v6 - 15.11.2023

Guy Revach - Research Statement

The Marriage of Statistical Signal Processing with Machine Learning

Classical statistical signal processing, exemplified by the work of Wiener [1] and Kalman [2], provides efficient, robust, and optimal solutions for fundamental real-life problems such as localization, tracking, and navigation [3]. These methods typically rely on statistical model-based (MB) approaches that perform well under simplified assumptions, such as known linear models with additive Gaussian noise (AGN). However, they often fall short in more complex practical scenarios characterized by missing model information, non-linearity, high-dimensional observations, and intricate observation models. The aim of my thesis is to address these more demanding use cases. To this end, my doctoral research demonstrates how to enhance classical principles of statistical signal processing by integrating them with classical machine learning algorithms, such as expectation maximization (EM) [4, 5] and sparse Bayesian learning (SBL) [6, 7], alongside state-of-the-art deep learning (DL) techniques [8], as in MB-DL research [9, 10, 11]. Next, we will explore methods that lie at the intersection of statistical signal processing and machine learning (ML) methodologies to address challenging use cases such as tracking (state estimation), decision-making, and signal detection.

1 KalmanNet - Data-Driven Kalman Filtering

State estimation of dynamical systems in real time is a core task in signal processing. For systems well-represented by a fully known linear Gaussian state-space (SS) model, the celebrated Kalman filter (KF) offers an optimal low-complexity solution. Although the KF has been successfully applied to various real-world problems, including radar target tracking [12], ballistic missile trajectory estimation [13], and space vehicle positioning and velocity estimation in the Apollo program [14], the linearity of the SS model and precise knowledge of it are often not encountered in practice.

Data-driven (DD) approaches are an alternative to MB algorithms, relaxing the requirement for explicit and accurate knowledge of the underlying model. Many of these strategies are now based on deep neural networks (DNNs), which have shown remarkable success in capturing the subtleties of complex processes [8]. When there is no characterization of the dynamics, one can train deep learning systems designed for processing time sequences, e.g., recurrent neural networks (RNNs) [15] and attention mechanisms [16], for state estimation in intractable environments. Yet, they do not incorporate domain knowledge such as structured SS models in a principled manner, while requiring many trainable parameters and large data sets even for simple sequence models and lack the interpretability of MB methods.

The limitations of MB Kalman filtering and DD state estimation motivate a hybrid approach that exploits the best of both worlds; i.e., the soundness and low complexity of the classic KF, and the model-agnostic nature of DNNs. Therefore, we build upon the success of previous work in MB-DL for signal processing [9, 10, 11] and propose KalmanNet [17, 18]. KalmanNet is a hybrid MB-DD online recursive filter, an efficient data-driven architecture for Kalman filtering—namely, time series tracking and state estimation. In particular, we focus on real-time state estimation for continuous-value SS models for which the KF and its variants are designed.

We assume that the noise statistics are unknown and the underlying SS model is partially known or approximated from a physical model of the system dynamics. To design KalmanNet, we identify the Kalman gain (KG) computation of the KF as a critical component encapsulating the dependency on noise statistics and domain knowledge, and replace it with a compact RNN of limited complexity that is integrated into the KF flow. The proposed KalmanNet learns the filtering operation by replacing the KG with an RNN that is integrated into the KF flow, rather than using data to explicitly estimate the missing model parameters. With this approach, our architecture maintains the MB filter's interpretability while addressing its limitations [1].

1.1 RTSNet - Data-Driven Kalman Smoothing

The smoothing task is core to many signal-processing applications. A widely popular smoother is the Rauch-Tung-Striebel (RTS) algorithm, which achieves minimal mean-squared error recovery with low complexity for linear Gaussian SS models, yet is limited in systems that are only partially known, as well as nonlinear and non-Gaussian.

In [19, 20], we build upon the interpretability and efficient design of KalmanNet and propose RTSNet, a highly efficient model-based and data-driven smoothing algorithm suitable for partially known SS models. RTSNet integrates dedicated trainable models into the classical RTS smoother's flow that learns the KG and the Kalman smoothing gain (KSG). We further iteratively refine our smoothing performance via *deep unfolding*. As a result, RTSNet learns from data to reliably smooth when operating under model mismatch and nonlinearities while retaining the efficiency and interpretability of the traditional RTS smoothing algorithm.

[1] The paper [18] has been cited more than 110 times and has been identified as one of the top 25 downloaded articles of the IEEE Signal Processing Society for the period from September 2022 to September 2023 in the IEEE Transactions on Signal Processing, as listed on IEEE Xplore®!

Our empirical study demonstrates that RTSNet overcomes nonlinearities and model mismatch, outperforming classic smoothers operating with both mismatched and accurate domain knowledge. Moreover, while RTSNet is based on compact neural networks, which leads to faster training and inference times, it demonstrates improved performance over previously proposed deep smoothers in nonlinear settings.

1.2 Uncertainty

Providing a metric of uncertainty alongside a state estimate is often crucial when tracking a dynamical system. Classic state estimators, such as the KF, provide a time-dependent uncertainty measure from knowledge of the underlying statistics; however, DL based tracking systems struggle to reliably characterize uncertainty.

In [21], we exploit the interpretable nature of KalmanNet and investigate its ability to estimate an uncertainty measure. We demonstrate that when the system dynamics are known, KalmanNet—which learns its mapping from data without access to the statistics—provides uncertainty similar to that provided by the KF; and while in the presence of evolution model-mismatch, KalmanNet provides a more accurate error estimation. Our initial findings were further elaborated with additional insights in [22].

1.3 Unsupervised Learning and Adaptive KalmanNet

Combining the classical KF with a DNN enables tracking in partially known SS models. A major limitation of current DNN-aided designs stems from the need to train them to filter data originating from a specific distribution and underlying SS model. Consequently, changes in the model parameters may require lengthy retraining. While the KF adapts through parameter tuning, the black-box nature of DNNs makes identifying tunable components difficult.

In [23] we consider an unsupervised training without requiring ground-truth states. The unsupervised adaptation is achieved by exploiting the hybrid MB-DD architecture of KalmanNet, which internally predicts the next observation as the KF does. These internal features are then used to compute the loss rather than the state estimate at the output of the system. With the capability of unsupervised learning, one can use KalmanNet not only to track the hidden state but also to adapt to variations in the SS model, and we demonstrate an online training mechanism when the testing distribution differs from the SS model from which the training data is generated.

Furthermore, in [24] we propose Adaptive KalmanNet (AKNet), a DNN-aided KF that can adapt to changes in the SS model without retraining. Inspired by recent advances in large language model fine-tuning paradigms, AKNet uses a compact hypernetwork to generate context-dependent modulation weights. Numerical evaluation shows that AKNet provides consistent state estimation performance across a continuous range of noise distributions, even when trained using data from limited noise settings.

2 KalmanNet Combined with a Decision Policy

In the setups previously described, KalmanNet was used solely for state estimation tasks. Subsequent applications have expanded its use, pairing KalmanNet with decision-making policies. It was trained end-to-end to maximize a utility function, shifting the focus from minimizing state estimation error to enhancing decision quality. Among the potential applications, stochastic control and pair trading were considered.

2.1 LQGNet for Stochastic Control

Stochastic control deals with finding an optimal control signal for a dynamical system in a setting with uncertainty, playing a key role in numerous applications. The linear quadratic Gaussian (LQG) is a widely-used setting, where the system dynamics is represented as a linear Gaussian SS model, and the objective function is quadratic. For this setting, the optimal controller is obtained in closed form by the separation principle. However, in practice, the underlying system dynamics often cannot be faithfully captured by a fully known linear Gaussian SS model, limiting its performance.

In [25] we propose LQGNet, a stochastic controller that leverages data to operate under partially known dynamics. LQGNet augments the state tracking module of separation-based control with a dedicated trainable algorithm. The resulting system preserves the operation of classic LQG control while learning to cope with partially known SS models without having to fully identify the dynamics. We empirically show that LQGNet outperforms classic stochastic control by overcoming mismatched SS models.

2.2 KalmanBOT for Pairs Trading

Pairs trading is a family of trading techniques that determine their policies based on monitoring the relationships between pairs of assets. A common pairs trading approach relies on describing the pair-wise relationship as a linear SS model with Gaussian noise. This representation facilitates extracting financial indicators with low complexity and latency using a KF, which are then processed using classic policies such as

Bollinger bands. However, such SS models are inherently approximated and mismatched, often degrading the revenue.

In light of these disadvantages In [26, 27] KalmanBOT was proposed as a DL aided policy that augments the operation of KF-aided black-box trading. More specifically the KF was replaced with KalmanNet, while the Bollinger bands trading policy was approximated with a differentiable mapping. While in [26] an SS model with co-integration was considered, and an end-to-end training, in [27] partial co-integration was considered and a two-stage training technique in which we first tune the tracking algorithm in an unsupervised manner independently of the trading task, followed by its adaptation to track the financial indicators to maximize revenue while approximating Bollinger bands with a differentiable mapping.

We empirically demonstrate that our proposed KalmanBOT systematically yields improved revenue compared with MB and DD benchmarks over various different assets.

3 Tracking Using Complex and High-Dimensional Observations

In many real-world applications, the observation model, i.e., the mapping from state to observations, is complex and nonlinear, or the observations lie in a high-dimensional space. For example, in tracking the state of an object from a video stream [28, 29], tracking the direction of arrival (DoA) of a radiating source from antenna array measurements [30], or in RF localization, using the standard flow of the KF can be inefficient or sometimes even impossible.

In [28, 29], a three-step architecture was proposed, useful across various applications. This architecture consists of two main concepts:

- The first concept is encoding the complex observations into a latent domain using an encoder. This encoder predicts the state from single or multiple observations. It can be MB, using methods such as sparse signal recovery (SSR) [30], among other approaches, or DD, trained in either a supervised manner, as in [28, 29], or an unsupervised manner, using an auto-encoder.
- The second concept utilizes the output of the encoder as a noisy input (observation) for the tracking algorithm, such as KF or KalmanNet. The encoder is provided with a prior distribution computed from the previous posterior of the tracking algorithm, using the evolution model. This prior can be characterized by two statistical moments: namely, the mean and the error covariance.

The primary advantage of this architecture is its ability to integrate state-of-the-art estimation algorithms, referred to as encoders, with a tracking architecture like KalmanNet. This is done in a straightforward manner, allowing for independent performance analysis.[2]

4 Filtering and Smoothing with Classical ML for ECG Signal Denoising

The use of the MB KF is not limited solely to the task of tracking the state of a dynamical system, and our application of ML is not confined to the use of DNNs. In [31, 32], we consider the task of Electrocardiogram (ECG) signal denoising and propose a KF. More specifically, we model the ECG waveform as a three-dimensional tensor within a hierarchical SS model with unknown parameters that are learned online using classical learning techniques.

Among the ML techniques employed, we utilize a windowed least-squares (LS) Taylor approximation to learn the inter-SS model evolution function, i.e., the patient-specific shape of the ECG waveform. To learn the covariance matrices of this SS model, we use an EM algorithm. For learning the process covariance of the intra-SS model, we apply a Riemann manifold gradient descent (RMGD) algorithm to ensure that the learned matrix is positive-semidefinite (PSD). The empirical evaluation demonstrates competitive results on real-world data.

5 DoA Estimation

An additional applicative example for our hybrid architecture of MB-DL, involving complex observations from an antenna array, is the challenging task of DoA estimation in the far field [30]. Notable MB algorithms based on subspace methods include MUSIC, Root-MUSIC, and ESPRIT. The primary statistic used is the covariance matrix of the snapshots.

In [33, 34], Deep-Augmented (DA) MUSIC was proposed, where a dedicated DNN was integrated into the MB MUSIC flow, primarily to replace the computation of the covariance matrix. This architecture was later utilized in collaboration with the SOREQ research center for the task of azimuth estimation in seismic arrays and proved useful for DoA estimation of seismic signals to localize seismic events accurately.

In [35], Root-MUSIC was augmented with a DNN. In [36], SubspaceNet was proposed as an extension of Deep-Root MUSIC. It was shown that the DNN-based surrogate learned to replace the covariance matrix is general, and therefore, it can be used as input to any subspace-based algorithm.

[2]This project was awarded best presentation in the 2022 IEEE-SPS/EURASIP Summer School.

6 Hypothesis Testing for Signal Detection

Most of the previous work dealt with estimation problems. The next body of work addresses hypothesis testing for signal and anomaly detection problems. The first body of work focuses on decision-making given noisy observations, while the second deals with active sampling.

6.1 Hypothesis Testing

The first body of work deals with hypothesis testing in challenging signal processing use cases, where classical tests, such as the z-test and t-test, are not optimal or even not applicable. Next, we employ SBL [6] and the sparsity-enforcing normal with unknown variance (NUV) [7, 37] prior as Bayesian techniques for Hypothesis Testing.

Here, we model the signal under the *alternative* hypothesis using the NUV prior, transforming the detection challenge into a variance estimation problem, using maximum likelihood estimation (MLE). We leverage the EM algorithm [4, 5] and devise an iterative algorithm for simultaneous joint detection and parameter estimation. In [38, 39], we propose an outlier-insensitive Kalman filter (OIKF), where we integrate our NUV detector into the KF flow to fine-tune the filter's update process and thereby reduce sensitivity to anomalous observations.

In [30], a NUV-based detector was proposed for multiple hypotheses testing, formulated as the task of SSR. This detector, combined with spatial filtering, was then utilized for the task of DoA estimation and showed promising results superior to both subspace and grid-based methods. This method is currently employed for the task of RF localization, where pinpointing the position of a radiating source is critical.

6.2 Active Sampling

In [40, 41], the task of active sampling was considered in combination with the problem of detecting multiple anomalies in a large number of stochastic processes with partially known distributions. To develop a dynamic and efficient sampling and detection policy, we assumed that at each time step, a decision-maker can observe a chosen subset of processes that conforms to a predetermined tree structure and gain access to aggregated observations drawn from a general distribution dependent on the chosen subset of processes.

A Appendix - KalmanNet Applications and Impact

The KalmanNet architecture has attracted considerable attention within the research community, as evidenced by a significant number of citations and a relatively large number of followers on GitHub [42]. Its popularity stems from the interpretability of its hybrid model, its efficient nature, the simplicity of its training procedure, and its proven robustness. Follow-up research, conducted by us and predominantly by independent groups, has further explored KalmanNet. These studies have employed KalmanNet in various real-world applications, positioning it as a state-of-the-art benchmark and as a foundation for modified architectures. Such research endeavors have confirmed KalmanNet's superior performance compared to its counterparts. Moreover, the utility of KalmanNet goes beyond academic theory; it has been successfully deployed in real-time, real-world, embedded applications, affirming its practical value and efficacy in live operational settings.

A.1 Applications

- In [43, 44], KalmanNet was applied to the task of velocity estimation in real-world scenarios. Specifically, in the former study, it was utilized in an autonomous racing car, while in the latter, it was employed in a multi-rotor, unmanned aerial vehicle (UAV). In [45] a modification of KalmanNet named Split-KalmanNet was used for SLAM.

- People with spinal cord injuries often find it challenging to perform basic tasks, impacting their ability to live independently. A brain-machine interface (BMI) offers a solution by enabling individuals to control devices through neural activity decoding. While existing methods like the KF are reliable and straightforward, they may not fully capture the complex relationships in brain signals. DL algorithms, though powerful, raise safety concerns due to their black-box nature.

  In [46], a KalmanNet-based hybrid approach was proposed, combining the reliability of traditional methods with the predictive power of DL. It is a DNN-based filter that learns to decode observations from brain signals, allowing KalmanNet to comprehend complex relationships in the data while maintaining high reliability.

  In a recent study, a rhesus macaque trained in a finger movement task with a brain implant served as the test subject. Both offline and online trials were conducted to compare KalmanNet with the traditional KF and with state-of-the-art DD methods. Preliminary results suggest that KalmanNet offers promising improvements in movement prediction and task performance compared to the MB-KF, and yields results comparable to DD-based approaches.

  Intriguing directions for future work seem promising, and we believe performance can be further improved. Our KalmanNet-based decoder represents a new frontier in BMI decoders. It holds the potential to significantly enhance the quality of life for people with spinal cord injuries by enabling more accurate and reliable device control.

- In [47, 48], a KalmanNet-based DD method was demonstrated to approach the accuracy of traditional MB-KF in estimating the wing shape of a T-Flex aerial demonstrator aircraft. In this study, KalmanNet was employed with two different RNN configurations: one with linear layers and the other with one-dimensional convolutional layers. The extended KF (EKF), which utilizes a Linear Parameter Varying (LPV) system model, served as a benchmark. This study suggests that the KalmanNet-based approach provides results comparable to the MB method, with the added advantage of using fewer design parameters.

- In [49], KalmanNet's architecture inspired the implementation of a spiking neural network (NN). In [50], a neuro-KalmanNet was explored for dynamic state estimation (DSE) of networked microgrids.

- In [51], KalmanNet was used in combination with an Elman network for the task of nonlinear system identification. In [52, 53], DD-LQG control design was considered, in combination with value iteration.

- Inn [54], KalmanNet was utilized within a hybrid architecture to enhance the stability of the electrostatic induction dust concentration detection task.

- In [55], KalmanNet was used as part of a physiological MB-deep learning framework for the cardiac transmembrane potential (TMP) recovery task. It was designed to overcome the challenge of accurately modeling and predicting the dynamic and complex behavior of cardiac TMP, especially in the presence of noisy and uncertain data.

- In [56], a KalmanNet-based approach named DDKF was investigated for the task of estimating missing data (e.g., pressure) in geographically distributed nodes, a fundamental challenge in water distribution networks (WDN). The MB-KF offers a simple solution for estimating missing data in systems with a linear Gaussian SS model. However, in large WDNs, the state model is nonlinear, and accurate system dynamics are often unknown, leading to approximation errors due to the model's nonlinearity. This work demonstrates numerically that DDKF can effectively overcome these approximation errors, particularly those caused by flow equations, and can reliably estimate missing data in a WDN.

A.2 Algorithmic Frameworks and Reviews

In addition to the utilization of KalmanNet across a multitude of applications, it has also been considered in algorithmic frameworks, as a state-of-the-art benchmark, and in review papers. .

In [57, 58, 59] KalmanNet was considered in various comparative reviews and performance analyses, such as DL supported KF, DL-based Multi-modal Sensors Fusion, and Data Assimilation and Uncertainty Quantification for Dynamical systems, respectively.

In [60, 61, 62], KalmanNet was used as a state-of-the-art benchmark for the following applications: vehicle velocity observer for regular and near-limits applications, multi-sensor fusion for trajectory tracking on the KITTI dataset, and beam tracking in millimeter waves, respectively.

In [63], KalmanNet was compared with DANSE: DD Non-linear State Estimation of Model-free Processes in an Unsupervised Learning Setup. Meanwhile, in [64, 65], it was compared to a Gated Inference Network for inferencing and learning SS models.

Furthermore, KalmanNet was recognized as a promising direction for future work to enhance the performance of existing architectures. For instance, in [66], it was considered for the task of reconstruction and segmentation from sparse sequential X-ray measurements of wood logs. Meanwhile, in [67], it was considered for the chorus signal positioning task.

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