STATE-NAV: Stability-Aware Traversability Estimation for Bipedal Navigation over Rough Terrain

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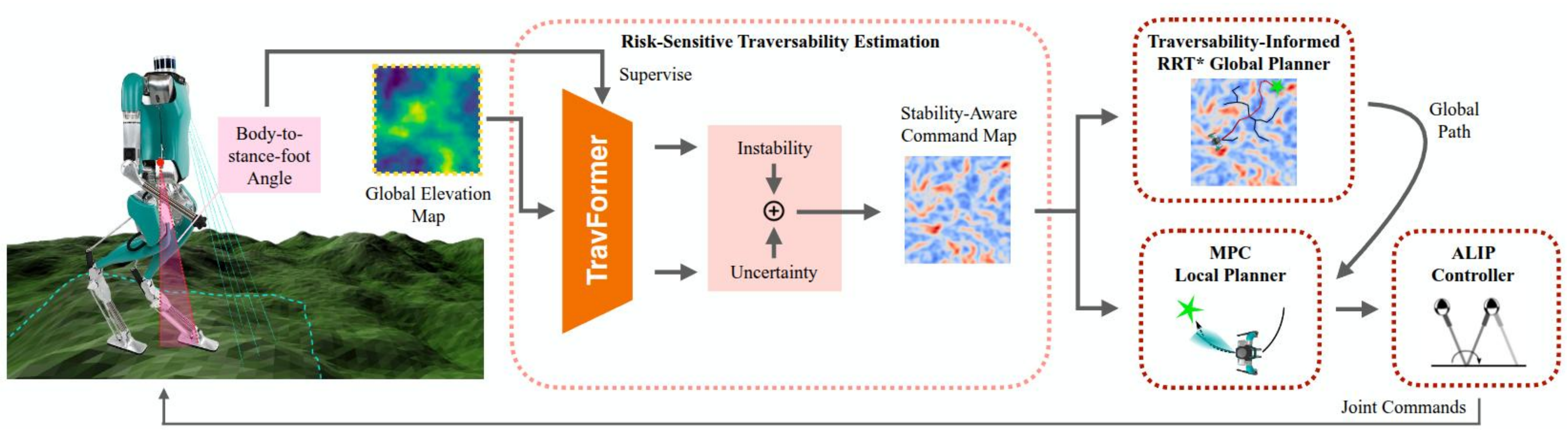
Introduction

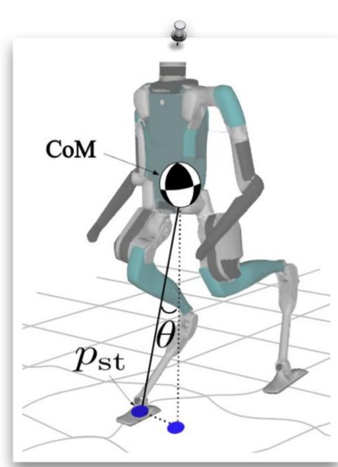


- **Bipedal traversability and navigation on rough terrain remain underexplored due to the higher risk of locomotion failure.**
- We achieve **safe while efficient** navigation in various environments with **(i) risk-sensitive traversability guided by bipedal locomotion stability (ii) stability-constrained navigation planning robust to environments**
- We propose the **first learning-based traversability** and **robust navigation framework for bipedal locomotion** on **diverse, rough terrain.**

Bipedal Traversability as Stability-Aware Command

Comparison of Locomotive Features for Fallover Risk Prediction

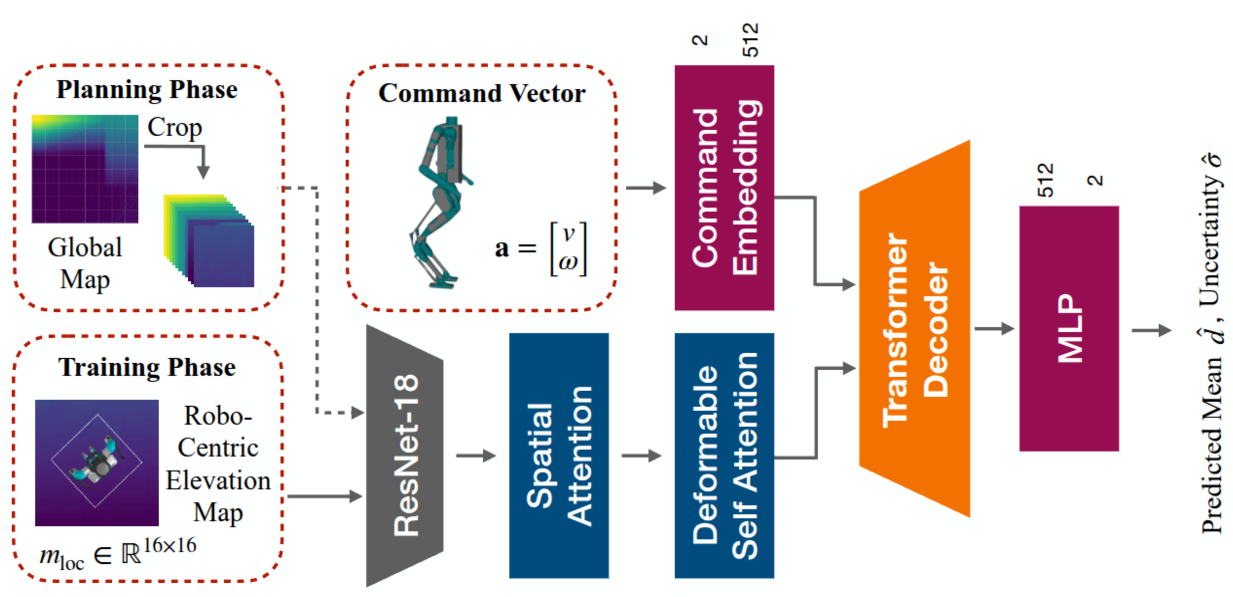
Locomotive Feature	McFadden's R^2	AUC-ROC
Tangential/normal force ratio	0.016	0.806
Center of pressure (x-dir)	0.025	0.859
Center of pressure (y-dir)	0.059	0.879
Footstep plan deviation	0.080	0.813
Lateral deviation	0.109	0.730
Energy (control effort)	0.184	0.784
IMU (PCA)	0.210	0.835
IMU (PSD)	0.217	0.837
Sagittal traction	0.097	0.770
Kinematics-based (Foot-body angle) ★	**0.356**	**0.906**

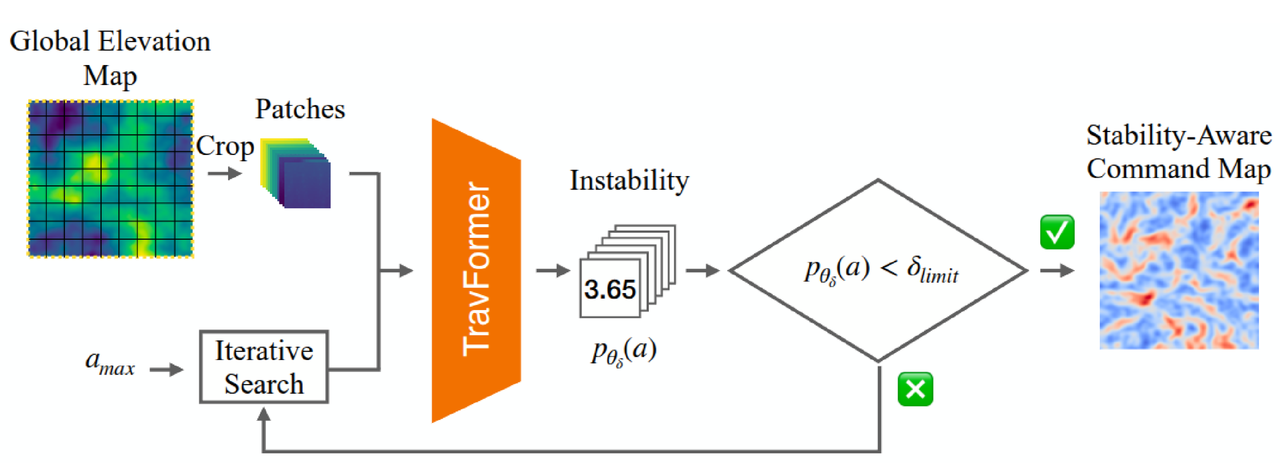


We identified **foot-body angle** as the strongest **fallover predictor (instability),** outperforming nine alternative metrics.

Our network - TravFormer predicts **instability** using elevation maps and velocity commands.

Uncertainty-aware training with Maximum Gaussian Likelihood loss provides confidence estimates for predictions.





$$v^*_{m_{\text{loc}}} = \max \{ v \mid \text{VaR}(p_{\theta_\delta}(m_{\text{loc}}, [v, 0]), \alpha) < \delta_{\text{limit}} \}$$
$$\omega^*_{m_{\text{loc}}} = \max \{ \omega \mid \text{VaR}(p_{\theta_\delta}(m_{\text{loc}}, [0, \omega]), \alpha) < \delta_{\text{limit}} \}$$

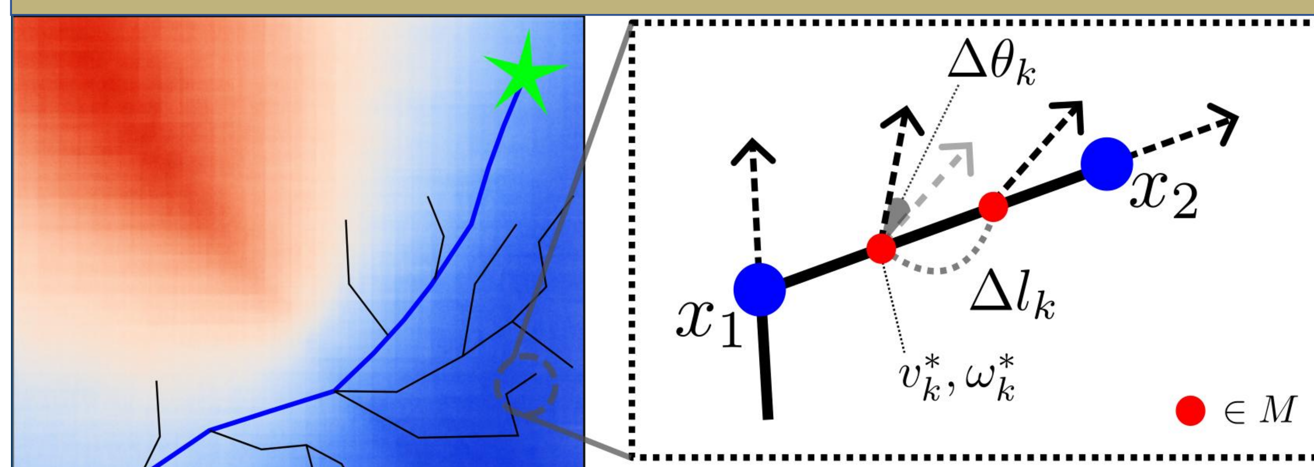
Traversability is defined as the **maximum command velocity** a robot can execute while maintaining instability below a given safety threshold and a risk level.

References

[1] Wellhausen, Lorenz, and Marco Hutter. "Rough terrain navigation for legged robots using reachability planning and template learning." 2021 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS). IEEE, 2021.

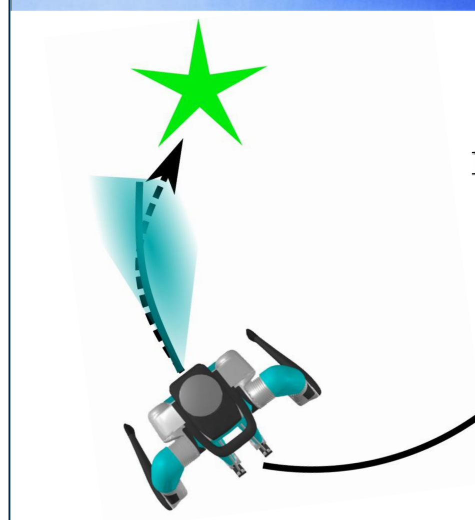
[2] McCrory, Stephen, et al. "Humanoid path planning over rough terrain using traversability assessment." arXiv preprint arXiv:2203.00602 (2022).

Hierarchical Planner: TravRRT*- Guided MPC



$$c_{ij} = \sum_{k \in M} \left(\frac{\Delta l_k}{v^*_k} + \frac{\Delta \theta_k}{\omega^*_k} \right)$$

Global TravRRT* Planner: Find the global path with **shortest expected navigation time** with **stability-aware command**

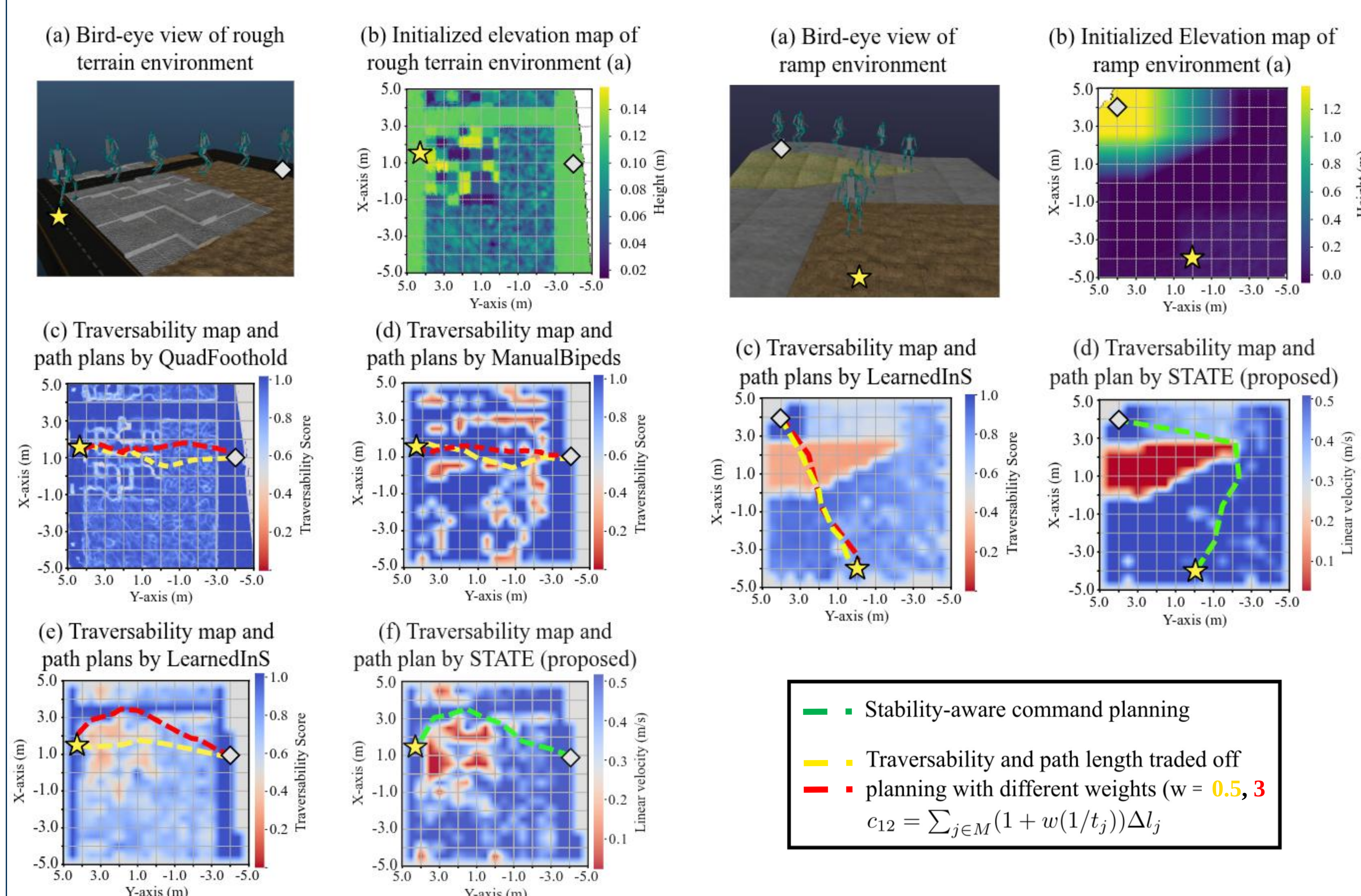


min $\sum$ **Control effort + Distance to goal**

s.t. **Dynamics Constraint**
Stability-Constrained Control Command Limit

Local MPC Planner: Follow the global path **safely with the command constraint**

Traversability Estimation and Navigation Planning



The proposed method properly estimates **the risk of dangerous area** in rough terrain and **robustly** produces safe global path plans **across varying environments**.

Navigation in Challenging Environment

	STATE	LearnedInS	ManualBiped	QuadFoodhold
Success Rate	**80%**	60%	30%	20%
Mean Instability	2.62 (+29%)	2.42 (+19%)	**2.03 (+0%)**	3.49 (+72%)
Max Instability	6.54 (+3.0%)	7.32 (+15%)	**6.35 (+0%)**	12.5 (+97%)
Navigation Time	61.6 s (+24%)	73.5 s (+48%)	255.3 s (+416%)	**49.5 s (+0%)**