

## Optimal Trajectory Planning and Motion Control of Autonomous Vehicles

*a dissertation to be defended by*

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**Abstract**—Autonomous vehicles and electric mobility are converging to redefine modern transportation, yet the full realization of their potential is constrained by persistent challenges in motion planning, energy-efficient motion control, and reliable operation in complex and unstructured environments. Existing approaches to trajectory planning often sacrifice solution optimality or rely on simplified geometric approximations for collision avoidance that over-constrain the feasible space and increase computation time. Motion control strategies, while sometimes sophisticated, frequently lack adaptability to varying operating conditions, limiting their effectiveness across nonlinear ranges encountered in practice. Moreover, constrained motion executed via nonlinear predictive control strategies rely on developing data-driven discrete-time model structures in the absence of analytical or mathematical models that compromise prediction accuracy for nonlinear dynamics, and are rarely evaluated across sufficiently diverse and safety-critical scenarios, including vulnerable road user interactions. To address these gaps, three contributions are presented. First, a bi-stage optimal trajectory planning framework is developed for autonomous vehicles in unstructured environments. At the first stage, a feasible path is generated using an optimal RRT-based sampling planner, then used as a warm-start initial guess for a constrained optimal control problem solved through direct multiple shooting. Obstacles and the vehicle are represented as convex polytopes, and collision avoidance is reformulated using convex duality to handle the full vehicle shape. An obstacle region reduction strategy combined with the first-stage path reduces computational complexity and accelerates convergence. The framework generates smooth, collision-free, dynamically feasible trajectories, achieving up to 60% reduction in computation time relative to baseline approaches. Second, a reinforcement learning–based adaptive motion control strategy is proposed for four in-wheel motor actuated electric vehicles. A TD3-QuadPID architecture is developed in which an actor-critic agent adaptively tunes multiple PID controllers for torque allocation and steering control subject to tight constraints on pitch, roll, and vertical acceleration. The approach is model-free and evaluated on a high-fidelity black-box vehicle model. The controller achieves smooth motion, improved constraint satisfaction, and more than 89% improvement in energy efficiency relative to a baseline controller, while generalizing to unseen environments. Third, a data-driven nonlinear model predictive control framework is developed for autonomous vehicles when no physical model is available. A continuous-time neural state-space model is learned from data using the Neural Ordinary Differential Equation framework and embedded into a nonlinear model predictive control formulation. A time-scheduled horizon strategy improves feasibility and closed-loop performance. The learned model achieves a state prediction accuracy averaging 84% for constant and varying inputs. The controller attains trajectory tracking errors below 0.04 RMSE across driving scenarios, while ensuring complete collision avoidance in safety-critical situations. Overall, this dissertation contributes new methods for trajectory planning and motion control by leveraging control theory, optimization, deep reinforcement learning, and data-driven neural dynamic modeling, advancing intelligent autonomous driving systems that are safe, efficient, adaptive, and applicable in realistic driving scenarios.

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