Zeroth-01 Push-Recovery and Controlled Kneel Controller

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Summary

Model	GRU PPO (195K params, 3 layers, 64 hidden)
Simulation	MuJoCo + K-Sim, 20-DoF Zeroth-01 humanoid
Hardware	MacBook Air M2 (24 GB, CPU-only)
Key Result	Total reward 2.0 → 2.4, forward velocity 0.64 → 0.78

1. Problem and Motivation

Uncontrolled falls are one of the most common and damaging failures of human movement. For older adults and people with mobility impairments, a single fall can mean fractures, head trauma, loss of confidence, and long-term loss of independence. Existing solutions like helmets, hip protectors, and grab bars are mostly passive: they help once impact happens, but they do not shape the dynamics of the fall itself.

Most wearable robots and exoskeletons focus on **positive work**—helping people walk farther, lift more, or move faster. In the scenarios that matter most for safety, however, the key problem is **negative work and controlled descent**: when balance is lost, can we slow the fall, lower the center of mass in a safe way, and avoid high-energy impacts to the hips, torso, and head?

This project is an early step toward that goal. I use a small humanoid platform (Zeroth-01) as a safe testbed for learning and evaluating control strategies that (1) detect when balance is failing, (2) attempt recovery when possible, and (3) if recovery is unlikely, transition into a **controlled kneel or sit-down** rather than a catastrophic fall. The long-term intent is to transfer these ideas to wearable robotic systems and assistive devices that help real people fall more safely, not just move more strongly.

2. System Overview

Simulation Framework

The project uses **MuJoCo** physics simulation via **K-Scale's KSIM** library, which provides:

- Vectorized environments for parallel rollouts
- MJCF robot model of the Zeroth-01 biped (20 actuated joints)

- Domain randomization (friction, mass, sensor noise)
- Push disturbance events during training

Training uses **Proximal Policy Optimization (PPO)** implemented in **JAX** with JIT compilation for efficient CPU/GPU execution.

Policy Architecture

Component	Specification
Policy Network	3-layer GRU (recurrent)
Hidden Size	64 units
Action Distribution	Mixture of 3 Gaussians per joint
Total Parameters	195,061
Observations	50 dimensions
Actions	20 joint position targets

The recurrent architecture allows the policy to integrate temporal information—essential for dynamic balance where history matters.

Observation Space (50 dims): - Joint positions: 20 dims - Joint velocities: 20 dims - IMU orientation: 4 dims (quaternion) - Velocity commands: 6 dims

Action Space (20 dims): - Position targets for each joint, output as mixture-of-gaussians for exploration

State Machine Concept

The full system design includes a deterministic state machine for mode switching:

```
RECOVER → KNEEL → STABLE
   ↑          |
   └──────────┘ (if conditions improve)
```

Transition triggers: - **RECOVER → KNEEL**: Tilt exceeds threshold (0.5 rad) for 10+ consecutive frames - **KNEEL → STABLE**: Robot reaches stable kneeling configuration

This project demonstrates the training pipeline; the state machine is designed but not yet integrated into training.

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3. Key Methods

Reward Design

The reward function balances multiple objectives:

Reward Component	Weight	Purpose
`forward_velocity`	+5.0	Encourage locomotion
`stay_alive`	+1.0	Survival bonus
`feet_airtime`	+2.5	Alternating gait timing
`arm_pose`	-2.0	Keep arms stable
`lateral_velocity`	-1.0	Discourage sideways drift
`joint_limits`	-10.0	Penalize limit violations
`action_rate`	-0.1	Smooth control outputs

The reward weights were tuned empirically. Higher weights on `forward_velocity` and `feet_airtime` produced more stable gaits than uniform weighting.

Curriculum Considerations

Training includes randomized push disturbances via `LinearPushEvent`:

Stage	Force Range (N)	Interval (s)
Easy	±20	2-4
Medium	±40	1.5-3
Hard	±60	1-2.5
Kneel Trigger	±100	1-2

Pushes are applied to the robot's torso at random intervals, teaching the policy to maintain balance under perturbation.

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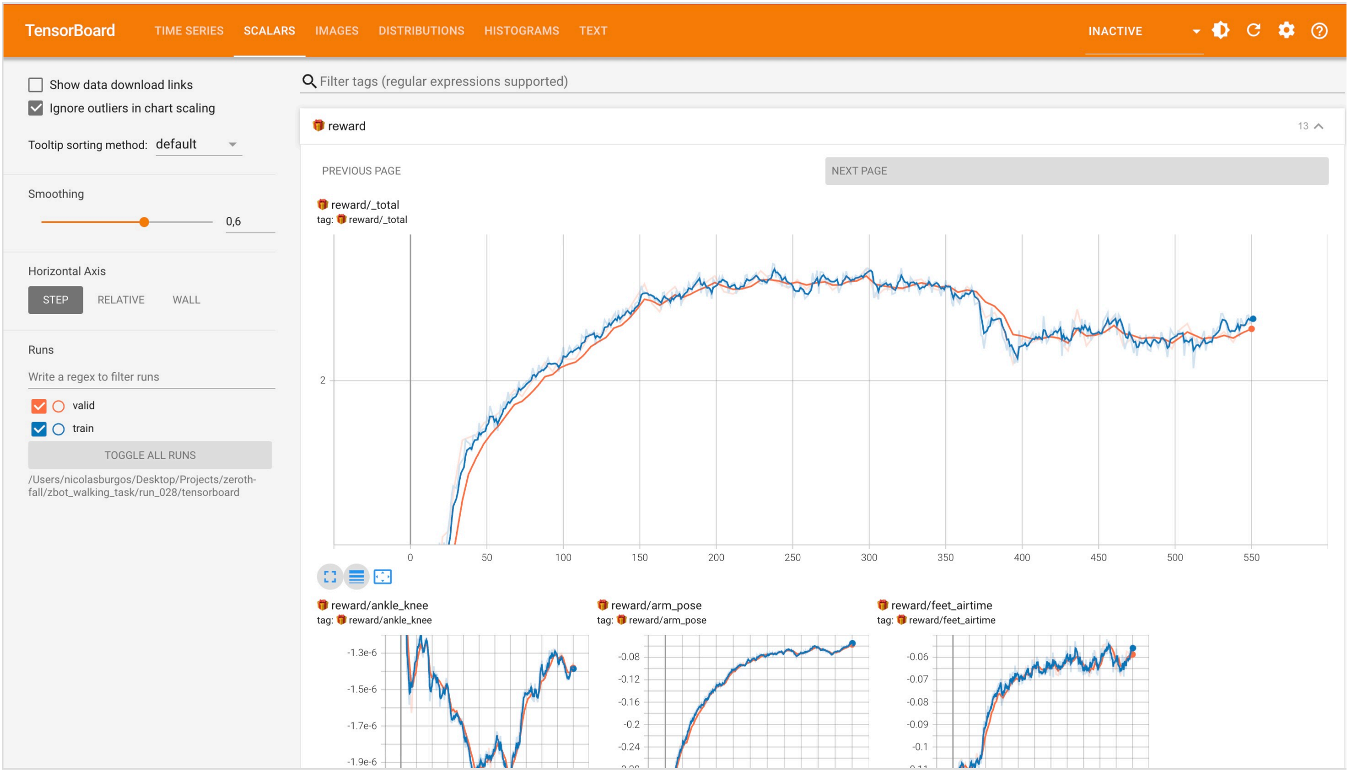
4. Results

Training Configuration

Parameter	Value
Environments	8 (parallel)
Batch Size	4
Rollout Length	2.0 seconds
Learning Rate	3×10^{-4}
Training Steps	~550
Hardware	MacBook Air M2 (CPU)

Learning Curves

Total Reward Progression



The policy converged from an initial reward of ~2.0 to a plateau around 2.2-2.4 over 550 steps. The plateau indicates the policy has reached a local optimum for the current reward weights.

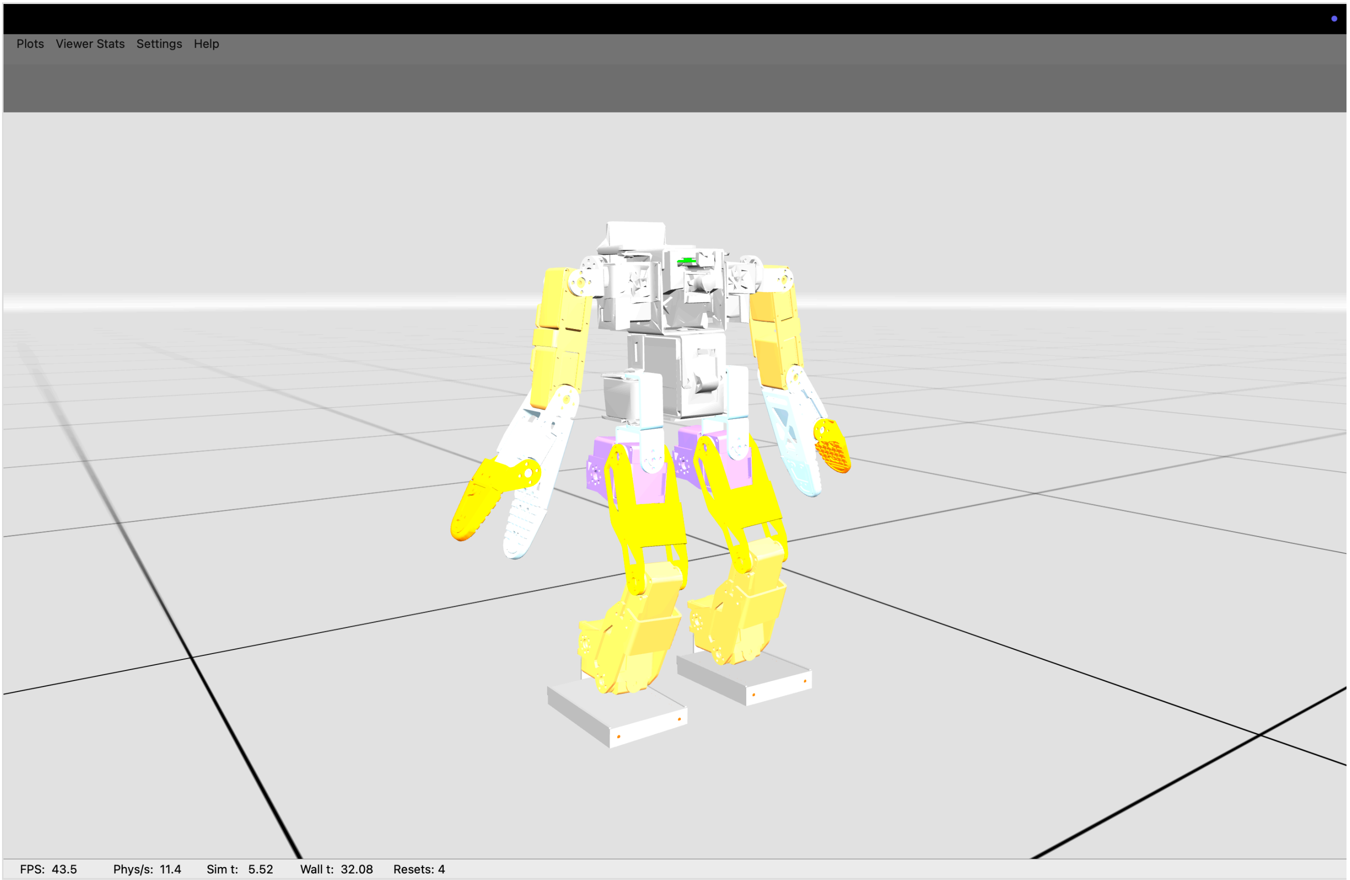
Forward Velocity Reward

Forward velocity improved from 0.64 to 0.78, demonstrating the policy learned to walk forward. Oscillations reflect exploration of different gait patterns.

Component Analysis

Reward	Start	End	Interpretation
`_total`	2.0	2.4	Overall improvement
`forward`	0.64	0.78	Better locomotion
`arm_pose`	-0.28	-0.08	Arms more stable
`feet_airtime`	-0.10	-0.06	Improved gait timing
`lateral_vel`	0.5	0.7	Less sideways drift

Simulation Demo



The trained policy demonstrates basic forward walking with reasonable gait timing. The robot maintains balance during normal operation and shows rudimentary push recovery behavior.

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5. Engineering Challenges

This section describes non-trivial problems encountered during development.

KSIM 0.2.10+ API Migration

The ksim-gym-zbot template was built for an older KSIM version. Updating required:

- **Dict-based observations**: Methods like `get_observations()` now return `dict[str, T]` instead of lists
- **New event system**: `LinearPushEvent` replaced `PushEvent` with different parameter names (`linvel` instead of `force`)
- **Termination API**: `BadZTermination` uses `min_z` / `max_z` instead of `unhealthy_z_lower` / `upper`
- **Noise specification**: `ksim.AdditiveGaussianNoise(std=...)` instead of float values

Mixture-of-Gaussians Implementation

The template's action distribution didn't match the current Equinox/JAX patterns. I implemented a local `MixtureOfGaussians` class that:

- Outputs mixture weights, means, and log-stds for each joint
- Computes log-probabilities correctly for PPO's objective
- Provides both `sample()` and `mode` for training vs. evaluation

A subtle bug: `mode` was implemented as a `@property`, but I initially called it as `mode()`. This caused shape mismatches that took time to debug.

Laptop-Scale Training

GPU clusters weren't available, so I adapted the training config for M2 Air:

Original	Laptop
256 envs	8 envs
batch_size=64	batch_size=4
hidden_size=128	hidden_size=64
depth=5	depth=3
num_mixtures=5	num_mixtures=3

This reduced parameters from ~1.1M to ~195K and made training feasible (~30s/step on CPU). The tradeoff is less expressive policy, but sufficient to demonstrate learning.

PPO Shape Debugging

JAX's JIT compilation defers errors until runtime, making shape mismatches hard to trace. Issues encountered:

- Actor/critic carry states had different shapes due to separate GRU instances
- Log-prob computation required careful broadcasting for mixture components
- Observation dict keys had to match exactly (silent failures otherwise)

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6. Limitations and Future Work

Current Limitations

Simulation Only: This project operates entirely in simulation. Real-world deployment would require: - Careful actuator modeling (the simulated Feetech servos may not match real dynamics) - Sensor noise characterization - Safety systems (e-stops, joint limit enforcement) - Tethered testing before untethered operation

Partial Implementation: Several designed components are not yet implemented: - State machine integration with training - Formal evaluation battery - Controlled kneel mode (design complete, training not started) - Domain randomization sweep

Scale Constraints: Training was performed on laptop CPU (~30s per step) rather than GPU cluster. Results demonstrate the pipeline works but are not optimized for performance.

What I Would Investigate Next

1. **Kneel Mode Training**: Train a separate policy with `mode=1` input, starting from unstable initial conditions
2. **State Machine Integration**: Run combined training where the mode switches based on tilt/angular velocity
3. **Quantitative Evaluation**: Implement `push_battery.py` and measure recovery rates systematically
4. **Sim-to-Real Gap**: If hardware access were available, characterize how policy performance degrades on real robot

Open Questions

- How should the kneel reward balance "lower COM quickly" vs "minimize impact"?
- What tilt threshold optimizes the RECOVER→KNEEL transition?
- Can a single policy handle both modes, or are two separate policies more robust?

References

- K-Scale Labs. *ksim-gym-zbot*. https://github.com/kscalelabs/ksim-gym-zbot
- Schulman et al. (2017). Proximal Policy Optimization Algorithms. arXiv:1707.06347
- MuJoCo Physics Engine. https://mujoco.org
- Zeroth Robotics. *Zeroth-01 Humanoid Platform*. https://github.com/zeroth-robotics/zeroth-bot

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Code and training artifacts: github.com/nicoburgos/zeroth-fall