DRIVE: Data-driven Robot Input Vector Exploration

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Context & Motivations

- A motion model is a key component of autonomous navigation systems, but Uncrewed ground vehicles (UGVs) behavior varies significantly depending on terrain and vehicle properties.
- Sensory measurements and information on ground properties are limited.
- Empirical training dataset gathering is energy and time consuming [1], two critical resources for remote deployments.
- Facilitating and automating the task of gathering a training dataset if of high importance for field operations.

Data-driven Robot Input Vector Exploration (DRIVE)

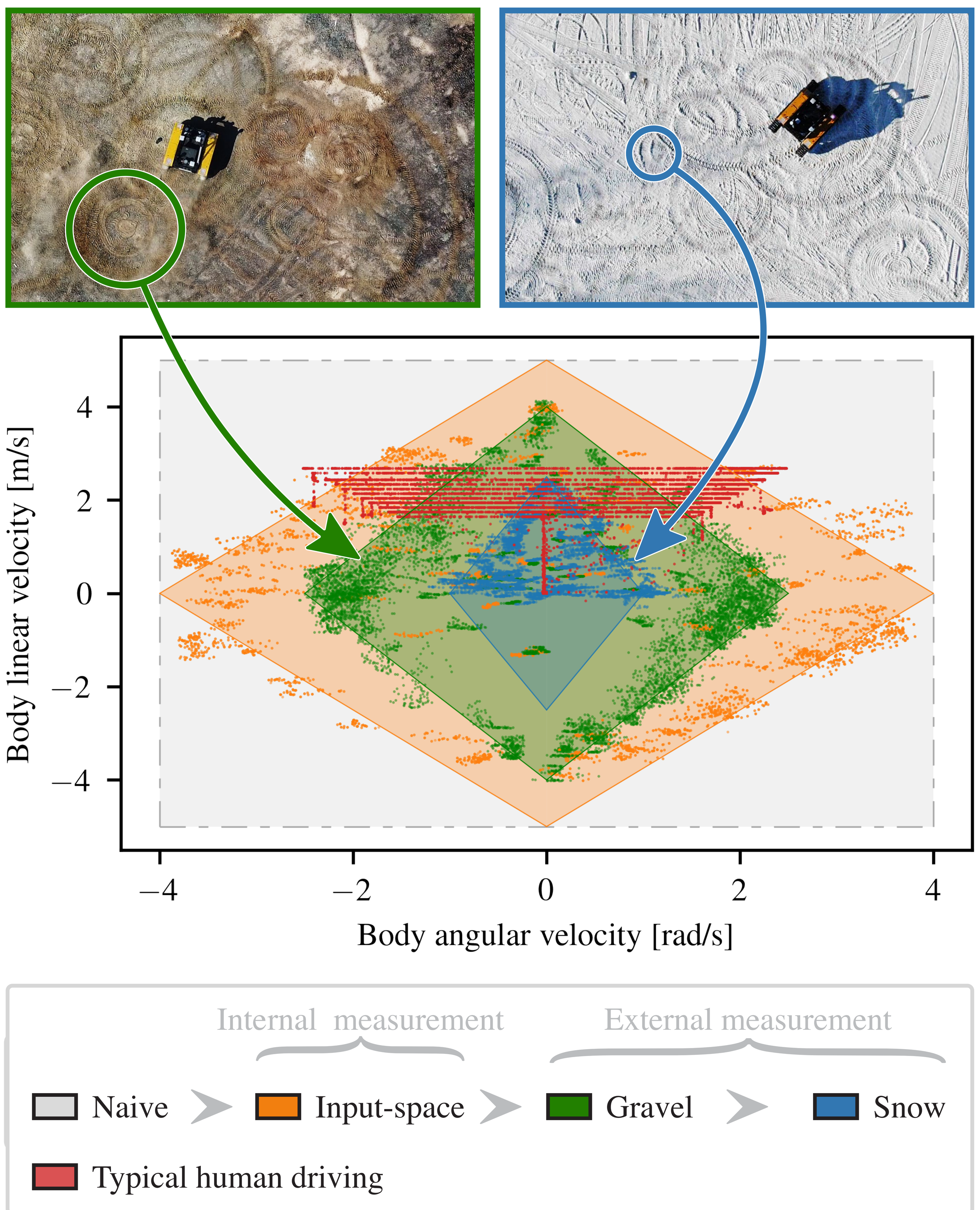

Figure 1: Vehicle and terrain characterization done through DRIVE. The manufacturer-defined Naive input-space region is drawn in gray. The vehicle's true input-space, characterized through internal measurements, is shown in orange. Typical human driving is shown in red. The resulting body velocities are represented in green for gravel and blue for snow.

- Automated protocol for input space characterization and dataset gathering.
- Random uniform input sampling minimized input bias and stimulates dynamic, transitory behavior.
- Improvement in prediction accuracy of 31.8 % in translation and 43.6 % in rotation over angular-focused and linear-focused methods respectively.
- 6 s intervals to stimulate transitory and steady behavior.
- Driving time of 46 s required to train a motion model.

Table: Median prediction improvement for all robots and terrains.

Prediction	Husky		HD2		Warthog	
improvement	Tile	Snow	Tile	Snow	Gravel	Ice
Translation (%)	35	10	33	31	50	11
Rotation (%)	18	61	27	51	61	7

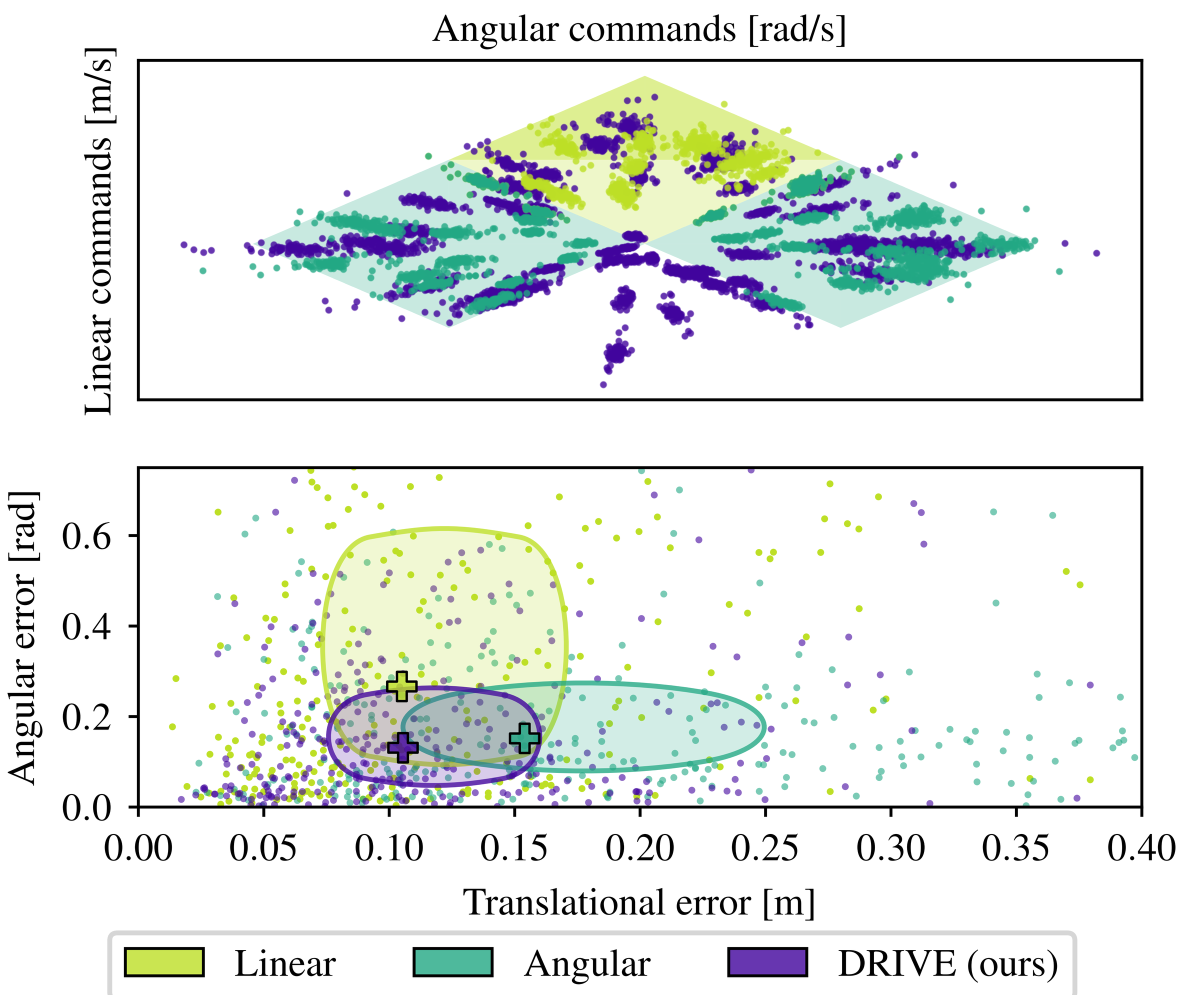

Figure 2: Data-gathering protocol performance for the *HD2* on snow experiment. In yellow, we have the linear-focused method. In teal, we have the angular-focused method. In blue-violet is our DRIVE approach. The crosses and regions on the bottom subplot show the medians and interquartile ranges for translational and angular prediction errors.

Experimental Setup

- Indoor tile, snow-covered terrain, gravel and surfaced ice.
- Three platforms: (1) the HD2 has a top speed of 1.2 m/s; (2) Husky has a top speed of 1 m/s; and (3) the the Warthog has top speed of 5 m/s.
- Over 7 km and 1.8 h of driving data.

Figure 3: Three different commercial platforms that were used for the experimental work: a *Superdroid* HD2 (1), a *Clearpath Robotics* Husky (2), and a *Clearpath Robotics* Warthog mounted on wheels (3). The platforms weigh 80 kg, 75 kg and 470 kg, respectively.

Slip-based Bayesian Linear Regression (BLR)

- Additive slip model based on dynamics-aware basis functions [2].
- Leveraging Bayesian Linear Regression (BLR) for learning motion parameters with minimal vehicle and terrain knowledge [3].
- BLR offers low computational complexity for fast learning.
- Each dimension of slip (longitudinal, lateral, angular) learned separately.
- First-order plus dead time transient response model for powertrain dynamics.
- Implimented and tested for skid-steering mobile robots (SSMRs).

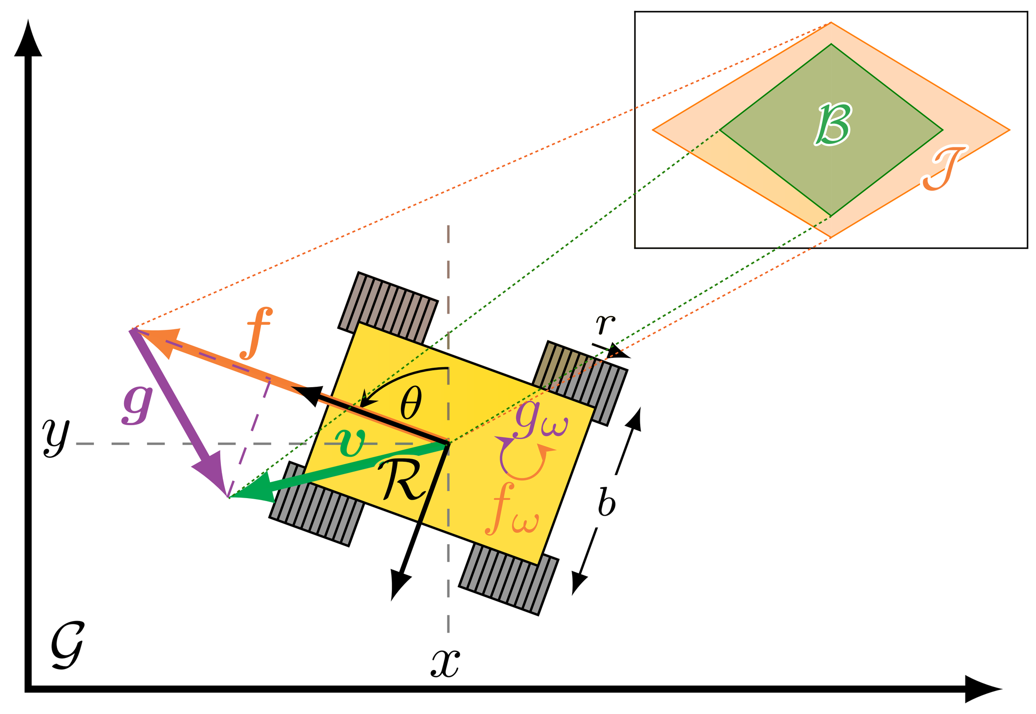

Figure 4: Top view drawing of a SSMR. In orange is the commanded body velocity ${}^{\mathcal{R}}\boldsymbol{f}$ and the resulting body velocity ${}^{\mathcal{R}}\boldsymbol{v}$ is shown in green. The input-space $\mathcal{J}$ is shown in orange and the body velocity space $\mathcal{B}$ is shown in green. The difference between commanded and resulting body velocity is represented as the slip velocity ${}^{\mathcal{R}}\boldsymbol{g}$ in purple.

- Slip-BLR outperforms the most similar model,which performs BLR on UGV actuator dynamics, by 6 % in translation and 22 % in rotation.
- Biggest improvement for Warthog on gravel with 23 % in translation and 71 % in rotation error. This is the highest top speed experiment.
- Model limit reached on surfaced ice, due to extreme slip and long transitory response.
- Powertrain model reduces prediction error for all models on each experiment.

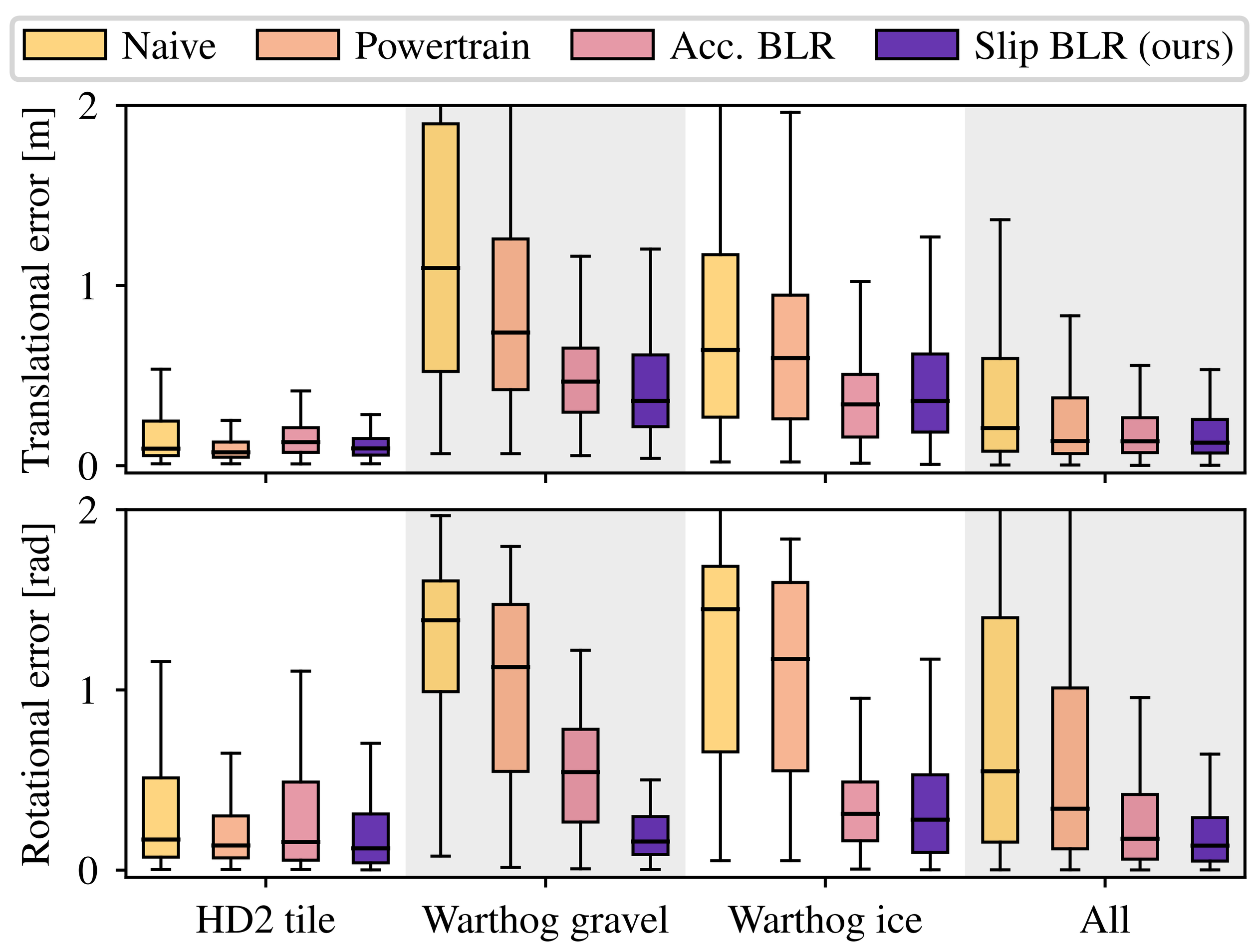

Figure 5: Translational and rotational prediction errors for all models studied in this work. In yellow is the manufactured-defined naive model, in orange is the powertrain-aware model, in red is the acceleration-based BLR model and in purple is our slip-based BLR model.

Acknowledgments and References

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