Unified Probabilistic Trajectory Generation for Multi-Domain Autonomous Systems

Background:

Current emergency response requires fast paced information that is rapidly provided to non-technical end users. Modern implementation of Unmanned Aerial Vehicles (UAVs) offer real-time aerial mapping and situational awareness but rely on accurate localization and perception pipelines to execute autonomous behavior effectively.[5] These UAVs are characterized by finite flight time, high maximum velocities, autonomous deployment, and a need for manual override. There is an interest in a localization, path planning, trajectory generation, and control system architecture which can autonomously maneuver a UAV in uncertain or contested applications. Disaster response requires integration of robust systems into existing well-tuned teams to current path planning and trajectory generation can be susecptible to errors in localization, and there is a need to demonstrate robustness and optimality under in uncertain environments. Current methods seek to minimize localization error by improved sensor fusion or state estimation, or design more informative paths to gain more helpful data, or to mapping-specific applications.

Autonomous vehicles estimate their state through probabilistic inference, often using Bayesian filters like the Extended Kalman Filter (EKF) or Particle Filters (PF).[5] While these methods yield accurate state estimates, estimation and planning are typically treated independently, while uncertainty grows during motion. Path planning computes feasible routes between states under vehicle and obstacle constraints.[1] Geometric planners ensure completeness but lack feasibility; sampling-based and learning-based methods scale better to high-dimensionality and uncertain settings but struggle with dynamic feasibility, constraint satisfaction, and stability.[1] Most assume perfect localization and rely on costly replanning when pose estimates degrade.[2] Trajectory generation refines paths into dynamically feasible, time-parameterized curves. Polynomial, spline, and optimization-based methods produce smooth and efficient trajectories but often neglect how localization uncertainty affects feasibility. Control systems including PID, LQR, adaptive, or MPC will track these trajectories despite modeling error and environmental disturbances, yet commonly assume deterministic references. Across all layers, uncertainty is handled locally rather than holistically. A unified probabilistic autonomy framework that propagates uncertainty through estimation, planning, and control would enable robust, adaptive operation of aerial and underwater vehicles in uncertain environments.[4]

Autonomous vehicles operate in dynamic environments with incomplete or degraded navigation data. Effective autonomy in rigorous conditions depends on robust localization, path planning, trajectory generation, and control systems able to operate under uncertainty. Prior work across these domains has established the foundations of modern autonomy but still treats localization and controls as separate problems. [what if instead it was one problem that crossed modules].

Research Question:

How can a probabilistic trajectory generation framework maintain stability and optimality under evolving state uncertainty for vehicles operating in GPS- or RF-denied environments?

Aim 1: Model localization uncertainty and its propagation through vehicle dynamics. Autonomous vehicles rely on estimated states that inevitably contain error due to sensor noise and degraded navigation signals. To capture this effect, I will develop a probabilistic state-space model coupling vehicle dynamics with stochastic localization error. The model will represent UAV motion using a Dubins, Reeds-Shepp or polynomial kinematic formulation with Gaussian uncertainty in state estimates. Using extended or particle filter principles, I will quantify how estimation error propagates over time and how feasible control inputs limit the reachable sets. Deliverable: A validated uncertainty-aware motion model in simulation and covariance-based metrics describing divergence between estimated and true trajectories.

Aim 2: Generate dynamically feasible trajectories robust to localization uncertainty. Building on Aim 1, I will design a trajectory generation framework that explicitly incorporates probabilistic uncertainty into the planning process. Chance-constrained optimization will be used to compute feasible, dynamically consistent trajectories that satisfy safety and control limits with specified confidence levels. To enable real-time performance, a lightweight reinforcement-learning heuristic will predict locally feasible trajectory segments, accelerating stochastic optimization.[3] Deliverable: A unified uncertainty-aware planner benchmarked against deterministic baselines in GPS-denied simulations, with performance evaluated in terms of safety-margin violations, success rate, and computation time.

Aim 3: Integrate and validate a unified probabilistic autonomy architecture.
The final aim will integrate estimation, planning, and control into a closed-loop architecture that propagates uncertainty through each layer of the autonomy stack. Implemented in ROS 2 with PX4 for hardware-in-the-loop testing, the system will execute probabilistic trajectories under injected sensor noise and degraded localization. Results will be compared to conventional deterministic controllers to assess stability, tracking accuracy, and robustness. Deliverable: A real-time demonstration of probabilistic trajectory control for UAVs, with an extension to underwater AUV simulation to demonstrate cross-domain generality.

Intellectual Merit

This research advances the foundations of autonomy under uncertainty. It leverages stochastic state estimation into probabilistic trajectory generation to create a unified framework for uncertainty-aware autonomy for an era of deployment for drones and underwater vehicles.

From a controls perspective, the project strengthens understanding of safe and stable behavior under imperfect information, addressing one of the most persistent challenges in nonlinear and stochastic control. By explicitly modeling localization uncertainty in the trajectory optimization process, this work extends traditional path planning beyond geometric feasibility toward dynamic robustness and probabilistic optimality.[1] By integrating stochastic optimization with lightweight reinforcement learning heuristics, the project develops hybrid controllers that combine the optimility and efficiency of physics-based models with the adaptability and performance of data-driven methods.[3] This integration reflects a growing national and international interest in optimal autonomous systems capable of operating in uncertain environments.

Ultimately, this work bridges control theory, probabilistic robotics, and modern learning-based planning to advance the science of autonomy apply that science to disaster response.

Broader Impacts:

Autonomous systems are overhauling the ways that humans respond to disasters, manage critical infrastructure, and interact with contested environments. This research supports that transformation by enabling robust, uncertainty-aware autonomy. In disaster response and humanitarian aid, the proposed framework will enable UAVs to navigate through smoke, debris, and collapsed structures when RF and visibility are limited.

Autonomous underwater vehicles (AUVs) operating in turbid conditions could inspect bridges, levees, or pipelines immediately after storms or floods, restoring vital infrastructure faster while mitigating the need to expose human divers to dangerous environments.

This work contributes to a future where UAVs and AUVs serve as reliable partners in protecting lives, supporting recovery, and strengthening global response capability by advancing reliability, efficiency, and trust in autonomous systems.

References:

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