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MAE SEMINAR SERIES

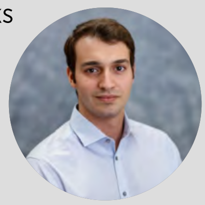
Toward Trustworthy Autonomy: Unifying Optimal Control and Machine Learning for Aerospace Systems

BORIS BENEDIKTER, PH.D

Dr. Boris Benedikter is a Postdoctoral Research Associate in the Space Systems Engineering Laboratory (SSEL) at the University of Arizona. He received his Ph.D. in Aeronautical and Space Engineering from Sapienza University of Rome in 2022.

Dr. Benedikter's research lies at the intersection of rigorous optimization, control theory, and modern machine learning. He develops trustworthy guidance and control frameworks for aerospace vehicles, with both aerial and space applications.

He currently leads projects in safe-by-design autonomy. His recent work includes physics-informed neural networks for constrained optimal control, reinforcement-learning-enhanced model predictive control, and imitation learning for fast trajectory generation.



ABSTRACT

Modern aerospace systems, ranging from autonomous UAVs to spacecraft operating far from Earth, must make fast, reliable decisions in environments that are uncertain, dynamic, and too complex to model perfectly. Traditional optimal control provides strong guarantees but relies on simplified models, while modern machine learning offers adaptability but often lacks the rigor required for safety-critical flight environments. This talk presents a research program that unifies these two perspectives to enable trustworthy autonomy for advanced air and space systems.

I will first introduce convex optimization and stochastic control methods that reformulate challenging nonlinear guidance and control problems into computationally efficient, real-time algorithms with probabilistic safety guarantees. These include lossless convexification, sequential convex programming, and covariance control applied to scenarios such as UAV navigation in cluttered environments and spacecraft proximity operations under uncertainty.

Next, I will show how machine learning, through physics-informed neural networks, imitation learning, and reinforcement-learning-enhanced control, can be incorporated into classical GNC pipelines to improve robustness and adaptability without compromising verifiability. These hybrid approaches enable faster trajectory generation, improved disturbance rejection, and better adaptation across mission conditions.

I will conclude by outlining my future vision for safe-by-design hybrid GNC architectures, real-time learning for rapidly changing environments, and runtime verification tools that quantify risk during flight. Together, these efforts aim to bridge the gap between AI-enhanced autonomy algorithms and the certification requirements of real-world aerospace systems.