following a human user’s teleoperation commands while ensuring collision avoidance. This setup introduces the concept of “Safe Teleoperation.”

In this test, the nominal humanoid controller’s target, $\mathbf{x}_{\text{target}}^R$, is not pre-designed but is instead generated in real-time by the human teleoperator. This adds complexity, as the robot must generate safe motions in an unpredictable and dynamic environment.

To implement this, we only needed to make a simple modification to the task module of SPARK, adding the operator’s hand positions as the goal positions for the robot’s arms. Meanwhile, other human participants were treated as obstacles to ensure safe human-robot interaction.

In our experiment, we created a realistic scenario where the robot attempts to retrieve objects from a table. Figure 11 shows if the human user reaches for the same object as the robot, the safe controller is triggered. The robot prioritizes collision avoidance over executing the teleoperation commands, ensuring safe interaction and protecting both the humanoid robot and the human from potential hazards caused by the limited perception of a remote teleoperator.

IX. LIMITATIONS

Aiming to be a general and user-friendly benchmark, SPARK has several potential limitations slated for future improvements.

In the current version, the safe control library supports first-order safe control, which implicitly assumes the robot can track an arbitrary velocity command immediately. However, as the motors have limited torques, if the velocity goal is generated to be too different from the current velocity, there may be delays in tracking the goal and impacting safety. To

mitigate this issue, we will need to support higher-order safe controls in the future.

Another limitation is that the current implementation does not distinguish between inevitable collisions from method failures (i.e., there are feasible collision-free trajectories but the method could not find one). Method failures happen when multiple safety constraints are in conflict, which does not necessarily imply a collision is inevitable. To mitigate this issue, more research is needed to either improve the safe control methods in handling multiple constraints or introduce advanced methods in detecting inevitable collisions.

Finally, the sim to real gap also exists in model-based control systems, although it is called differently as “model mismatch”. For the real deployment, the robot trajectory might be different from the simulation due to “model mismatch”. To mitigate this problem, the system model needs to be robustified and the system control needs to be aware of potential gaps, which will be left for future work.

X. CONCLUSION AND FUTURE WORK

In this paper, we presented SPARK, a comprehensive benchmark designed to enhance the safety of humanoid autonomy and teleoperation. We introduced a safe humanoid control framework and detailed the core safe control algorithms upon which SPARK is built.

SPARK offers configurable trade-offs between safety and performance, allowing it to meet diverse user requirements. Its modular design, coupled with accessible APIs, ensures compatibility with a wide range of tasks, hardware systems, and customization levels. Additionally, SPARK includes a simulation environment featuring a variety of humanoid safe control tasks that serve as benchmark baselines. By utilizing SPARK, researchers and practitioners can accelerate humanoid robotics development while ensuring robust hardware and environmental safety.

Beyond what was mentioned in the previous section, there are several future directions for SPARK that could benefit from community collaboration. First of all, it is important to further lower the barrier for users to adopt state-of-the-art safety measures [15], e.g., safe reinforcement learning approaches [44][45][13] [46], by integrating them into SPARK algorithm modules. Secondly, to enhance the robustness and reliability of the deployment pipeline of SPARK, future works are needed to extend SPARK compatibility with standardized safety assessment pipelines, such as stress testing tools and formal verification tools [47]. Thirdly, simplifying task specification is critical for usability. Enhancements to SPARK’s interface, such as intuitive configuration, natural language-based task definitions [48], and interactive visualizations [49], will enable more efficient safety policy design and debugging. Finally, automating the selection and tuning [50] of safety strategies will make SPARK more adaptive. Future efforts may explore automatic model-based synthesis approaches such as meta-control [51] techniques to dynamically optimize safety measures based on task requirements and environmental conditions.

XI. ACKNOWLEDGEMENT

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XII. APPENDIX

A. Software framework

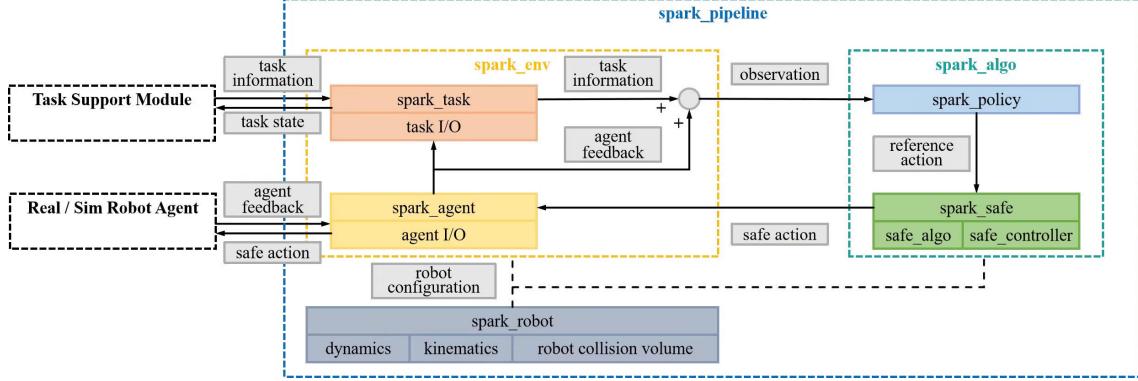


Figure 13: SPARK system framework.

B. Robot configuration

Table 3: Robot configuration

Degree of freedom	Fixed	Whole
WaistYaw	✓	✓
WaistRoll	✓	✓
WaistPitch	✓	✓
LeftShoulderPitch	✓	✓
LeftShoulderRoll	✓	✓
LeftShoulderYaw	✓	✓
LeftElbow	✓	✓
LeftWristRoll	✓	✓
LeftWristPitch	✓	✓
LeftWristYaw	✓	✓
RightShoulderPitch	✓	✓
RightShoulderRoll	✓	✓
RightShoulderYaw	✓	✓
RightElbow	✓	✓
RightWristRoll	✓	✓
RightWristPitch	✓	✓
RightWristYaw	✓	✓
LinearX		✓
LinearY		✓
RotYaw		✓

C. Self-collision configuration

Joint 1	Joint 2
left_shoulder_roll_joint	left_elbow_joint
left_shoulder_roll_joint	right_shoulder_roll_joint
left_shoulder_roll_joint	right_elbow_joint
left_shoulder_roll_joint	L_ee
left_shoulder_roll_joint	R_ee
left_shoulder_roll_joint	torso_link_3
left_elbow_joint	right_shoulder_roll_joint
left_elbow_joint	right_elbow_joint
left_elbow_joint	L_ee
left_elbow_joint	R_ee
left_elbow_joint	torso_link_1
left_elbow_joint	torso_link_2
left_elbow_joint	torso_link_3
right_shoulder_roll_joint	right_elbow_joint
right_shoulder_roll_joint	L_ee
right_shoulder_roll_joint	R_ee
right_shoulder_roll_joint	torso_link_3
right_elbow_joint	L_ee
right_elbow_joint	R_ee
right_elbow_joint	torso_link_1
right_elbow_joint	torso_link_2
right_elbow_joint	torso_link_3
L_ee	R_ee
L_ee	torso_link_1
L_ee	torso_link_2
L_ee	torso_link_3
R_ee	torso_link_1
R_ee	torso_link_2
R_ee	torso_link_3

Table 4: Self-collision joint pairs

D. Use cases

Table 5: Use Cases

Use Cases	Configuration	Agent	Task		Policy	Safety
			Objective	Constraints		
Benchmark V	All	Simulation	All (Autonomy)	All	PID+IK	All
Simulation teleoperation VI	G1FixedBase	Simulation	Arm Goal (Teleoperation)	Static	PID+IK	SSA
Real autonomy VII	G1FixedBase	Real Robot	Arm Goal (Autonomy)	Dynamic	PID+IK	SSA
Real teleoperation VIII	G1FixedBase	Real Robot	Arm Goal (Teleoperation)	Dynamic	PID+IK	SSA

E. Task configuration

Table 6: Configuration Parameters for Different Test Cases

Task Name	Robot Class	Num Obstacles	Obstacle Velocity	Arm Goal Velocity	Base Goal Velocity
G1WholeBody_WG_SO_v1	G1WholeBodyConfig	10	0.0	0.0	0.0
G1WholeBody_WG_SO_v0	G1WholeBodyConfig	50	0.0	0.0	0.0
G1WholeBody_WG_DO_v1	G1WholeBodyConfig	10	0.005	0.0	0.0
G1WholeBody_WG_DO_v0	G1WholeBodyConfig	50	0.005	0.0	0.0
G1FixedBase_AG_SO_v1	G1FixedBaseConfig	10	0.0	0.0	N/A
G1FixedBase_AG_SO_v0	G1FixedBaseConfig	50	0.0	0.0	N/A
G1FixedBase_AG_DO_v1	G1FixedBaseConfig	10	0.005	0.0	N/A
G1FixedBase_AG_DO_v0	G1FixedBaseConfig	50	0.005	0.0	N/A

F. Collision volume configuration

Table 7: Collision Volume Properties by Frame

Frame Name	Type	Radius	EnvCollision	SelfCollision
WaistYaw	Sphere	0.05		
WaistRoll	Sphere	0.05		
WaistPitch	Sphere	0.05		
LeftShoulderPitch	Sphere	0.05	✓	
LeftShoulderRoll	Sphere	0.06	✓	✓
LeftShoulderYaw	Sphere	0.05	✓	
LeftElbow	Sphere	0.05	✓	✓
LeftWristRoll	Sphere	0.05	✓	
LeftWristPitch	Sphere	0.05	✓	
LeftWristYaw	Sphere	0.05	✓	
RightShoulderPitch	Sphere	0.05	✓	
RightShoulderRoll	Sphere	0.06	✓	✓
RightShoulderYaw	Sphere	0.05	✓	
RightElbow	Sphere	0.05	✓	✓
RightWristRoll	Sphere	0.05	✓	
RightWristPitch	Sphere	0.05	✓	
RightWristYaw	Sphere	0.05	✓	
L_ee	Sphere	0.05	✓	✓
R_ee	Sphere	0.05	✓	✓
TorsoLink1	Sphere	0.10	✓	✓
TorsoLink2	Sphere	0.10	✓	✓
TorsoLink3	Sphere	0.08	✓	✓
PelvisLink1	Sphere	0.05		
PelvisLink2	Sphere	0.05		
PelvisLink3	Sphere	0.05		

G. Algorithm hyperparameters

Table 8: Task and Algorithm Parameter Relationships

Task	SSA (η_{ssa})	SSS (λ_{sss})	CBF (λ_{cbf})	PFM (c_{pfm})	SMA (c_{sma})
G1WholeBody_WG_SO_v1	0.8	60.0	80.0	0.9	6.0
G1WholeBody_WG_SO_v0	0.2	60.0	100.0	0.8	9.0
G1WholeBody_WG_DO_v1	0.9	200.0	3.0	2.0	7.0
G1WholeBody_WG_DO_v0	0.4	100.0	100.0	0.7	0.1
G1FixedBase_AG_SO_v1	0.2	10.0	20.0	0.1	40.0
G1FixedBase_AG_SO_v0	0.01	0.4	6.0	1.0	7.0
G1FixedBase_AG_DO_v1	0.01	0.7	0.5	0.4	6.0
G1FixedBase_AG_DO_v0	0.01	0.01	1.0	0.01	6.0

H. Robot frame

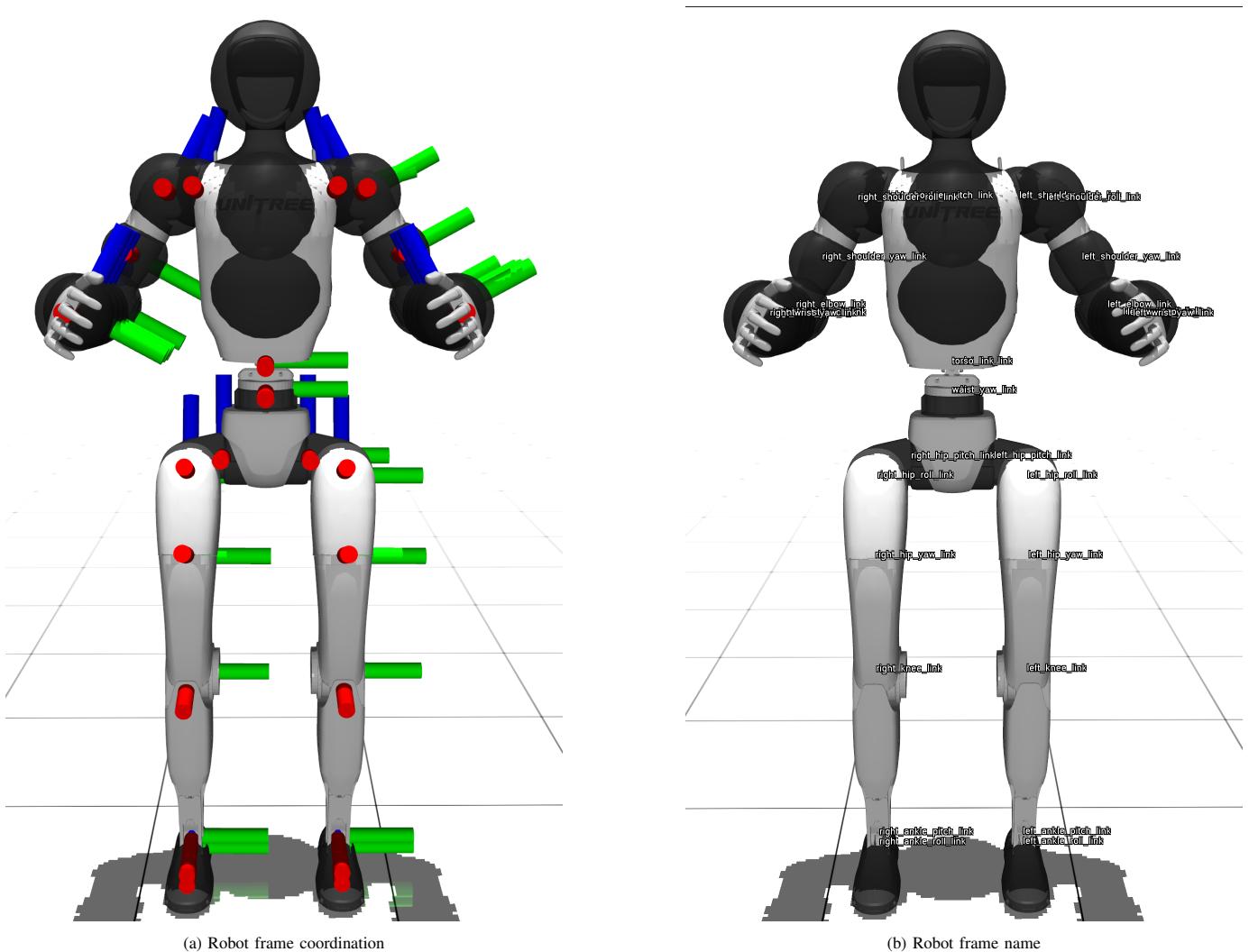
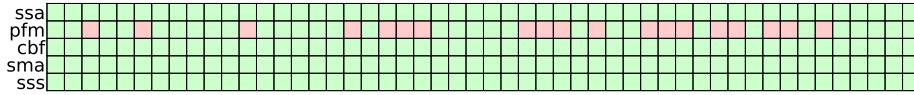
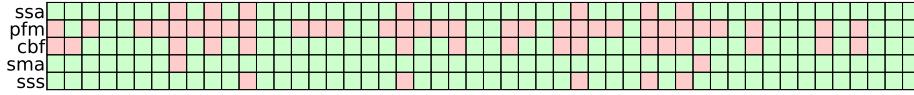


Figure 14: Figure of robot frames

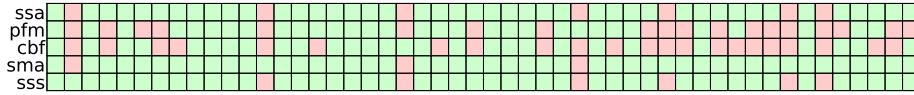
I. Success rate



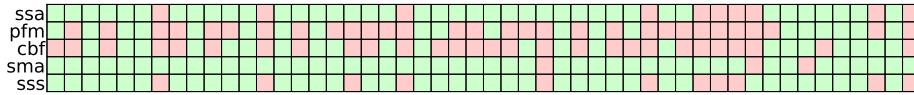
(a) G1FixedBase_AG_SO_v1



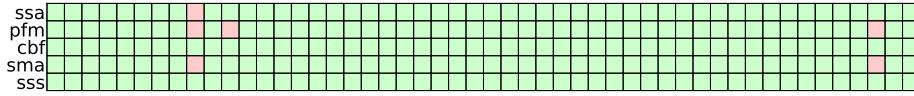
(b) G1FixedBase_AG_SO_v0



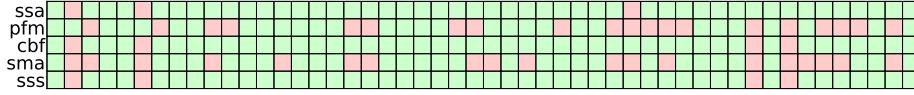
(c) G1FixedBase_AG_DO_v1



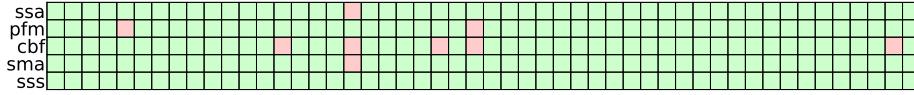
(d) G1FixedBase_AG_DO_v0



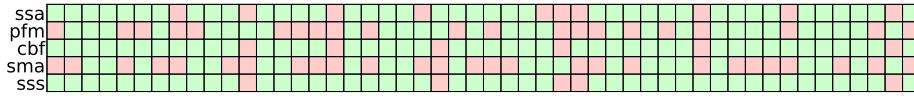
(e) G1WholeBody_WG_SO_v1



(f) G1WholeBody_WG_SO_v0



(g) G1WholeBody_WG_DO_v1



(h) G1WholeBody_WG_DO_v0

Figure 15: Success matrices for different tasks

J. Algorithm comparison

Table 9: Success Matrices for Different Scenarios

(a) G1FixedBase_AG_DO_v0

Algorithm	SSA	PFM	CBF	SMA	SSS
SSA	1.0000	0.5000	0.5250	0.9500	0.9500
PFM	1.0000	1.0000	0.7500	0.9500	1.0000
CBF	0.9545	0.6818	1.0000	0.9545	0.9545
SMA	0.8085	0.4043	0.4468	1.0000	0.7872
SSS	0.9744	0.5128	0.5385	0.9487	1.0000

(b) G1FixedBase_AG_DO_v1

Algorithm	SSA	PFM	CBF	SMA	SSS
SSA	1.0000	0.6977	0.6279	1.0000	1.0000
PFM	0.9677	1.0000	0.7742	0.9677	0.9677
CBF	0.9643	0.8571	1.0000	0.9643	0.9643
SMA	0.9149	0.6383	0.5745	1.0000	0.9149
SSS	0.9773	0.6818	0.6136	0.9773	1.0000

(c) G1FixedBase_AG_SO_v0

Algorithm	SSA	PFM	CBF	SMA	SSS
SSA	1.0000	0.4419	0.7907	0.9767	1.0000
PFM	1.0000	1.0000	0.9474	1.0000	1.0000
CBF	1.0000	0.5294	1.0000	0.9706	1.0000
SMA	0.8750	0.3958	0.6875	1.0000	0.8958
SSS	0.9556	0.4222	0.7556	0.9556	1.0000

(d) G1FixedBase_AG_SO_v1

Algorithm	SSA	PFM	CBF	SMA	SSS
SSA	1.0000	0.6200	1.0000	1.0000	1.0000
PFM	1.0000	1.0000	1.0000	1.0000	1.0000
CBF	1.0000	0.6200	1.0000	1.0000	1.0000
SMA	1.0000	0.6200	1.0000	1.0000	1.0000
SSS	1.0000	0.6200	1.0000	1.0000	1.0000

(e) G1WholeBody_WG_DO_v0

Algorithm	SSA	PFM	CBF	SMA	SSS
SSA	1.0000	0.6250	0.9750	0.5000	0.9750
PFM	0.8621	1.0000	0.8966	0.5862	0.8966
CBF	0.8864	0.5909	1.0000	0.4773	0.9773
SMA	0.8696	0.7391	0.9130	1.0000	0.9130
SSS	0.8667	0.5778	0.9556	0.4667	1.0000

(f) G1WholeBody_WG_DO_v1

Algorithm	SSA	PFM	CBF	SMA	SSS
SSA	1.0000	0.9592	0.9184	1.0000	1.0000
PFM	0.9792	1.0000	0.9167	0.9792	1.0000
CBF	1.0000	0.9778	1.0000	1.0000	1.0000
SMA	1.0000	0.9592	0.9184	1.0000	1.0000
SSS	0.9800	0.9600	0.9000	0.9800	1.0000

(g) G1WholeBody_WG_SO_v0

Algorithm	SSA	PFM	CBF	SMA	SSS
SSA	1.0000	0.5957	0.9574	0.6596	0.9574
PFM	0.9333	1.0000	0.9333	0.8000	0.9333
CBF	0.9783	0.6087	1.0000	0.6739	1.0000
SMA	1.0000	0.7742	1.0000	1.0000	1.0000
SSS	0.9783	0.6087	1.0000	0.6739	1.0000

(h) G1WholeBody_WG_SO_v1

Algorithm	SSA	PFM	CBF	SMA	SSS
SSA	1.0000	0.9592	1.0000	0.9796	1.0000
PFM	1.0000	1.0000	1.0000	1.0000	1.0000
CBF	0.9800	0.9400	1.0000	0.9600	1.0000
SMA	1.0000	0.9792	1.0000	1.0000	1.0000
SSS	0.9800	0.9400	1.0000	0.9600	1.0000

K. Performance comparison of the benchmark

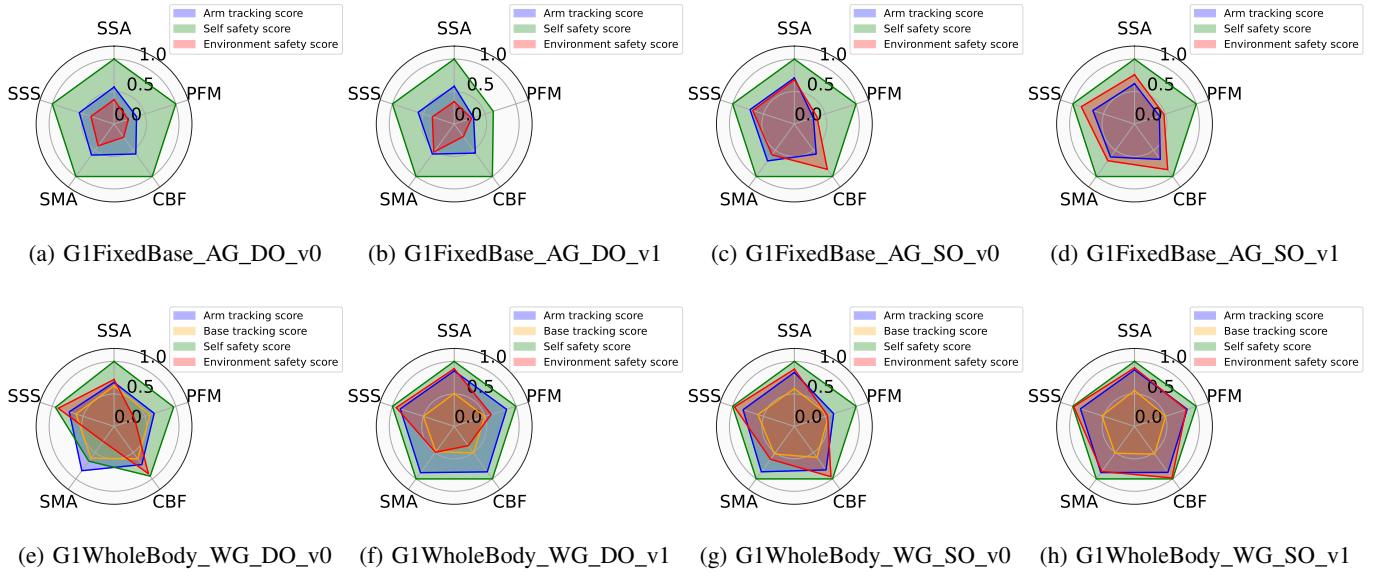


Figure 16: Performance comparison of the benchmark

L. Trade-off curves between safety and efficiency

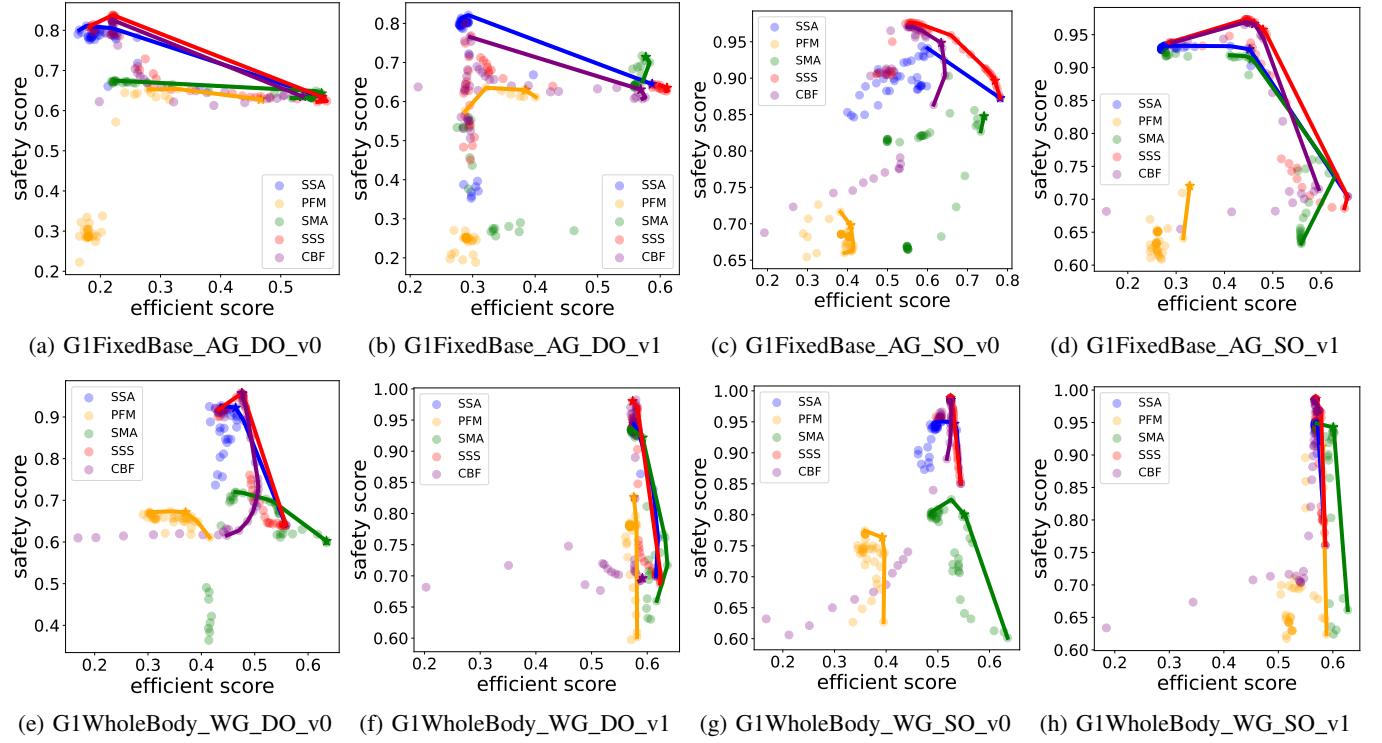


Figure 17: Trade-off curves between safety and efficiency.

M. Conditional success plots

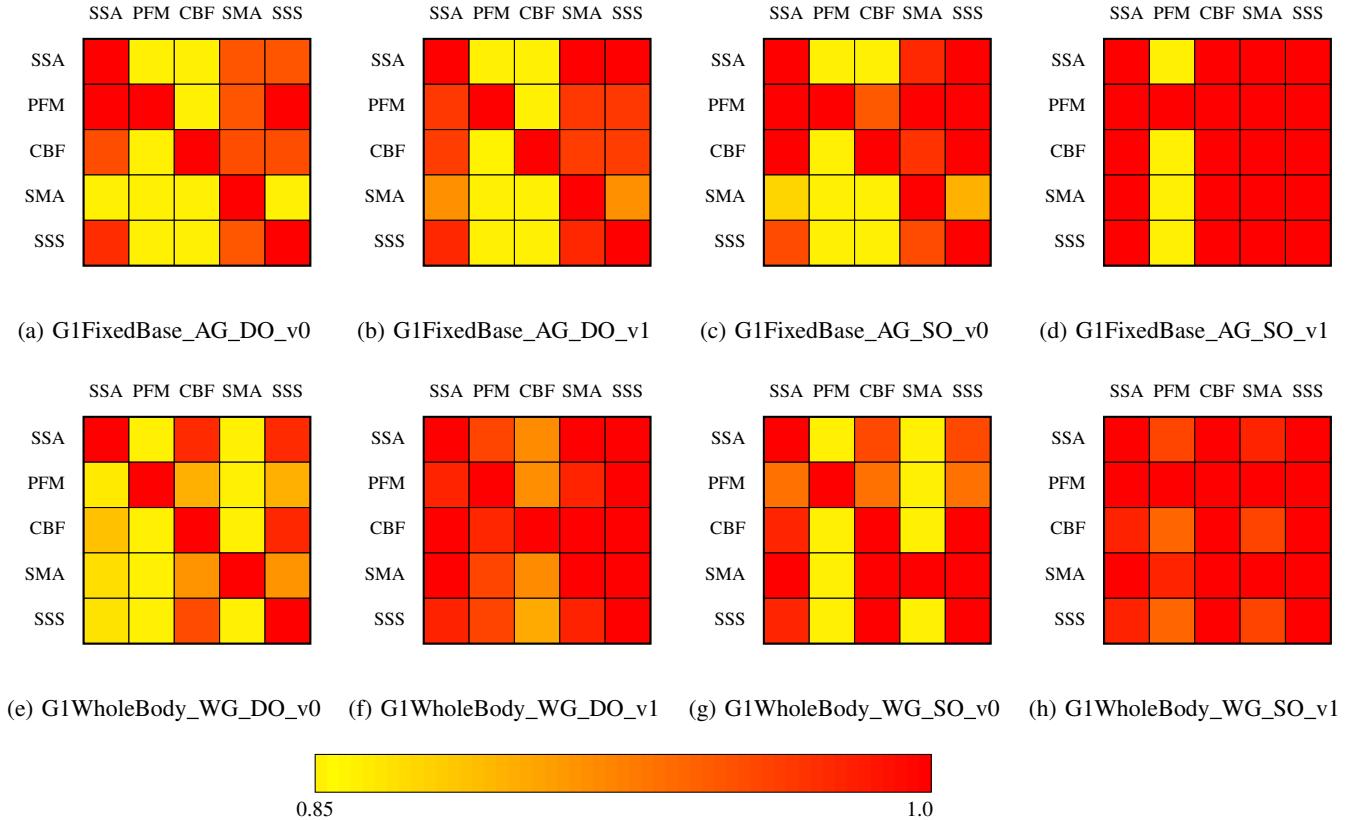


Figure 18: Conditional success plots for different tasks. The value at cell (i, j) represents the proportion of environment settings successfully completed by the i -th algorithm that are also successfully completed by the j -th algorithm.