Nonlinear Kalman filtering-based data-driven digital twin:
Damage and uncertainty quantification in large-scale systems with missing data

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In today's world, critical infrastructure like bridges, power plants, and industrial machinery are equipped with sensors that generate a continuous stream of data. Yet, despite this wealth of information, we are far from fully realizing its potential. During my time in the hydro industry, I observed firsthand how clients favored established software like ANSYS over data-driven insights. This reliance on traditional software, even with the availability of sensor data, underscores a critical gap: we are not effectively translating raw data into actionable insights. In this talk, I will present how did we use Kalman filtering to develop a data-driven, interpretable digital twins (DTs) for large-scale structures like tall buildings, bridges, and hydroelectric power stations. I envision the DT as a real-time module that handles specific tasks like data analysis, estimate latent states (virtual sensing), identify parameters, quantifying their change with confidence interval, predict response, real-time reliability analysis, and long-term monitoring with low-sampling-rate sensor data. The overarching goal is to empower engineers with real-time, actionable insights for risk-informed decision-making in maintenance and operation processes. However, the performance of the Kalman filtering strongly depends on the proper choice of specific hyperparameters which is impossible to tune in some situations. To avoid cumbersome trial-and-error manual settings in finding the optimal hyperparameters, we introduce a hands-off meta-optimization framework, which incorporates a nonlinear mesh adaptive direct search optimization algorithm in an offline outer loop, paired with a physics-aware loss function. The novelty of this approach is twofold. First, a physics-aware loss function is used to optimize the filter hyperparameters. It minimizes the physical discrepancy induced by the data-driven correction of the prior states during filtering. Notably, sensor data are not directly incorporated into the calculation of the loss function, which expedites the tuning of the filter in weakly informative data scenarios, especially when the underlying physics is well understood. Second, UKF relaxation is embedded in the optimization to make the measurement and process noise covariance matrices adaptive, which greatly reduces the dimension of the optimization space while remaining very general with respect to the structure of the matrices. We demonstrate the effectiveness of the proposed framework, as the cornerstone of a future digital twin technology combining data- and physics-based models, through various classical problems in solid mechanics, rotating machinery, civil engineering, and fluid-solid interaction.