# RINA: Rapid Introspective Neural Adaptation for Out-of-Distribution Payload Configurations on Quadruped Robots


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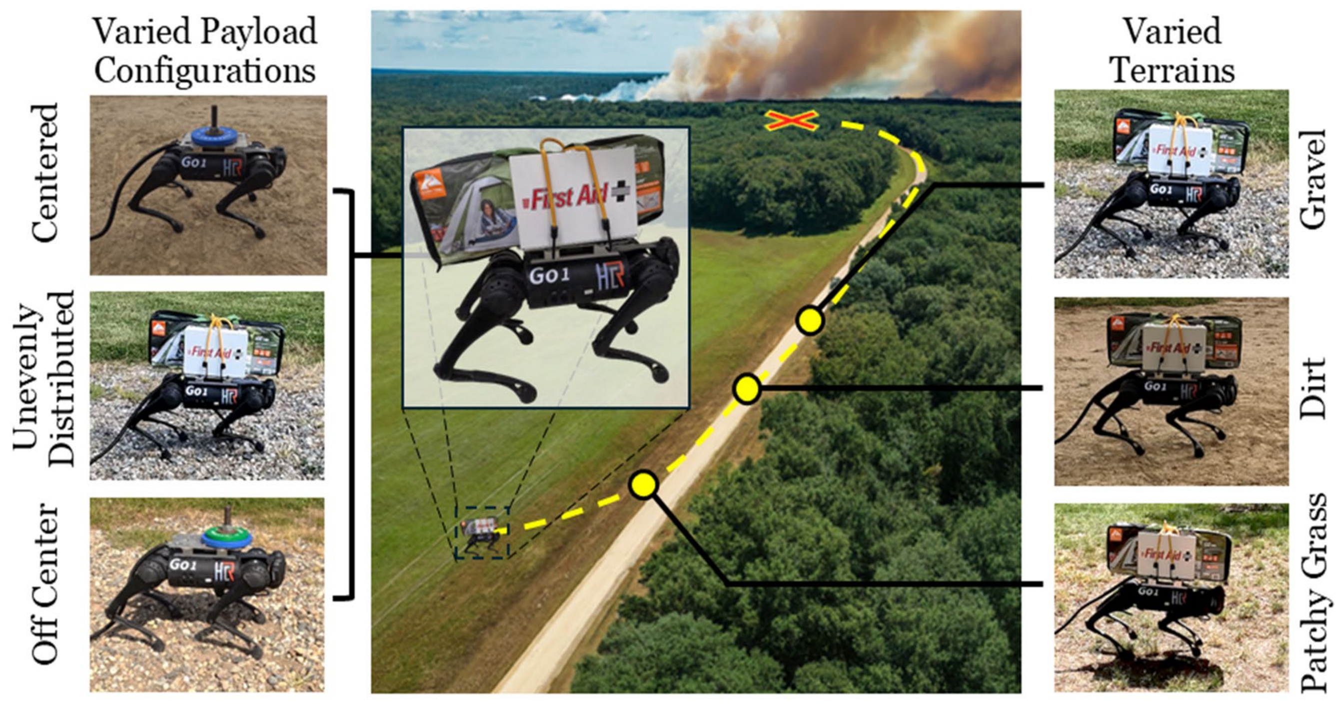
## Motivation

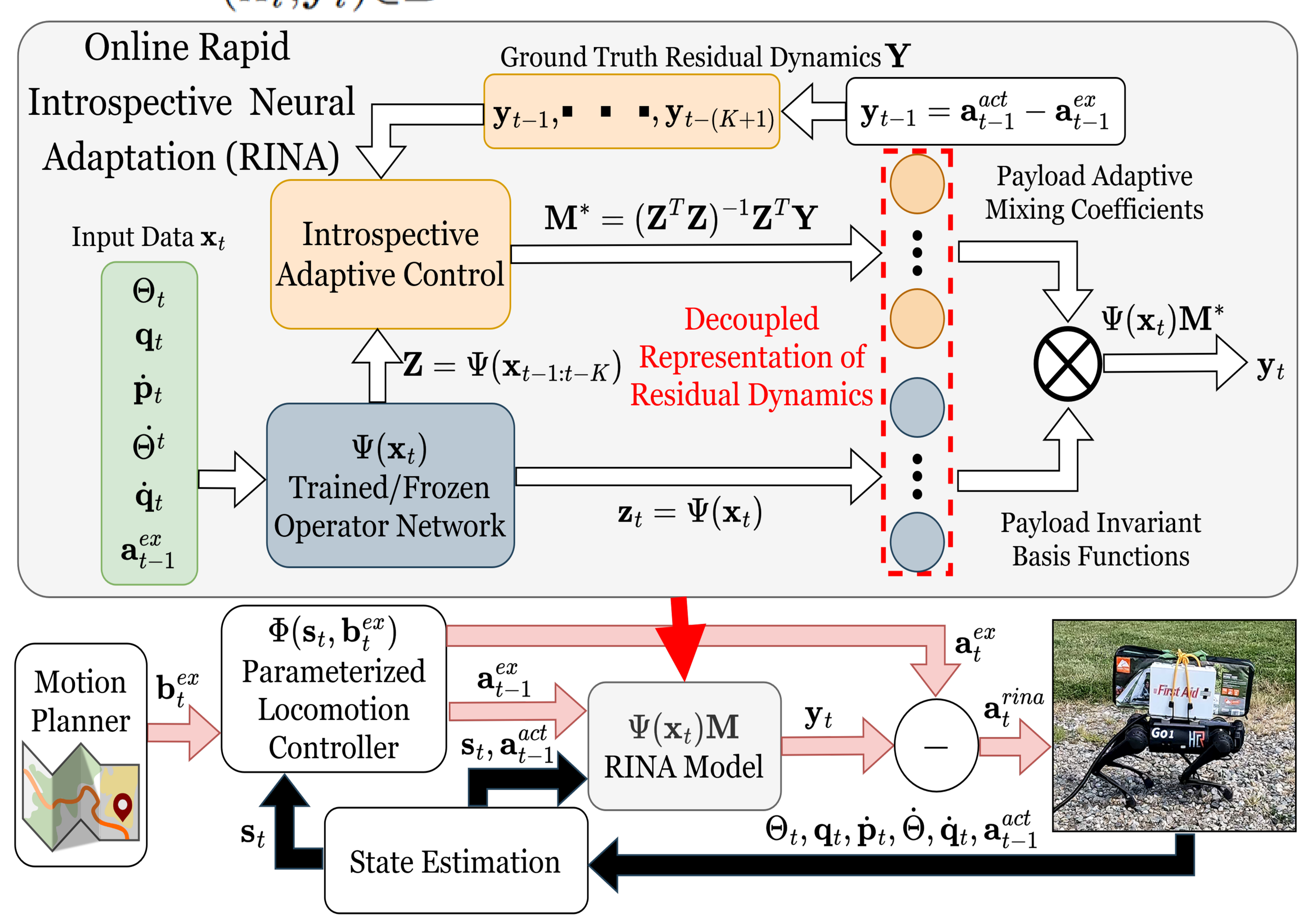
- Adaptive locomotion is a fundamental capability for quadruped robots, particularly in real-world scenarios when they must transport novel or out-of-distribution (O.O.D.) payloads across diverse terrains.
- Previously unseen payloads and unstructured terrains result in the actual locomotion behaviors not matching the expected behaviors from a locomotion controller, requiring the robot to rapidly adapt its locomotion controller's output in real time without additional training (i.e. on-the-go).
- We address the problem of adapting quadruped locomotion controllers to O.O.D. payloads by enabling quadruped robots to observe and rapidly compensate for differences between the actual and expected joint torques induced by payloads unaccounted for by the locomotion controller on-the-go.




## Approach

- We propose the novel *Rapid Introspective Neural Adaptation* (RINA) method that learns to rapidly compensate for differences between the actual $\mathbf{a}^{act}$ and expected $\mathbf{a}^{ex}$ joint torque output from a locomotion controller caused by O.O.D. payloads.
- The loss function learns a decoupled residual dynamics operator representation as a set of basis functions $\Psi(\mathbf{x}_t)$, which are combined using linear coefficients $\mathbf{M}$ to predict the joint torque residual dynamics $\mathbf{y}_t$ from the robot state $\mathbf{x}_t$.
- Predicted residual dynamics $\hat{\mathbf{y}}_t$ are used to adjust the locomotion controller's $\Phi(\cdot)$ output, compensating for O.O.D. payloads: $\Phi(\mathbf{s}_t, \mathbf{b}_t^{ex}) - \hat{\mathbf{y}}_t = \mathbf{a}_t^{rina}$.
- Additionally, this formulation also introduces a discriminator network $\zeta(\Psi(\mathbf{x}_i))$ to prevent $\Psi(\cdot)$ from overfitting to the conditions in the training data.
- RINA achieves the capability of rapid on-the-go adaptation through learning a decoupled representation of the residual dynamics that can adapt to O.O.D. payload configurations during execution by only updating $\mathbf{M}$ with an efficient closed-form solution while leaving the trained parameters of $\Psi(\cdot)$ fixed.

$$\max_{\zeta}\min_{\Psi,\mathbf{M}} \sum_{(\mathbf{x}_i,\mathbf{y}_i)\in\mathbf{D}} \left\|\boxed{\mathbf{y}_i - \Psi(\mathbf{x}_i)\mathbf{M}}\right\|^2 - \lambda\mathcal{L}\left(\zeta(\Psi(\mathbf{x}_i))\right)$$




## Experiments

We experimentally validate RINA using the Unitree Go1 quadruped robot transporting O.O.D. payload configurations indoors and on unseen outdoor terrains and compare against two baselines.

### Results on Adaptation to O.O.D. Payload Configurations

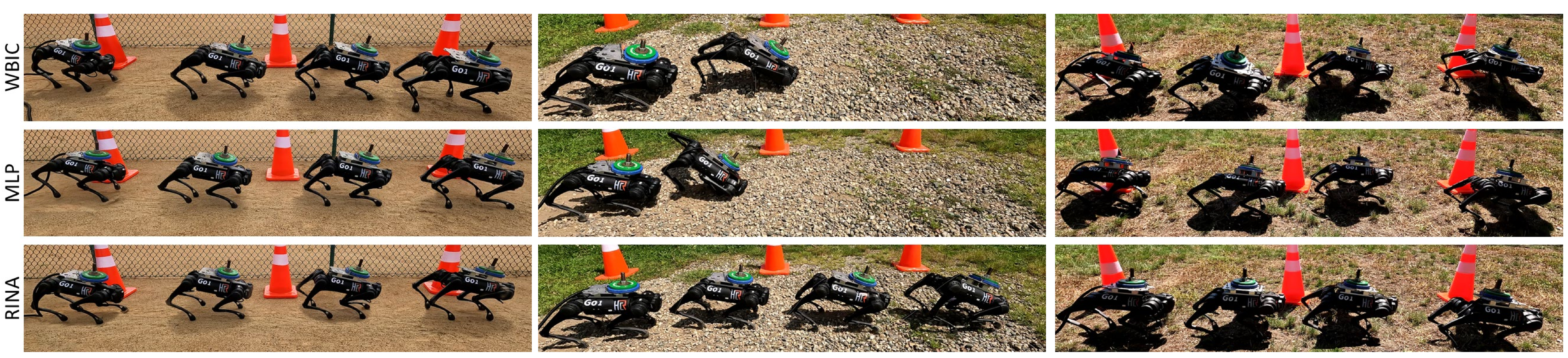
- Robots are evaluated on O.O.D. payloads mounted off-center with respect to the robot's center-of-mass (COM).
- No online learning is needed to perform rapid on-the-go O.O.D. payload adaptation during execution.
- The expected vs. actual torso velocity errors are from 31,646 time steps (63 seconds) per condition on average.

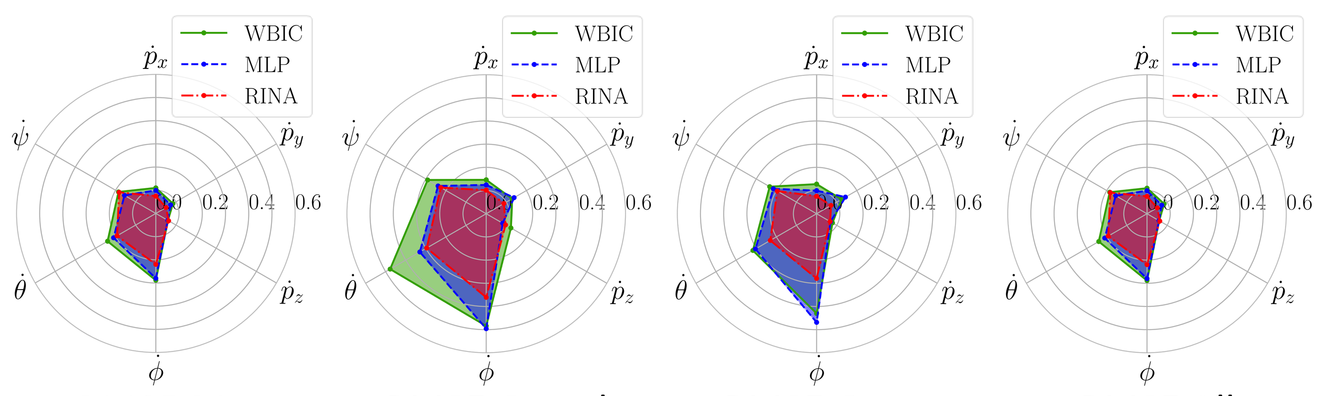
| Payload | Linear-Velo. Error $(m/s)$ | | | Angular-Velo. Error $(rad/s)$ | | |
|---|---|---|---|---|---|---|
| | WBIC | MLP | RINA | WBIC | MLP | RINA |
| **0 C** | 0.091 | 0.108 | **0.081** | 0.398 | 0.418 | **0.397** |
| **5 C** | 0.108 | 0.133 | **0.104** | 0.416 | 0.512 | **0.407** |
| **10 C** | 0.124 | 0.135 | **0.110** | 0.464 | 0.495 | **0.457** |
| **5 F** | 0.125 | 0.132 | **0.091** | 0.466 | 0.472 | **0.410** |
| **7.5 F** | 0.131 | 0.126 | **0.102** | 0.463 | 0.467 | **0.429** |
| **5 L** | 0.117 | 0.130 | **0.097** | 0.427 | 0.473 | **0.413** |
| **7.5 L** | 0.117 | 0.133 | **0.105** | 0.424 | 0.470 | **0.408** |
| **5 FL** | 0.118 | 0.138 | **0.108** | 0.477 | 0.487 | **0.431** |
| **7.5 FL** | 0.133 | 0.125 | **0.104** | 0.480 | 0.450 | **0.397** |
| **Avg.** | 0.119 | 0.130 | **0.101** | 0.446 | 0.473 | **0.416** |
| **% Im.** | - | -9.24% | **15.13%** | - | -6.05% | **6.73%** |

### Results for O.O.D. Payload Adaptation on Varied Terrains

- This experiment evaluates the ability of the methods to adapt on-the-go to real-world outdoor terrains unseen during training without additional data collection or training.
- Both baseline methods encountered multiple failures while RINA was successful in all conditions.
- Error metrics are computed from an average of 8,777 time steps (17.5 seconds) per condition.

| Payload | Linear-Velo. Error $(m/s)$ | | | Angular-Velo. Error $(rad/s)$ | | |
|---|---|---|---|---|---|---|
| | WBIC | MLP | RINA | WBIC | MLP | RINA |
| **5 C** | 0.106 | 0.095 | **0.070** | 0.272 | 0.283 | **0.220** |
| **7.5 C** | 0.122 | 0.106 | **0.079** | 0.403 | 0.363 | **0.251** |
| **5 F** | $0.109^{\dagger}$ | $0.106^{\dagger}$ | **0.074** | $0.347^{\dagger}$ | $0.276^{\dagger}$ | **0.222** |
| **7.5 F** | $0.107^{\ddagger}$ | $0.099^{\dagger}$ | **0.076** | $0.333^{\ddagger}$ | $0.326^{\dagger}$ | **0.251** |
| **5 L** | 0.106 | 0.099 | **0.076** | 0.334 | 0.326 | **0.251** |
| **7.5 L** | $0.112^{\ddagger}$ | 0.118 | **0.096** | $0.316^{\ddagger}$ | 0.381 | **0.305** |
| **Avg.** | $0.114^{\ddagger}$ | $0.105^{\dagger}$ | **0.079** | $0.349^{\ddagger}$ | $0.327^{\dagger}$ | **0.251** |
| **% Im.** | - | 7.89% | **30.70%** | - | 6.30% | **28.08%** |




RMSE Dirt Terrain | RMSE Gravel Terrain | RMSE Grass Terrain | RMSE All Terrains

## Summary

- We introduced RINA as a novel learning-based residual dynamics compensation method for adapting quadruped locomotion controllers to O.O.D. payload configurations.
- RINA introduces an adaptive residual dynamics model that separates the learning model's parameters from those used for adaptation.
- Our experiments demonstrate that RINA enables rapid, on-the-go adaptation to O.O.D. payloads across multiple terrains without online training and outperforms baseline methods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