icassp 2022 Singapore

Paper ID: 2297

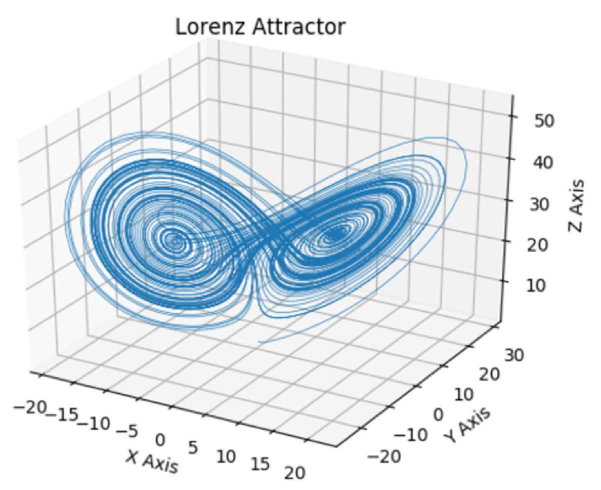
RTSNET: DEEP LEARNING AIDED KALMAN SMOOTHING

Xiaoyong Ni,[1] Guy Revach,[1] Nir Shlezinger,[2] Ruud J. G. van Sloun,[3] and Yonina C. Eldar.[4]

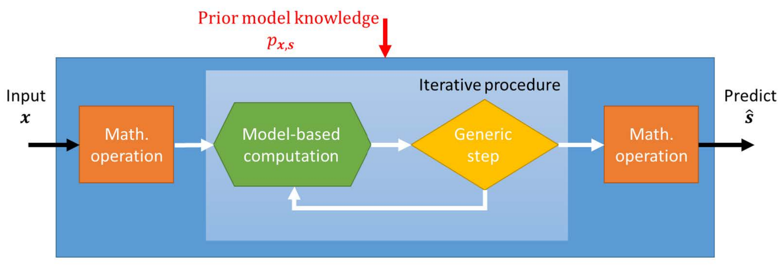
[1]ETH Zürich, Switzerland, [2] Ben-Gurion University of the Negev, Israel, [3] Eindhoven University of Technology, The Netherlands, [4] Weizmann Institute of Science, Israel.

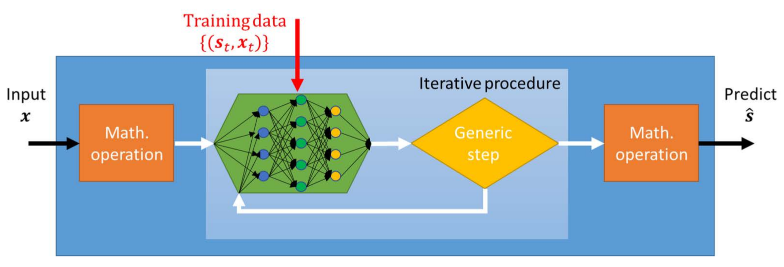
MOTIVATION

Tracking of dynamic systems is encountered in many applications: Localization, Navigation, Task Planning, etc. Such settings can often be represented as smoothing tasks, which are typically tackled using either a Model-Based(MB) or a Data-Driven(DD) method.



In this work we aim to design a hybrid MB DD smoother.





Key idea: replace part of the MB computation by NN, in order to incorporate the advantages of both domains.

PROBLEM FORMULATION

Consider *fixed-interval* smoothing: the recovery of a state block $\{\mathbf{x}_t\}_{t=1}^{T}$ given a block of noisy observations $\{\mathbf{y}_t\}_{t=1}^{T}$ for a fixed length T. The state and the observations are related via a dynamical system represented by

$$\mathbf{x}_t = \mathbf{f}(\mathbf{x}_{t-1}) + \mathbf{e}_t, \qquad \mathbf{e}_t \sim \mathcal{N}(\mathbf{0}, \mathbf{Q}), \quad \mathbf{x}_t \in \mathbb{R}^m, \tag{1a}$$

$$\mathbf{y}_t = \mathbf{h}(\mathbf{x}_t) + \mathbf{v}_t, \qquad \mathbf{v}_t \sim \mathcal{N}(\mathbf{0}, \mathbf{R}), \quad \mathbf{y}_t \in \mathbb{R}^n. \tag{1b}$$

In (1), $\mathbf{f}(\cdot)$ and $\mathbf{h}(\cdot)$ are (possibly) non-linear functions, while $\mathbf{e}_t$ and $\mathbf{v}_t$ are Gaussian noise signals with covariance matrices $\mathbf{Q}$ and $\mathbf{R}$, respectively.

TRADITIONAL APPROACH

Solution:

- Linear case: Rauch-Tung-Striebel (RTS) Smoother achieves the optimal MMSE for linear State Space model
- Non-linear case: linear approximations of $\mathbf{f}(\cdot)$ and $\mathbf{h}(\cdot)$ through Jacobian matrices, or heuristic methods like particle smoothing

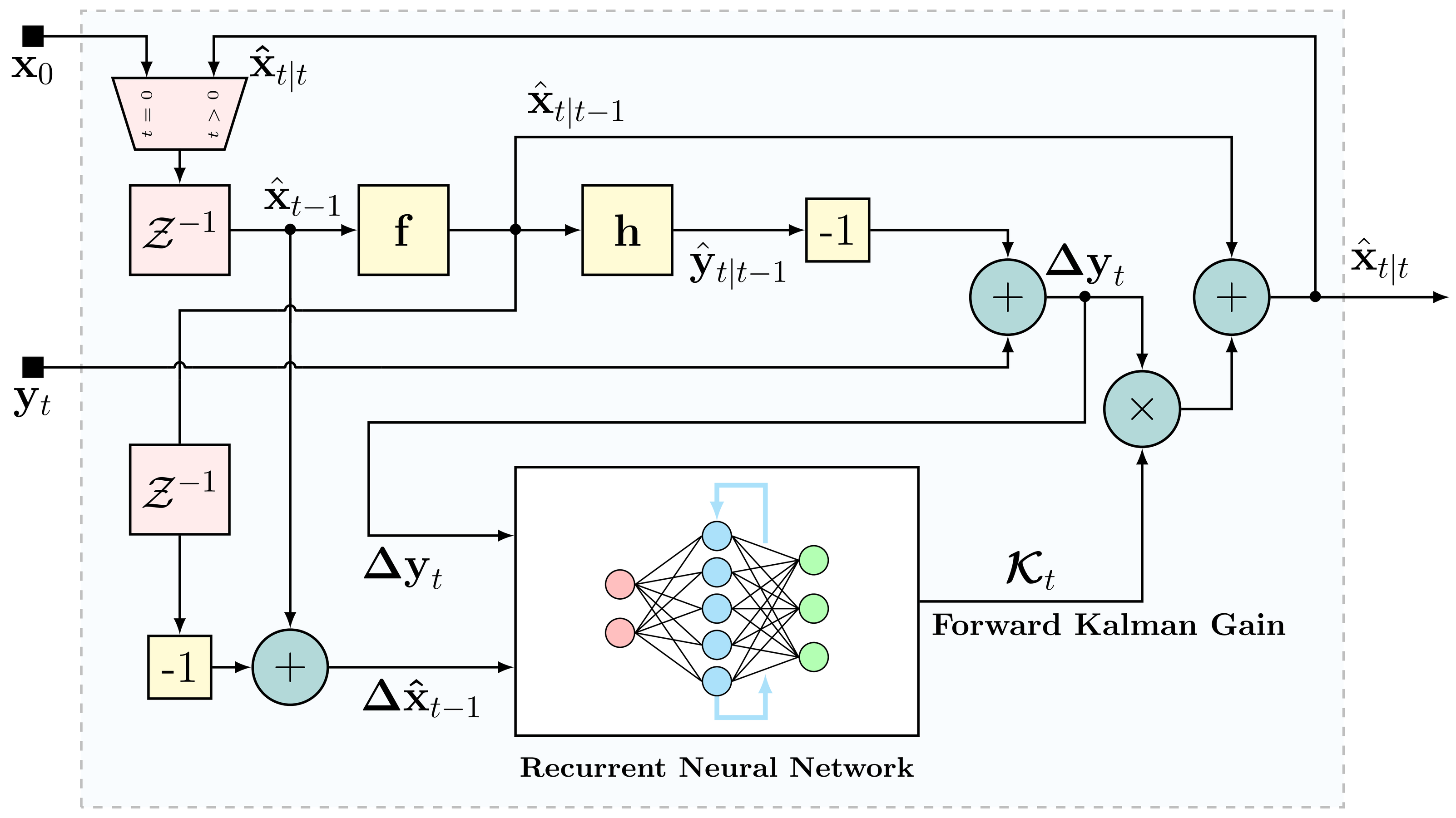
Drawbacks:

- Require full knowledge of the underlying model and is notably degraded in the presence of model mismatch
- limited accuracy in highly non-linear setups

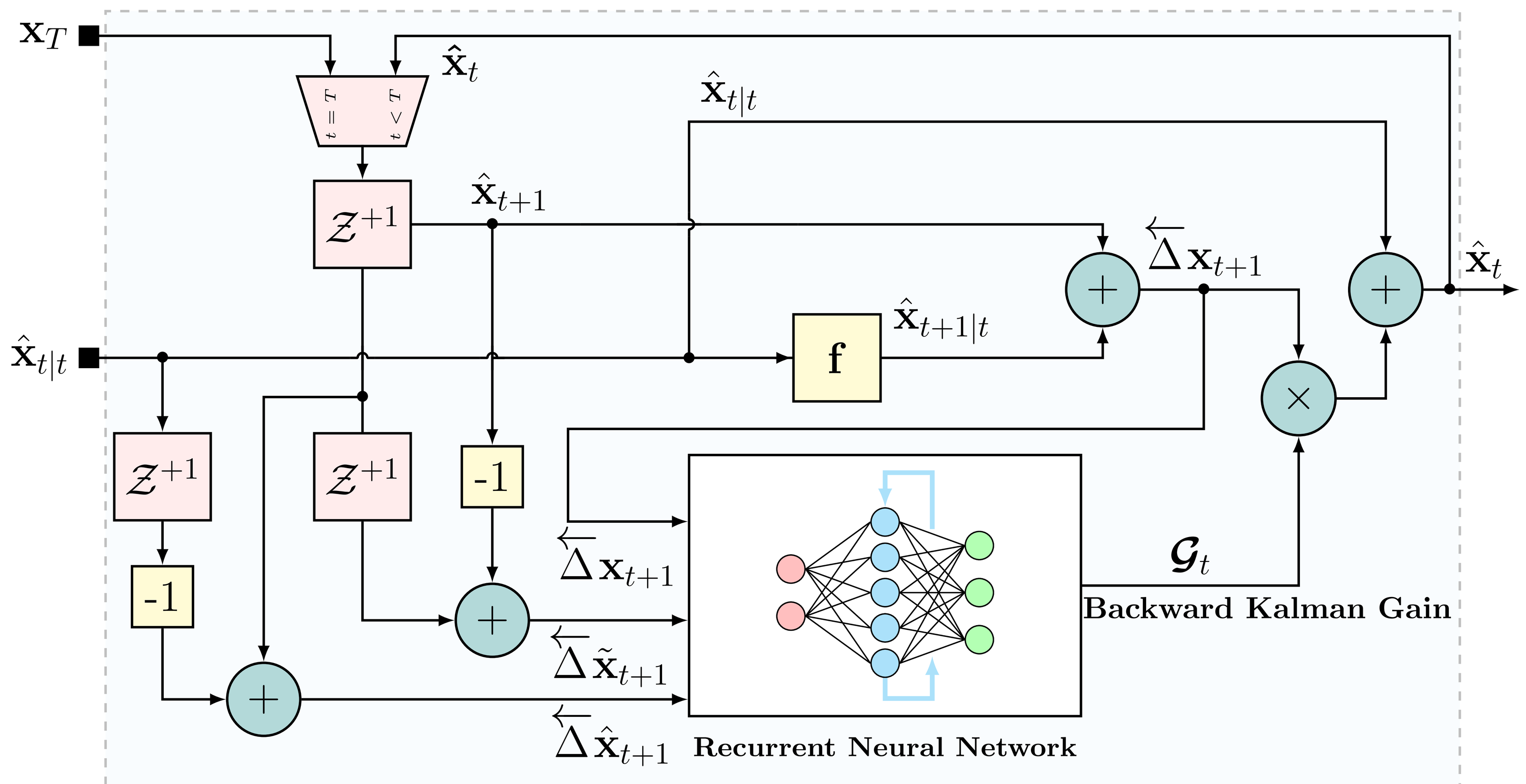
RTSNET - OUR APPROACH

The basic design idea of RTSNet is to utilize the structure of the model-based RTS smoother and to replace modules depending on unavailable domain knowledge with trainable Recurrent Neural Networks (RNNs).

- NN-aided Kalman Gains compensate for model mismatch
- Avoid linearization and is less sensitive to non-linearities
- Not require inverting matrices while inferring rapidly with low computation complexity due to efficient RNNs
- Can be extended to carry out multiple passes via deep unfolding



(a) Forward pass

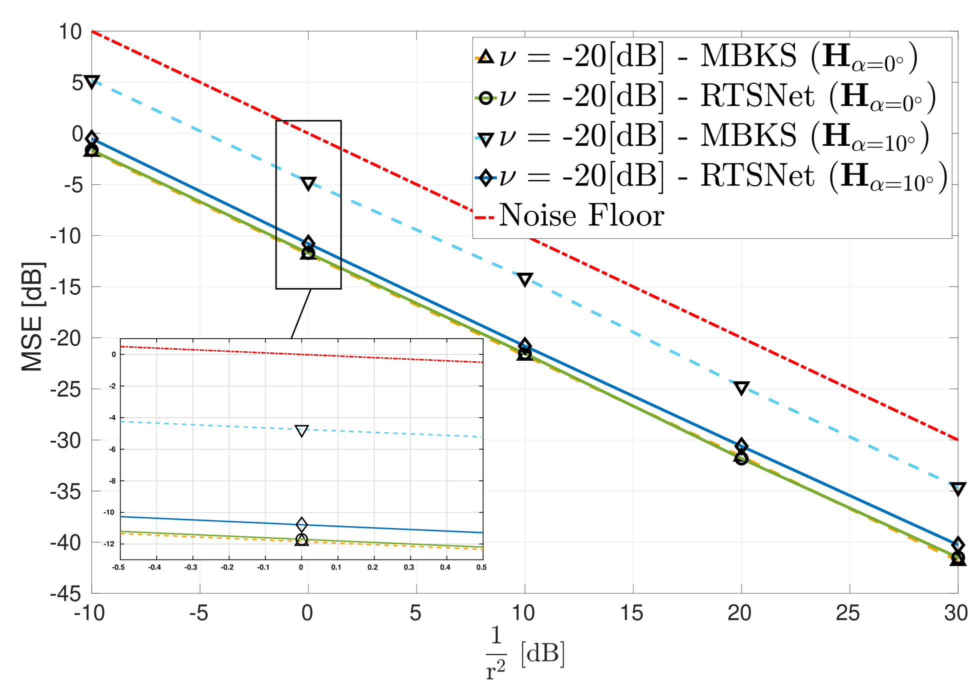


(b) Backward pass

RTSNet architecture

EXPERIMENTS

Linear case:



Highly non-linear Lorenz Attractor case: