Student:	..
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Client:	..
Thesis:	Bachelor or Masters Thesis

Deep Kalman Filtering to Reduce Error Variance in V2X Pose Forecasting

Keywords: Kalman Filter, Recurrent Neural Network, Long-Short-Term Memory, Vehicle2X

Motivation. Vehicle to Everything (V2X) communication and 5G connectivity in vehicles enable advanced driver assistance systems (ADAS), collaborative perception, and vehicle platooning. V2X efficiently distributes object data, intentions, and route predictions and recognizes vehicles in situations without direct visual contact, so that future manual or autonomous vehicles can cope with traffic and roads more efficiently and safely. The basis of V2X, the 5G network, enables real-time applications that require high speeds, high availability, low latency, cloud computing, and artificial intelligence. In the cloud, enormous amounts of data are processed by many different sensors of vehicles, infrastructure, and pedestrians, which are shared by the participants, especially the vehicles. Computationally intensive learning algorithms can use this data and pass aggregated results on to the participants in almost real time.

Related work. The trajectory estimation for tasks such as object and vehicle location and tracking is generally noisy, and temporal filters have been used extensively for regularization. One of the most widely used methods is the Kalman filter (KF), which is both extremely simple and general. However, KFs require a priori the specification of a motion and measurement model, which burdens the modeler and at the same time requires the use of explicit models that are often only rough approximations of reality. E.g., in the position estimation task, it is common to use motion models that assume constant acceleration or velocity, and these simplified representations are known to be highly limiting. And similar to prominent models like ARIMA, KF only relies on the last past sample to predict the next future pose. However, the future movement is not only influenced by the last movement step, but long-term dependencies often form the shape of a trajectory and so affect the future pose.

Overall goal. Thus, in this thesis, the student will investigate a hybrid method that combines KF with neural networks that learn rich, dynamic representations of the motion and noise models instead. In particular, the student will learn these models from data using, e.g., long short-term memory, which enables representations that are dependent on all previous observations and all previous states. The student will evaluate the method using the latest trajectory prediction methods. The student will further examine how the number of historical samples, their intra-delay, changes and gaps in the sample rate and input stream affect the robustness and accuracy of the predictors. In a final step, the student will implement the model in a real demonstrator that uses, e.g., Time-of-Arrival (ToA) values or positions as input to the model. The student will show that the model learns easily from noisy labels and can be adapted to new environments or different vehicles or objects with very few samples.

Timetable (6 months, in person weeks [PW]).

4PW Literature and patent research; Familiarization with relevant work on the subject areas.

4PW Adaptation of the individual components.

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6PW Methodological work: Data-driven fusion, learning process for complementing the absolute and relative components with RNN and KF.

4PW Evaluation and real-world demonstration.

6PW Transcript.

Expected results and scientific contributions.

- Modular processing pipeline that consists of, e.g., an Extended KF plus deep (recurrent) neural networks that replace the measurement, process, and transition matrices. Based on the work of Becker et al. [1, 2, 3, 4, 5]
- A localization pipeline that is real-world applicable and replaces state-of-the-art KF [2]. The real-world applicability is given by a live demonstrator.
- The sensor information streams should consists of data such as ToA and position.
- ToA or position values will be collected for different motion dynamics and different propagation scenarios.
- The pipeline will be implemented in python with support from pytorch scipy, and scikit.learn.
- KF + LSTM (motion model), i.e., deep bayes, reduce error variance, share some light on uncertainty, delay and gap filling.
- Uncertainty will be estimated implicitly by the KF and explicitly by the data-driven approach with Monte Carlo dropout, ensembles, Bayesian inference, SWAG or Laplace [1],ex4.
- Information fusion architecture: AI-based multihypothese filter, i.e., when to fuse what and how, and with which architecture.
- Fusion evaluation: classic (KF as is) vs. mixed (KF+AI) vs. "end-to-end" AI. [1]

References

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