

Hybrid Statistical Learning Methods for Embedded Implementation of Vehicle Safety Functions

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Automotive Safety Technologies

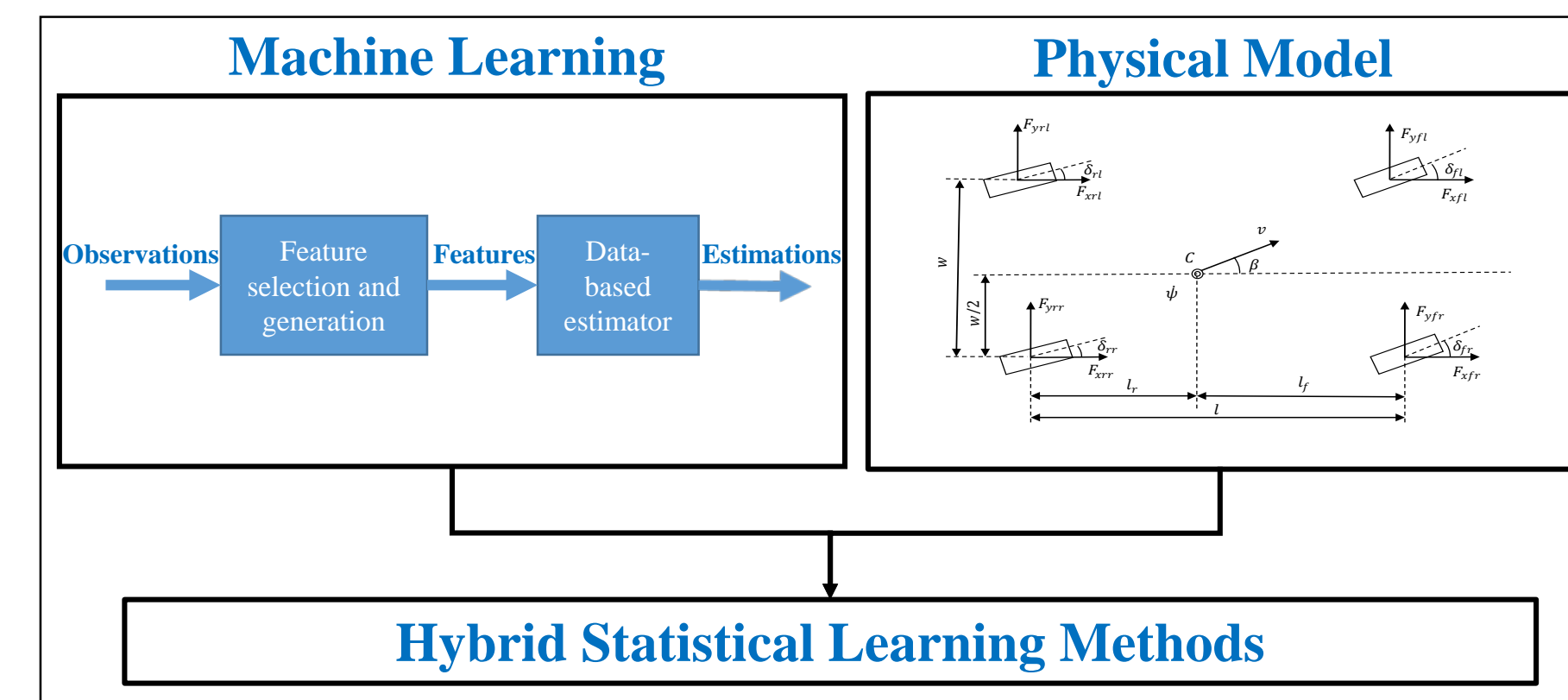


1. Introduction

- Requirements for safe trajectory planning in critical, complex traffic-scenarios are
 - Simultaneous **intervention in longitudinal and lateral dynamics**
 - Consideration of **multiple static and dynamic objects** along with their predictions
 - Consideration of **predicted severity of injury**
 - Efficiency** in terms of computational resources to run in real time
- Statistical learning algorithms find solutions for complex problems with low computing resources, but they are not used in safety critical applications as they are pure data based methods

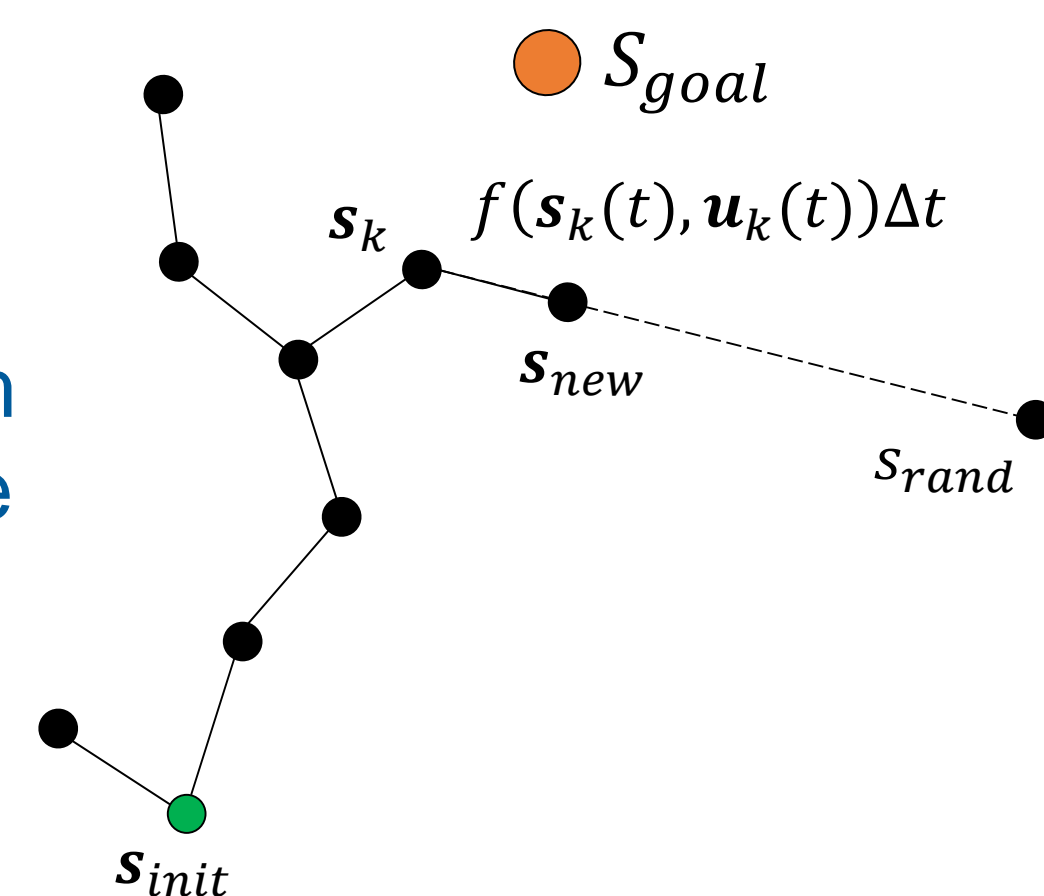
2. Aim

- Hybrid machine learning algorithms, combination of machine learning algorithms and physical models, are used with three main aims: 'safety', 'interpretability' and 'low computing resources'



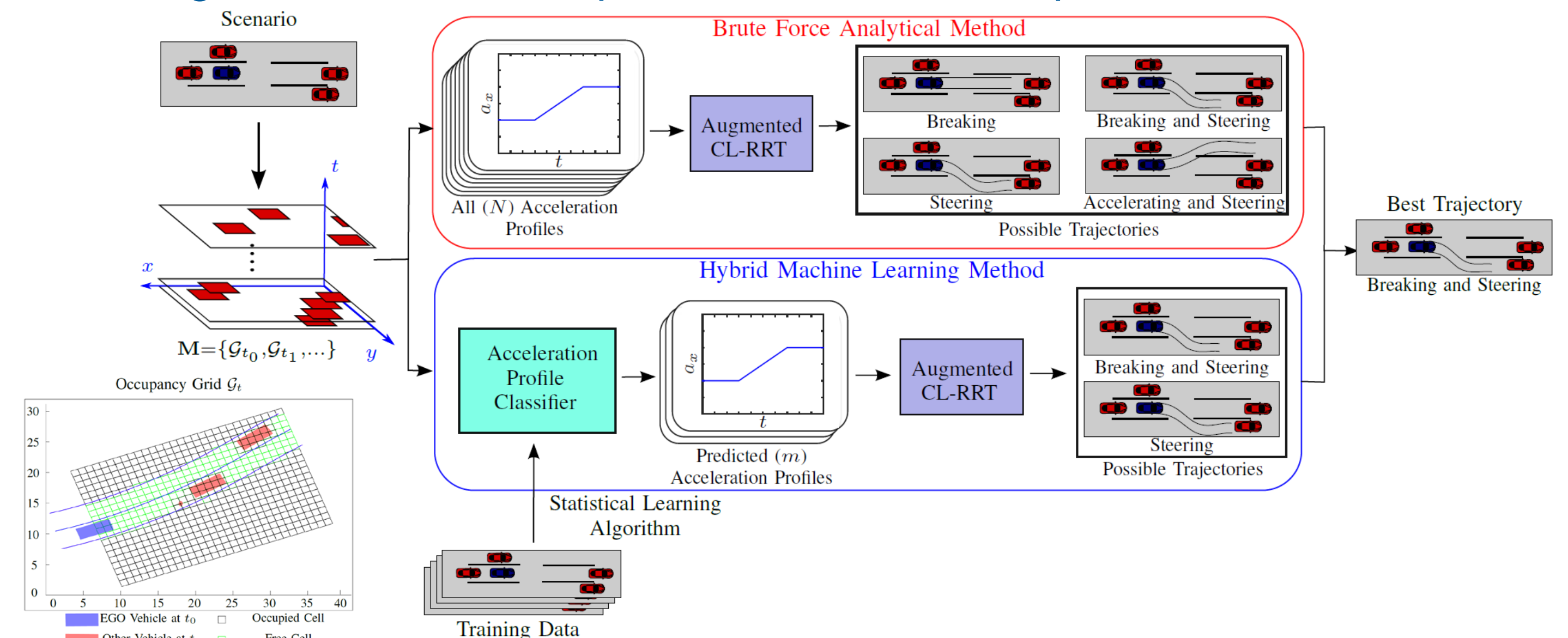
3. Augmented CL-RRT Algorithm

- Variant of Rapidly-exploring Random Tree (RRT) algorithm
- Lateral dynamic intervention by iteratively extending a tree towards a random sample s_{rand} from the nearest state $s_k(t)$ using vehicle differential constraints
- Multiple predefined longitudinal acceleration profiles for longitudinal dynamic intervention
- $s_{new}(t + \Delta t)$ is added to the tree if path from $s_k(t)$ to $s_{new}(t + \Delta t)$ is either a collision-free path or with a non-severe collision
- Advantages: 1) Provide drivable trajectories
2) Probabilistically complete
- Disadvantage: Guarantees solution only in infinite time, if exists



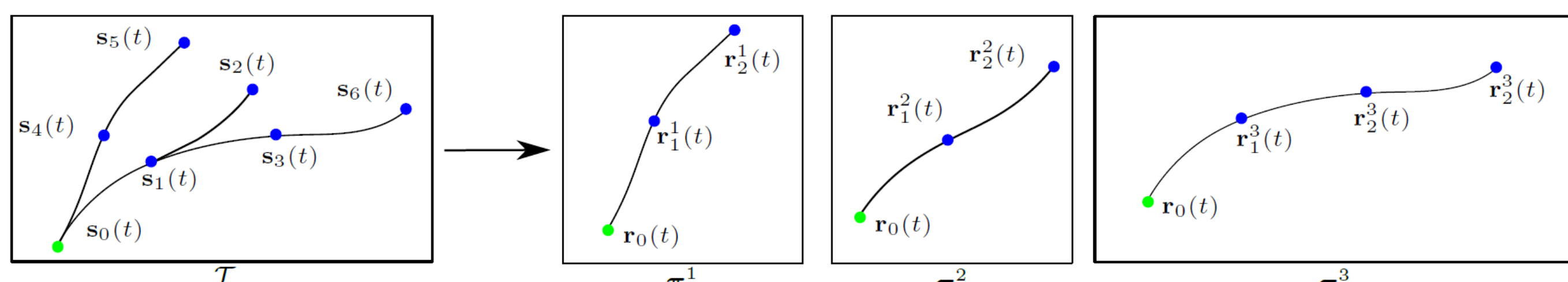
4. Hybrid Augmented CL-RRT Algorithm

- Use of only few m predefined predicted acceleration profiles instead of using all N acceleration profiles to reduce computation time



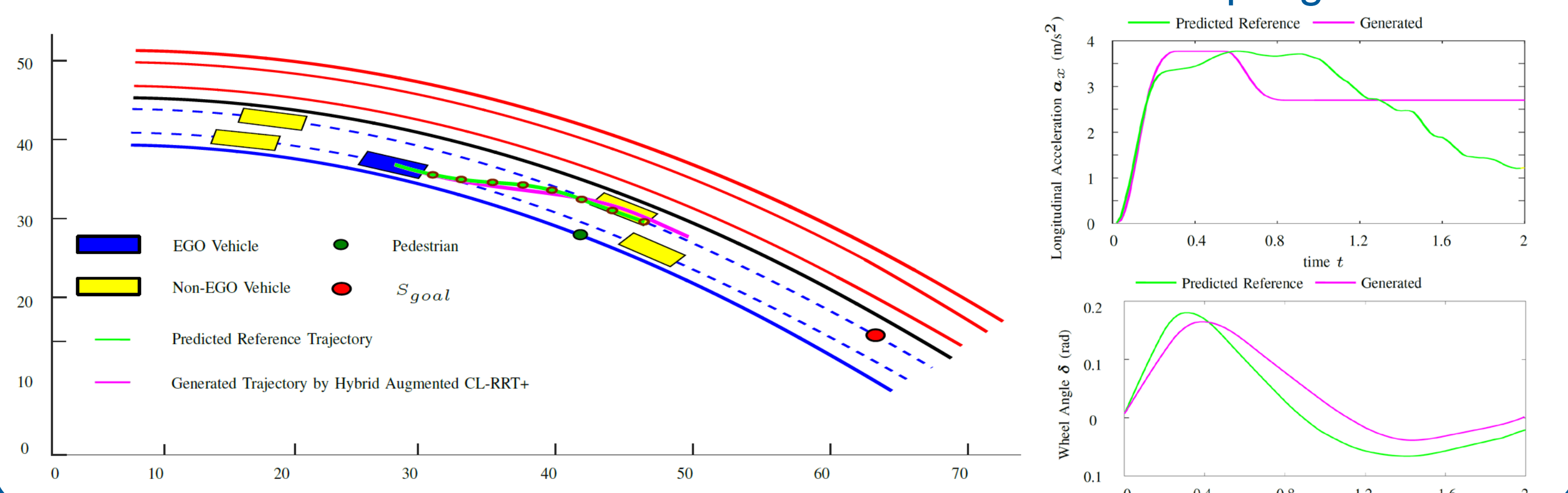
5. Augmented CL-RRT+ Algorithm

- Extension for sampling in longitudinal dynamics as well and no predefined longitudinal acceleration profiles
- Constraints for sampling longitudinal acceleration
 - Actuator limits (acceleration and jerk)
 - Avoiding acceleration or deceleration in small time intervals in individual trajectories π^k of a tree \mathcal{T}



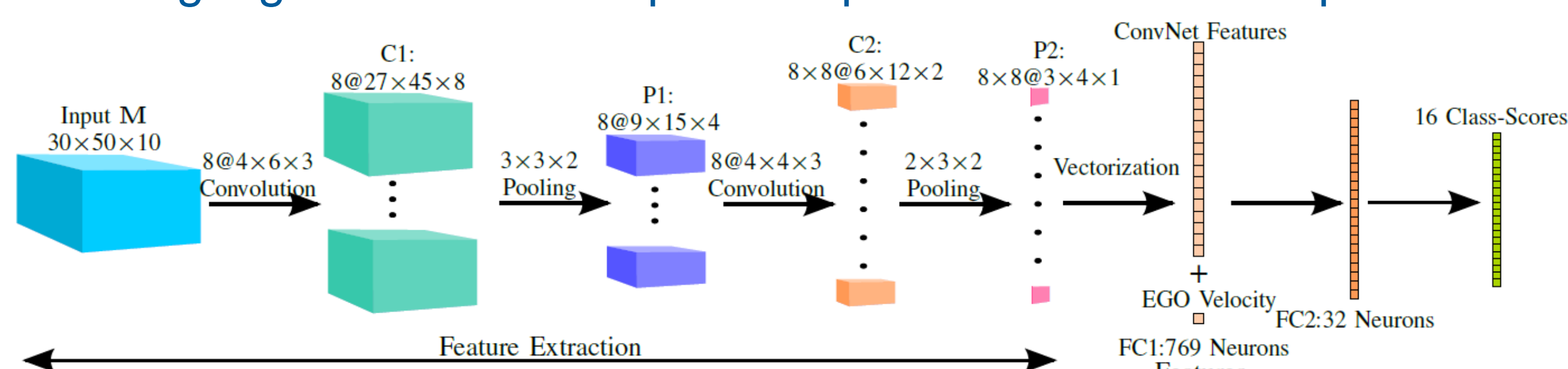
6. Hybrid Augmented CL-RRT+ Algorithm

- Machine learning based simultaneous biased-sampling in longitudinal and lateral dynamics with predicted reference trajectory
- Suitable trade-off between randomized and biased sampling



7. Machine Learning Algorithm

- A 3D convolutional neural network (3D-ConvNet) is used as a machine learning algorithm to learn spatiotemporal features from input M



- Labels for 3D-ConvNet
 - Hybrid Augmented CL-RRT → Longitudinal acceleration profiles
 - Hybrid Augmented CL-RRT+ → Combination of cluster of longitudinal acceleration and steering wheel angle profile

8. Simulation Results

- Criterion for comparison of trajectory planning algorithms
 - Efficiency:** Computation time and the number of states required
 - Safety:** Percentage of scenarios in which a safe (collision-free or with a non-severe collision) trajectory is found

Criteria	4-object Scenario (405 Scenarios)		6-object Scenario (478 Scenarios)	
	Aug. CL-RRT	Aug. CL-RRT+	Aug. CL-RRT	Aug. CL-RRT+
Average # States	595	210	629	201
Average Time (Sec.)	6.11	3.59	6.76	4.19
Collision-free Trajectory Found (%)	98.76	96.79	77.84	90.37
No Safe Trajectory Found (%)	0	0	0.05	0.09

Criteria	Training Curves Test data (994 Scenarios)		Non-Training Curves Test data (403 Scenarios)	
	Aug. CL-RRT+	Hybrid Aug. CL-RRT+	Aug. CL-RRT+	Hybrid Aug. CL-RRT+
Average # States	163	101	186	112
Average Time (sec.)	4.06	1.03	4.26	1.27
Collision-free Trajectory Found (%)	96.50	95.83	96.66	90.60
No Safe Trajectory Found (%)	0	0.80	0.99	1.74