Neural network as a tool capable of acquiring hydraulics of a pipeline

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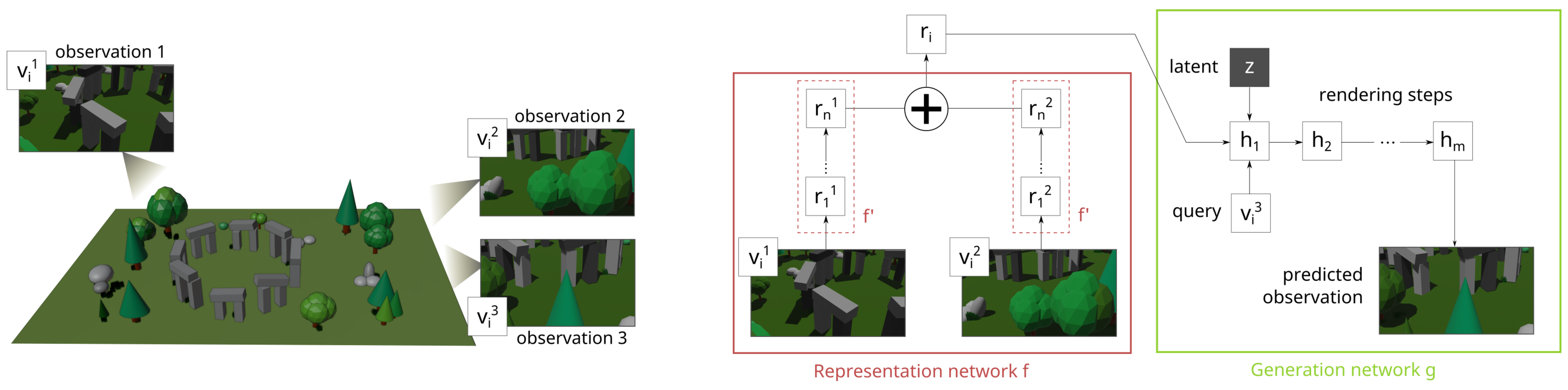
Abstract

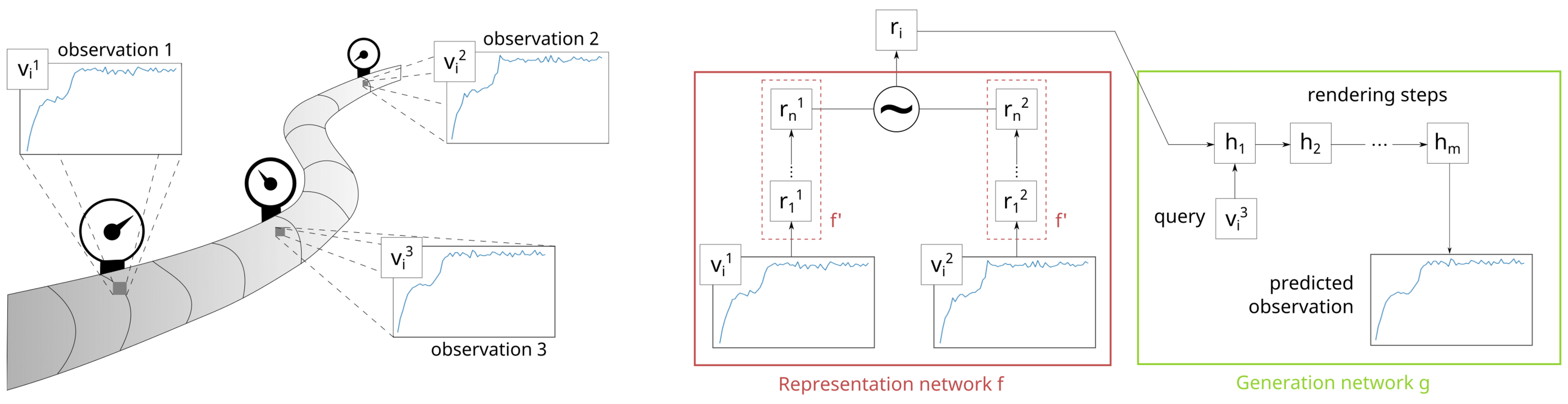
The proposed study represents an extension of our prior work in the realm of RGQN model development. This approach involves the adaptation of GQN concepts to sequential data. The resulting neural architecture is capable of generating/predicting time series with given properties where the supporting, independent information is expressed as a scene of other time series complemented by static meta-information. In this study we demonstrate the practical application of this approach using real pipeline pressure data.

RGQN architecture

- Initial inspiration with Generative Query Network from DeepMind [1]
- **Observation**: an image and associated meta-information (position and orientation of a camera)
- **Scene:** Collection of observations
- GQN model: representation network + generation network
- Scene is introduced into representation network and transformed into latent state
- At inference phase: latent state and query are introduced into generation network, predicted image is generated

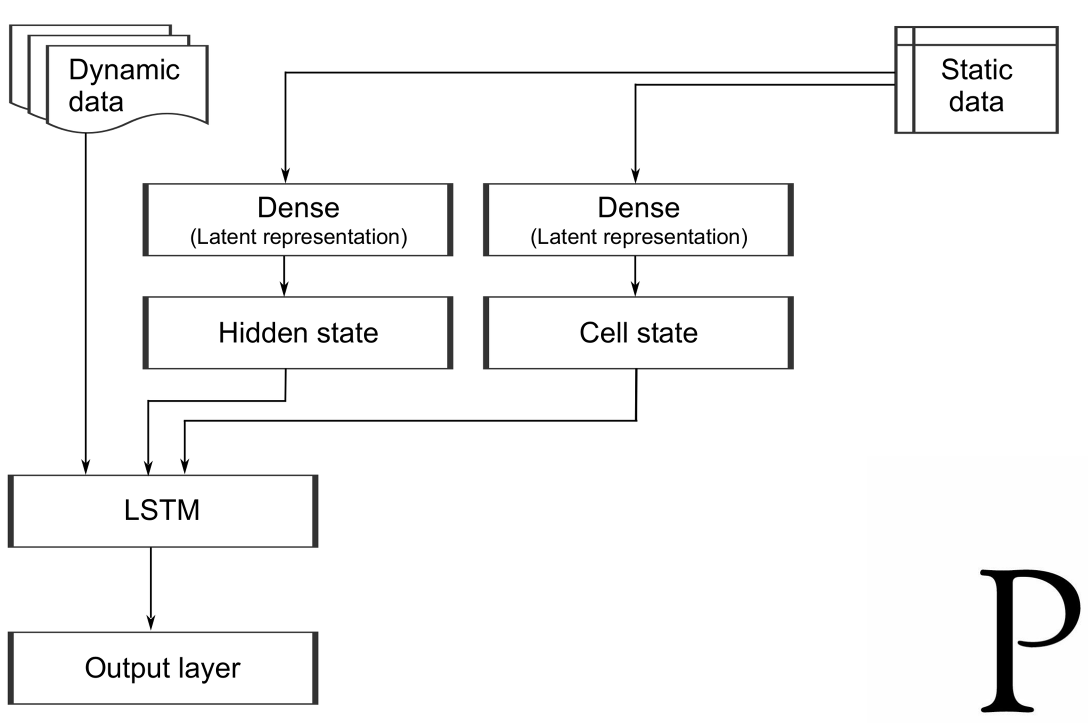


- RGQN: analogous architecture oriented on sequences (here: time series) [2]
- The recurrent neural network (RNN) responsible for transforming sequences
- Meta information introduced as preconditioned hidden/cell states of LSTM units
- **Observation**: a time series and associated meta-information (location on a pipeline)
- At inference phase: latent representation of the scene and query lead to a time series prediction at certain location of a pipeline



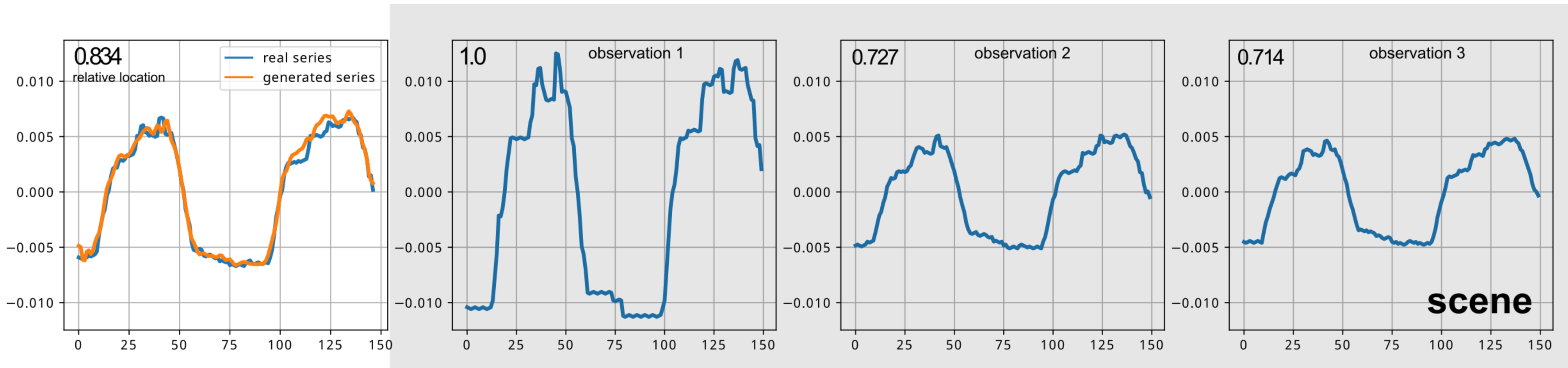
RNNs and static features

- How to incorporate both dynamic (sequences) and static (meta-information) features simultaneously into the RNN?
- The transformation with fully connected layers
- Static meta-information introduced as an initial form of hidden/cell states of LSTM units [3]
- Dynamic features (sequences) introduced in a traditional way

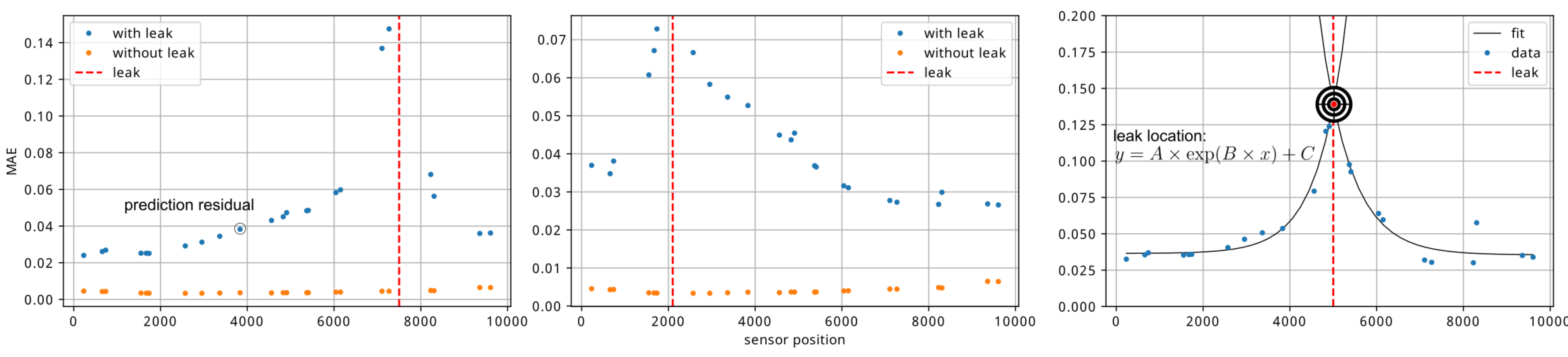


Applications

- RGQN model as an efficient tool for capturing pipeline hydraulics
- The training is carried out during standard, i.e. non-leak, periods
- Incorporating routine, not anomaly, pipeline hydraulics into the RGQN model
- High reconstruction potential
- The training data acquired on large industrial pipeline in Europe



- RGQN model can support Leak Detection and Location Systems (LDS)
- The residuals resulting from anomalous state rise with leak proximity
- Analysis of prediction residuals



PSIlds-ai – a product utilizing RGQN

- The RGQN approach was developed as a part of the project co-funded by the National Centre for Research and Development (NCBR, project identifier: POIR.01.01.01-00-0300/19)
- The PSIlds-ai product combines the standard LDS solutions and the elaborated analytical environment
- The data needed for the algorithms development were acquired on a real pipeline transporting multiphase medium
- The PSIlds-ai system allows an analyst to develop custom algorithms for predictive and prescriptive maintenance
- The RGQN model supports elimination of false leak alarms

Conclusions

- The RGQN turned out to be an efficient neural architecture allowing for modeling hydraulics of the pipeline
- The RGQN model trained on relevant data allows for anomaly detection supporting Leak Detection and Location systems
- The previously developed methodology of static features incorporation into RNN allows for efficient scene creation
- The RGQN architecture is generic enough to incorporate a pipeline of any complexity involving arbitrary number of time series

References

(1) Eslami, et al.; Neural Scene Representation and Rendering. Science 2018, 360 (6394), 1204–1210. https://doi.org/10.1126/science.aar6170.

(2) Miebs, G.; Wojcik, M.; Karaszewski, A.; Mochol-Grzelak, M.; Wawdysz, P.; Bachorz, R. A. Predicting a Time-Dependent Quantity Using Recursive Generative Query Network. Int. J. Neur. Syst. 2022, S0129065722500563. https://doi.org/10.1142/S0129065722500563.

(3) Miebs, G.; Mochol-Grzelak, M.; Karaszewski, A.; Bachorz, R. A. Efficient Strategies of Static Features Incorporation into the Recurrent Neural Network. Neural Process Lett 2020, 51 (3), 2301–2316. https://doi.org/10.1007/s11063-020-10195-x.

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