RECURRENT NEURAL NETWORKS ON DRIFTING TOF MEASUREMENTS

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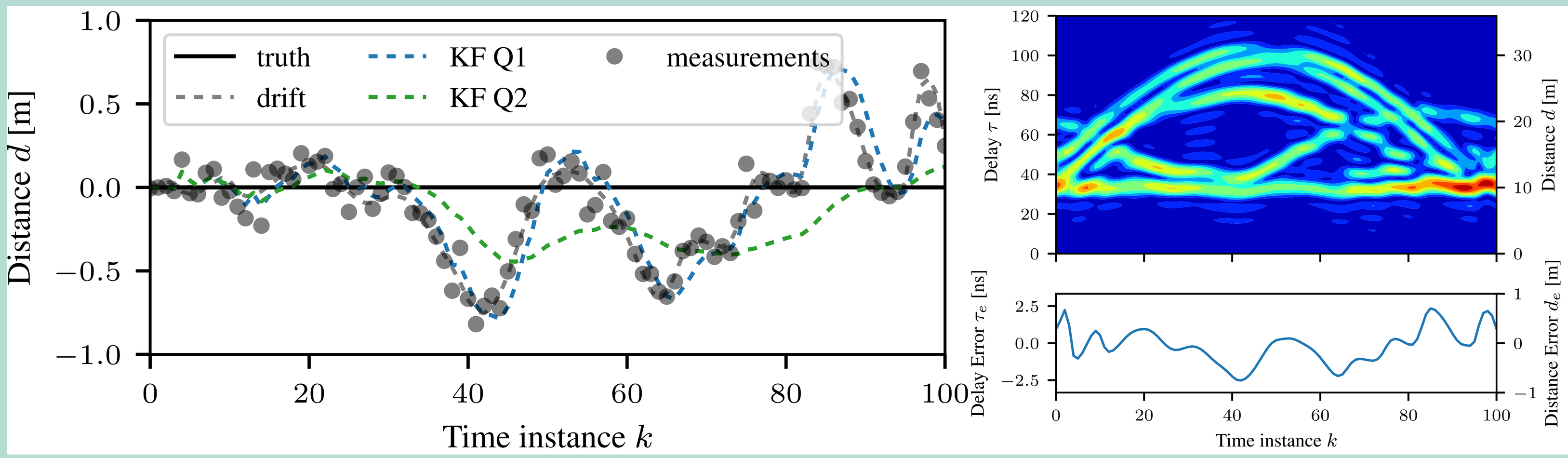
PROBLEM DESCRIPTION

Position estimation from a set of time-of-flight (ToF) radio frequency values suffers from multipath propagation:

- In dynamic motion scenarios the phases of the multipath components change (dynamic bias, i.e., *drift*).
- ToF *drift*: biased delay errors (due to multipath) affect consecutive ToF measurements.



Kalman Filters are optimal under zero-mean Gaussian error distributions, but cannot distinguish between drift (multipath induced motion) and true motion, because of:

- Short-term errors of consecutive measurements,
- Long-term motion dependencies,
- Limitation of empirical knowledge.

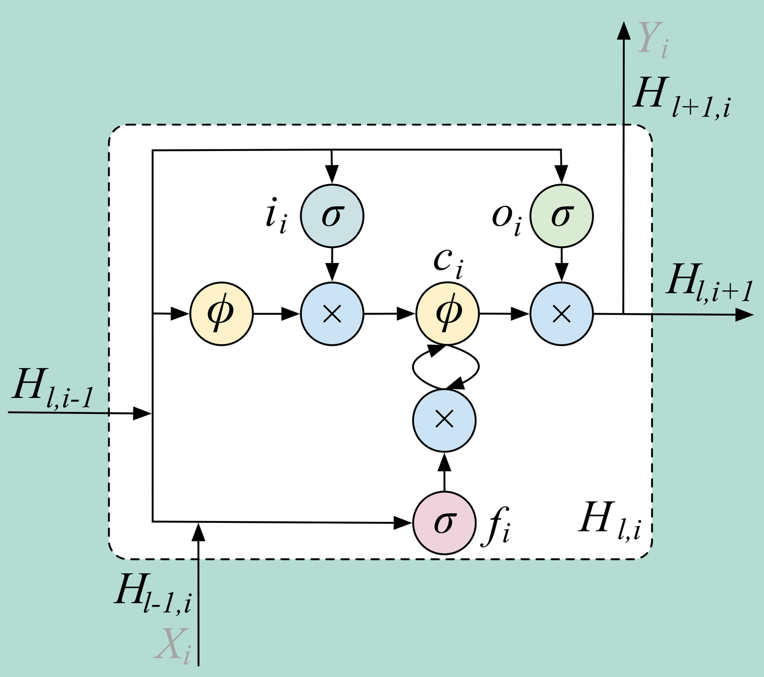
Solution: (Very) rigid motion models cause filter balance problems: *flexible* → follows drift vs. *rigid* → motionless.

METHOD

RNNs are successful at time- and context-sensitive tasks and process sequences of consecutive sets of ToF measurements.

Data-driven approach to exploit Recurrent Neural Networks (RNN) that learn to interpret drifting errors in ToF measurements from raw ToF data.

- Learns time-dependent motion relations (e.g., changes in acceleration, velocity, displacement, and trajectory)



Persistent internal states, i.e., the cell's memory state, (1) updated from the input sequence and (2) carried across transitions to (3) capture dynamic behavior from the input data and (4) predict the output.

Data Processing:

- **Training**: Slice the complete trajectory into consecutive sequences (sub-trajectories) starting from random offsets.
- **Live**: Predict positions on consecutive sets of ToF measures.

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EVALUATION

We split the data into a training (90%) and a test set (10%).

Linear KF model is perturbed by Gaussian noise:

- Linear motion transition function = const. velocity; measurement noise, $R=\sigma=0.1$; process noise, $Q=0.1$; start state $x_0=0$; covariance $P=1$.

With empirical knowledge an KF perfectly fits the input data.

RNN-LSTM model optimized by a Grid Search:

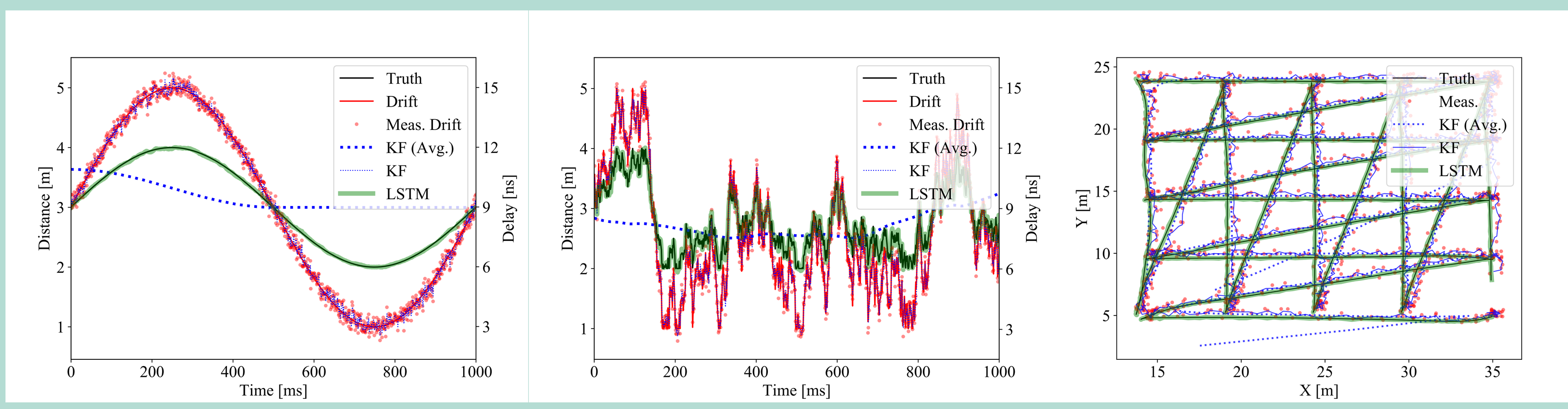
- Batch size =100, epochs ≥1000, layers ≥4, sequence length ≥20, *Adam* optimizer, no drop-out, width ≥256, no peepholes, learning rate ≤0.001, sigmoid and tanh as activation; uniform weights.
- Mean-Squared Error loss, i.e., the convergence error between the predicted and the baseline position.

RESULTS

KF: Smooths out random noise, but either (1) follows the drifting ToF values in the measurements (*flexible*), or (2) ignores the measurements completely, over/undershoots (*rigid*)

	MAE KF	MAE LSTM	CEP_{95} KF	CEP_{95} LSTM
Sinusoidal	2.13ns, 64cm	0.029ns, 0.009cm	-	-
Random Walk	1.72ns, 51cm	0.12ns, 3.6cm	-	-
Real-World	-	-	*35.34cm*	*12.93cm*

RNN-LSTM: Fits the line of ground truth values and also follows the real ToF values very closely (optimal balance)



CONCLUSION

(I) The deeper (more layer) the network the more time-dependent relations can be modeled by the network. (II) A larger cell (more neurons) handles more complex problems. (III) Our Batching guarantees that our model learns completely independent trajectories.

- Stacked LSTM model to predict consecutive positions from raw/drift-affected ToF measurements and to learn to cope with time dependent errors (multipath and drift).
- LSTM outperforms state-of-the-art KFs on drifting ToF measurement errors and understands, interprets, and learns the time-dependent context.

IN COOPERATION WITH

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