Hybrid Machine Learning for Real-Time Machine Data and Physical Systems

Abstract:

This work addresses hybrid machine learning architectures for the detection of anamolous time-series, in large volumes of **m**ultivariate real-time **m**achine **d**ata (MMD). In our context, one MMD is generated for each element produced; typically, there will be several thousand MMD. The goal is to implement an unsupervised detection of an anomalous MMD, indicating the production of an anomalous element. The process of anomaly detection needs to be robust; given, the safety relevance associated with anomalous elements. In the ground improvement application presented here, the subsurface properties are inferred from the real-time machine data. Unfortunately, this precludes the acquisition of “ground-truth” to calibrate the process. Consequently, the anomaly detection must proceed from uncalibrated and unlabeled MMD.

Hybrid learning, also called *physics informed learning*, is still considered a highly relevant research topic. Currently, there are no standard approaches available. The architecture proposed here, consists of a variational-autoencoder (VAE), combined with the classical computation of key performance indicators (KPI) and descriptive statistics.

The ground improvement process is utilized to create stable foundations for buildings. In this application detecting anomalies is crucial, since the repercussions of having an instable foundation are both dangerous and very costly to rectify. The KPI, computed from the MMD, embody the expert knowledge about the process and what is considered to be anomalous. Additionally, the VAE performs an unsupervised classification of the MMD. Multiple approaches to training the VAE in conjunction with the KPI are discussed. A number of cases have been identified where the VAE has detected an anomaly, not indicated by the KPI. The anomalous MMD triggers a knowledge discovery process; whereby, domain experts manually evaluate the data with the goal of defining additional KPI.

An outlook is given into using constrained basis functions in the decoder of the VAE, as a means of deeply embedding physical knowledge of the system behavior into the ML.

Bio:

Anika Terbuch obtained her B.Sc. and M.Sc. in Industrial Logistics from the University of Leoben. During her studies, she specialized in computational optimization and automation.

She is currently pursuing her PhD at the Chair of Automation at the University. Her current research efforts involve the development of machine learning architectures that combine statistical methods and machine learning techniques as well as embedding prior knowledge in the architectures. This hybrid machine learning architecture is currently used for outlier detection and system identification. The areas of interest of her current research are: unsupervised learning, embedding prior knowledge about the system into machine learning architectures and meta-heuristics for optimizing the hyperparameters.

Periodic-Aperiodic Signal Separation using the Method of Variable Projection

Abstract:

This presentation adresses computational methods for the separation of periodic signals, with unknown frequency, from an aperiodic background, using basis functions and the method of variable projection.

Periodic and Aperiodic signal mixtures often occur in the monitoring and control of industrial processes. Repetitive activities; i.e. rotational motions, are typically the source of periodic patterns in measurement data. Extraneous influences, in conjunction with the dynamic response of the control system, add an aperiodic time varying portion to the signal. Moreover, the rotational motion might be feedforward controlled without a measurement feedback. This leads to the actual frequency of the periodic component being unknown. A high-fidelity separation of the periodic and aperiodic portions of the signal is essential if an exact control of the dynamic process is to be enabled. Such tasks occur, e.g., in: roundness error separation in journal bearings; control of milling chatter or when controlling robotic manipulators.

Here a model based on basis functions and the method of variable projection is proposed. The periodic portion is modelled as a Fourier series, including harmonics, with unknown frequency ω; whereas, the aperiodic portion is modelled using C^n continuous B-spline basis functions. This formulation is linear in the coefficients of the basis functions, but nonlinear in ω. Consequently, the method of variable projections offers a numerically efficient and stable solution. Additionally, the range of convergence wrt. ω can be explicitly computed. Currently, iterative solutions to the method of variable projection are being tested, these should enable the implementation of the method on the embedded process controllers. The performance of the algorithms is demonstrated using synthetic data, as well as real-time measurement data emanating from a mechanical system.

Bio:

Johannes Handler received a B.Sc. and M.Sc. in Mechanical Engineering with a focus on Mechatronics from the University of Leoben, Austria, in 2019.

He is currently pursuing his PhD at the Chair of Automation at the University of Leoben, Austria. His research efforts involve the development of signal separation algorithms, especially focusing on periodic and aperiodic signal mixtures, as well as numerical methods for optimal control. In cooperation with Prof. Harker (Ontario Tech University) new algebraic methods for optimal path tracking, which avoid dealing with the Hamiltonian were developed.