OPTIMAL DESIGN OF EXPERIMENTS IN A DIGITAL TWIN FRAMEWORK

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Extension: Sensor steering



Figure ACT Optimal sensor placement for pollutant prediction after 8 seconds in the yellow rectangle. The pollutant concentration is measured after 2 seconds. Application of [1] for an Urban Physics Simulation [3]

Motivation

In the context of a digital twin, sensor This leads to a Bayesian inverse technology represents the interface problem for the parameter m:



miniaturization The Of sensor technology has reached a point where devices can be easily transported. Additionally, drones or robot dogs are capable of swiftly reaching locations that are difficult to access. This opens up the possibility of using them as mobile sensors. The following sketch possible autonomous presents a control of the mobile sensors' steering:

between the physical and the virtual worlds. The question of optimal sensor placement becomes important in the context of large-scale infrastructure, such as bridges, chemical plants, cities, or even entire regions.



Methodology

 $\pi_{post}(m|d) \propto \pi_{like}(d|m)\pi_{prior}(m)$

The posterior probability distribution characterizes how well the estimated parameter m matches the measured values d. In addition, the distribution provides candidates for the solution and, most importantly for sensor placement, an evaluation of the uncertainty of the system.

In order to develop an optimal sensor design, it is necessary to determine the following quantities:

In the provided scenario (Figure ACT), 1. an objective function prediction of the pollutant 2. a forward model (physical or the concentration $m = u(T, \cdot)$ at a specific data-driven model, e.g. FEM or ML) time (T=8s) and at a specific location 3. prior knowledge of the parameter (yellow rectangle) is to be determined. to be estimated 4. knowledge about uncertainty of This should be based on the measured the measured system (sensor noise, concentration d at the sensor positions uncertainty of the forward model etc.) (white circles, measurement time T=2s).



Procedure for sensor steering taken from [2]

The poster employs the example of pollutant transport to illustrate how optimal sensor placement can be achieved for an abstract Bayesian inverse problem.

[1] K. Wu, P. Chen, O. Ghattas, An offline-online decomposition method for efficient linear bayesian goal-oriented optimal experimental design: Application to optimal sensor placement, SIAM Journal on Scientific Computing [2] Sonja Wogrin, Arjun Singh, Douglas Allaire, Omar Ghattas, Karen Willcox: From Data to Decisions: A Real-Time Measurement–Inversion–Prediction– Steering Framework for Hazardous Events and Health Monitoring, Handbook of Dynamic Data Driven Applications Systems [3] Bonari, J., Kuehn, L., Danwitz, M. von, & Popp, A. (2024). Towards Real-Time Urban Physics Simulations with Digital Twins. Preprint submitted for publication http://arxiv.org/pdf/2405.10077

