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PhD Candidate

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PhD Dissertation Defense Presentation

Physics-Guided Deep Generative Learning for Data-Efficient Aerospace Autonomy

Abstract:
Designing reliable control policies for real-world tasks such as guiding aircraft and drones through turbulence, planetary landing missions, steering self-driving cars through rare traffic events, and operating robots and medical devices safely depends on data that captures how these systems behave across uncertainty, disturbances, and rare conditions. Yet this is precisely the data the real world withholds: flight tests are expensive, planetary missions happen once, critical events such as collisions and failures cannot be recreated at scale, and inducing failure scenarios in healthcare is unacceptable. The systems that would benefit most from data-driven control are the ones for which real data is scarcest. The common workaround, simulations, are imperfect: modeling approximations, unknown parameters, and unmodeled dynamics cause simulated trajectories to drift from reality, producing a reality gap that undermines controllers trained on synthetic data alone. This dissertation investigates Generative Artificial Intelligence Models (GAIMs) for addressing data insufficiency in control engineering. The central contribution is a family of deep generative architectures that incorporate the underlying physics of the system, either directly or indirectly, into training, enabling high-quality synthetic data generation from datasets containing only a small number of observed trajectories.

The research follows two threads. The first develops physics-informed generative models for optimally controlled systems, where Hamiltonian invariance governs optimal trajectories. Using Zermelo minimum-time and minimum-exposure navigation as case studies, the work introduces Z-GAN, Z-VAE, Split-VAE, and S-VRNN architectures for generating trajectories and evolving threat fields under limited or imperfect physics. The second thread addresses data scarcity in planetary landing. Because real descent trajectories are extremely limited while RL requires large datasets, the proposed MI-VAE learns from scarce real data and abundant simulated data by separating domain-specific and shared latent factors. The derived joint ELBO enables synthetic trajectory generation, and offline RL results show improved policy performance over raw real data and standard VAE-generated data in low-data regimes.