Neural Autonomous Navigation with Riemannian Motion Policies

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Motivation

Image-based navigation has numerous advantages over lidar based methods

Slow
Expensive
No semantics

Laser Scanner

Fast
Cheap
Rich semantics

RGB Camera

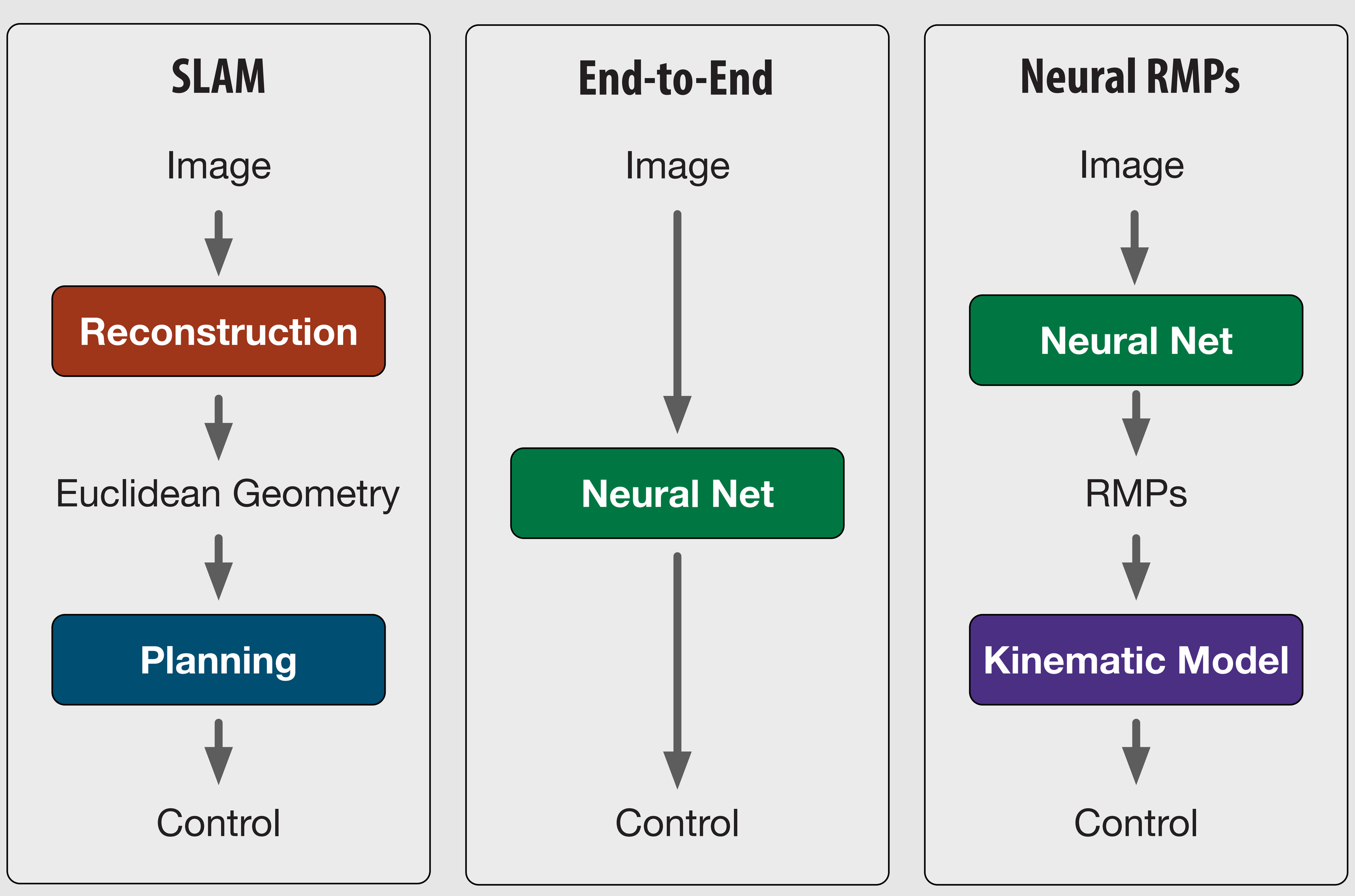
However, image-based methods face many challenges

- Textureless areas
- Dynamic environments/objects
- Fast-moving camera

Our Approach

A new representation based on the Riemannian Motion Policy framework

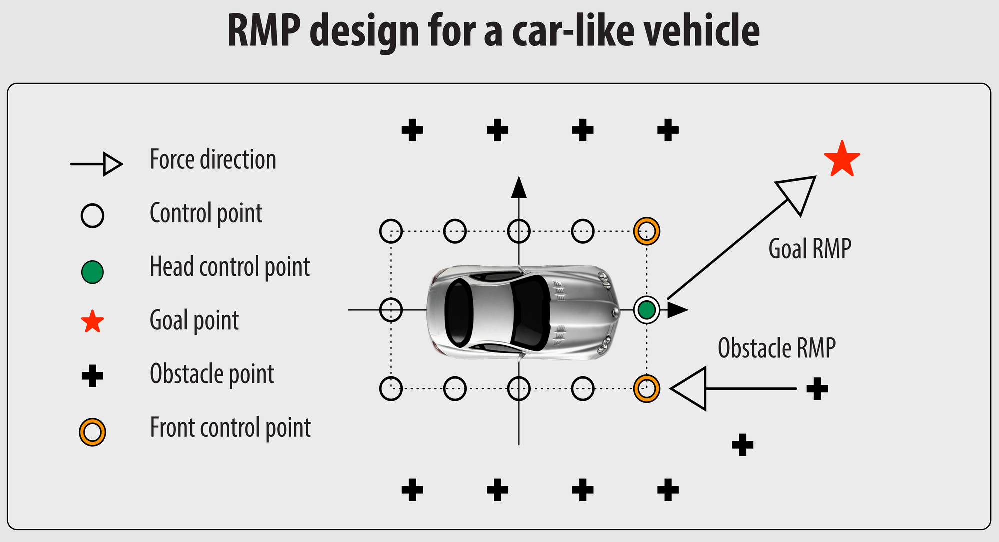
- A joint representation of the robot state and the environment
- Unifies robot geometry, robot dynamics and local obstacles into a single representation



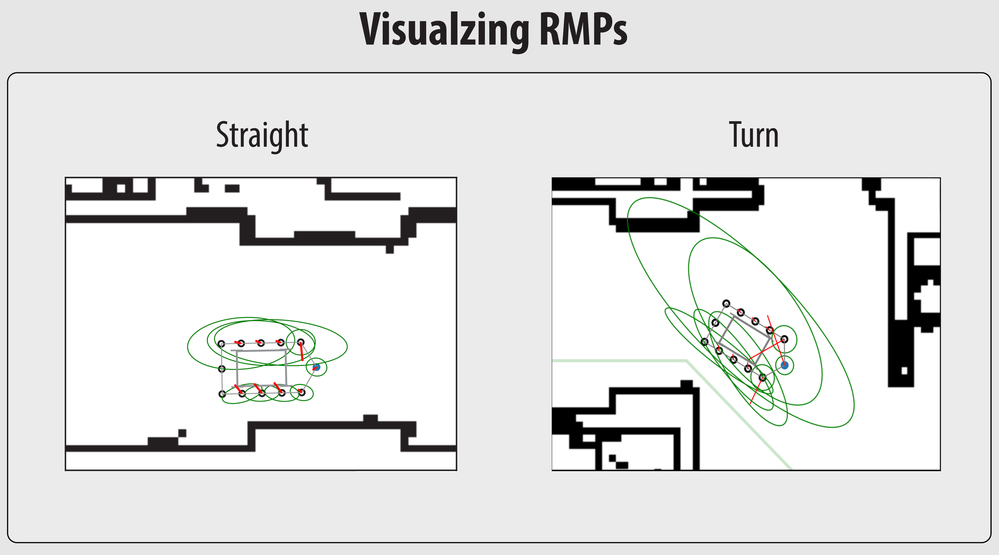
Approach	Data-driven	Semantics	Interpretable	Robustness
SLAM	No	No	Good	Hard for dynamic objects
End-to-end	Yes	Yes	Poor	No guarantee
Neural RMP	Yes	Yes	Good	Locally robust

Model

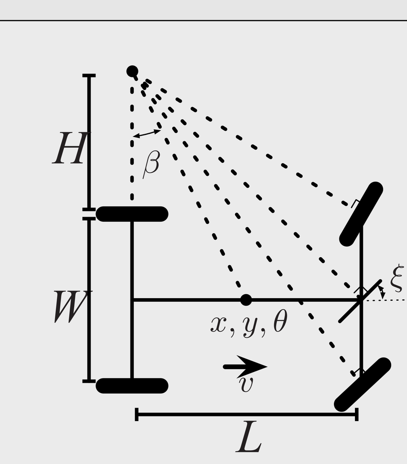
RMP design for a car-like vehicle



Visualzing RMPs



Applying motion constraints



$$\tan\xi = \frac{L}{H + W/2}$$

$$\tan\beta = \frac{L/2}{H + W/2}$$

$$\dot{x} = v\cos\theta$$

$$\dot{y} = v\sin\theta$$

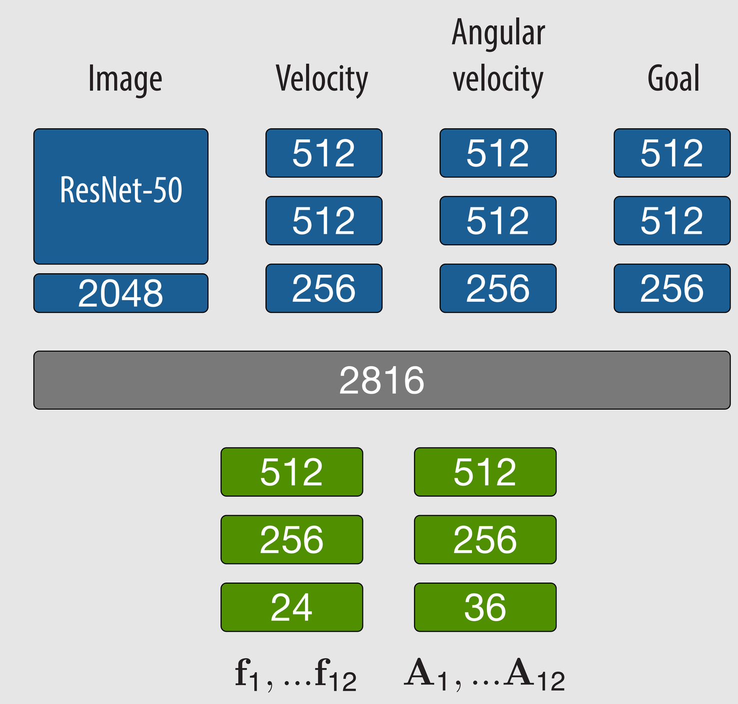
$$\dot{\theta} = \frac{v}{L}\sin 2\beta$$

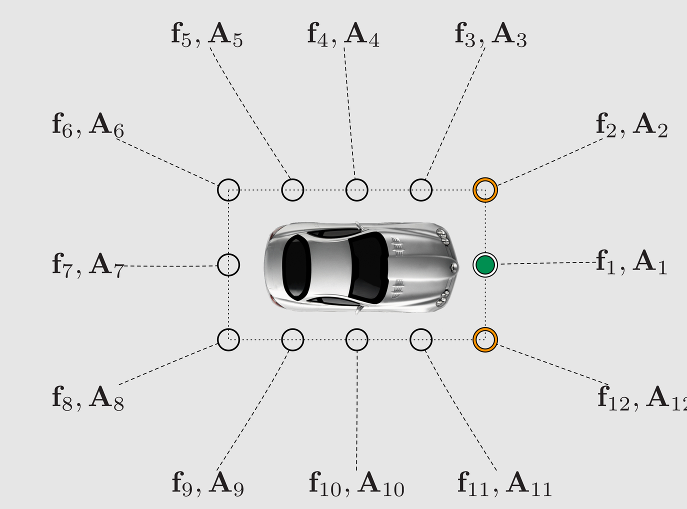
Solving the optimal control while satisfying motion constraints

$$\dot{v}^*, \dot{\xi}^* = \underset{\dot{v},\dot{\xi}}{\operatorname{argmin}} \sum_i \frac{1}{2} \|\mathbf{f}_i - \mathbf{J}_{\phi_i}\mathbf{J}[\dot{v}, \dot{\xi}]^\top\|^2_{\mathbf{A}_i}.$$

Neural RMP

A neural network that predicts RMPs from a single RGB image





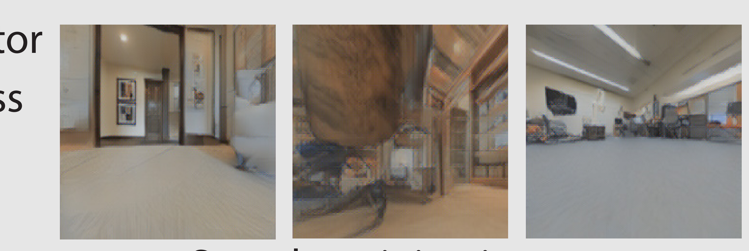
Optimal control commands are solved analytically

$$\dot{v}^*, \dot{\xi}^* = \underset{\dot{v},\dot{\xi}}{\operatorname{argmin}} \sum_i \frac{1}{2} \|\mathbf{f}_i - \mathbf{J}_{\phi_i}\mathbf{J}[\dot{v}, \dot{\xi}]^\top\|^2_{\mathbf{A}_i}.$$

Evaluation

Training

- 60k trajectories generated in the Gibson simulator
- Direct supervision of predicted RMPs with L2 loss
- Data augmentation with DAgger



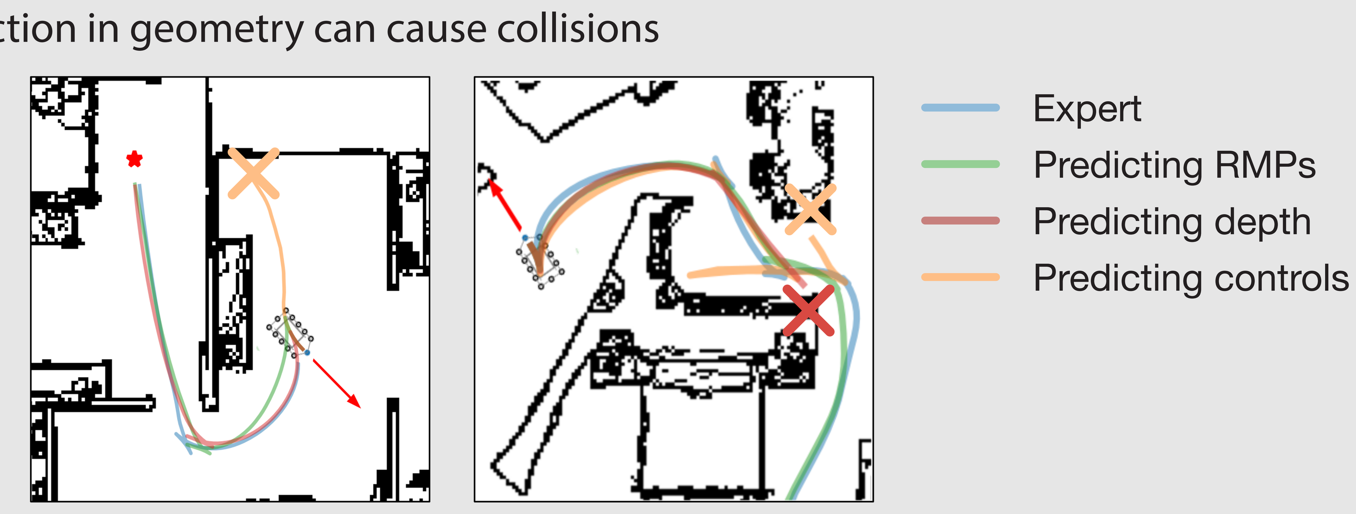
Sample training images

Generalization in Unseen Environments

Neural RMP achieves higher success rate with lower collisions

Models	Space8		House57		House29	
	Reach%	Collision%	Reach%	Collision%	Reach%	Collision%
Expert	97.9	0.4	95.0	1.4	94.5	2.4
Predicting RMPs	**88.1**	**7.4**	**89.5**	**5.9**	**93.7**	**1.6**
Predicting Depth	85.4	10.3	78.1	17.8	89.0	9.4
Predicting Controls	51.3	19.9	56.6	21.9	68.5	14.2

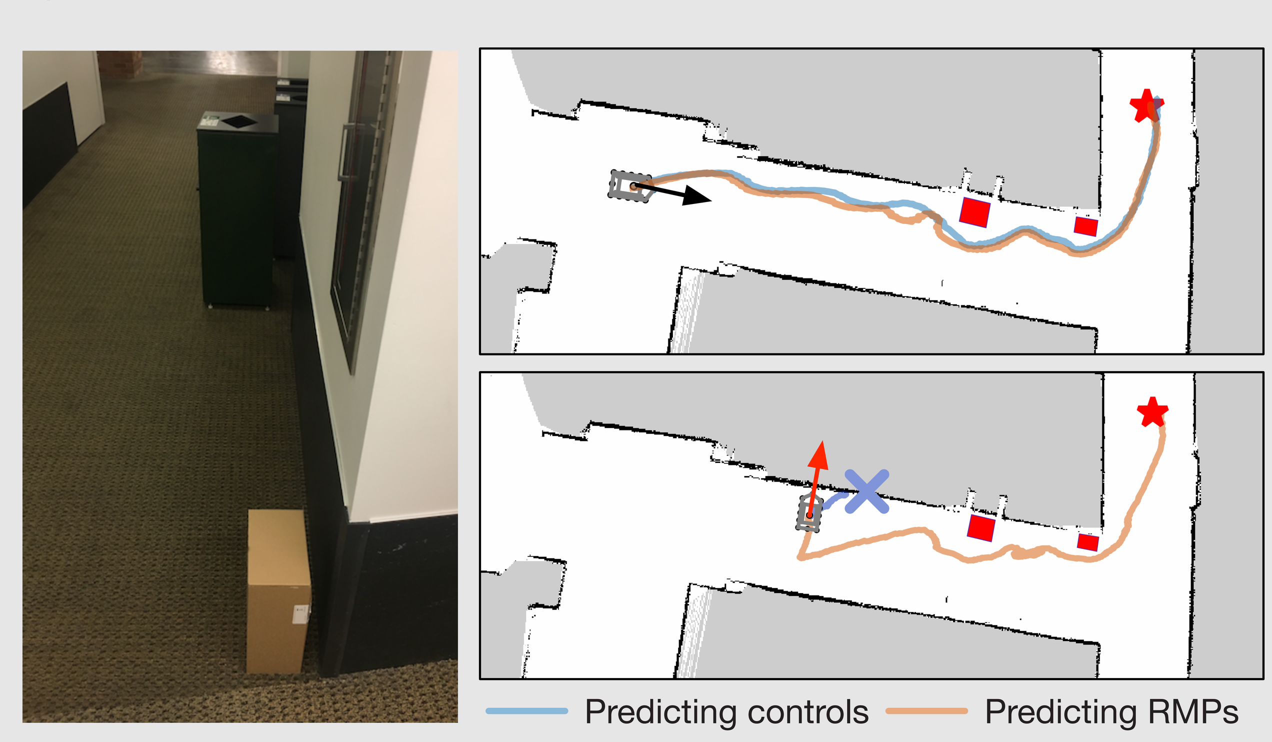
Neural RMP is more robust when the robot is operating in tight spaces, where slight mis-prediction in geometry can cause collisions



Real-world experiments

- 1/12 RCCar based on the MIT RaceCar
- Jetson TX2 with TensorRT
- 120 deg fov RGB Camera
- 25 fps end-to-end inference time

Neural RMP exhibits more robust obstacle avoidance behavior with unseen obstacles and ambiguous/uninformative observations.



Conclusion and Future Work

The Neural RMP model unifies the geometry and dynamics of the vehicle and its interaction with the environment, making it a promising approach for solving challenging robotic tasks with unknown obstacles, with usually only RGB images as input.

Future works include

- Apply it to manipulation, policy transfer and agile robot maneuver
- Unsupervised RMP learning to reduce the overhead of manual RMP tuning

References

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