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High-rate Machine Learning for Structural State Estimation

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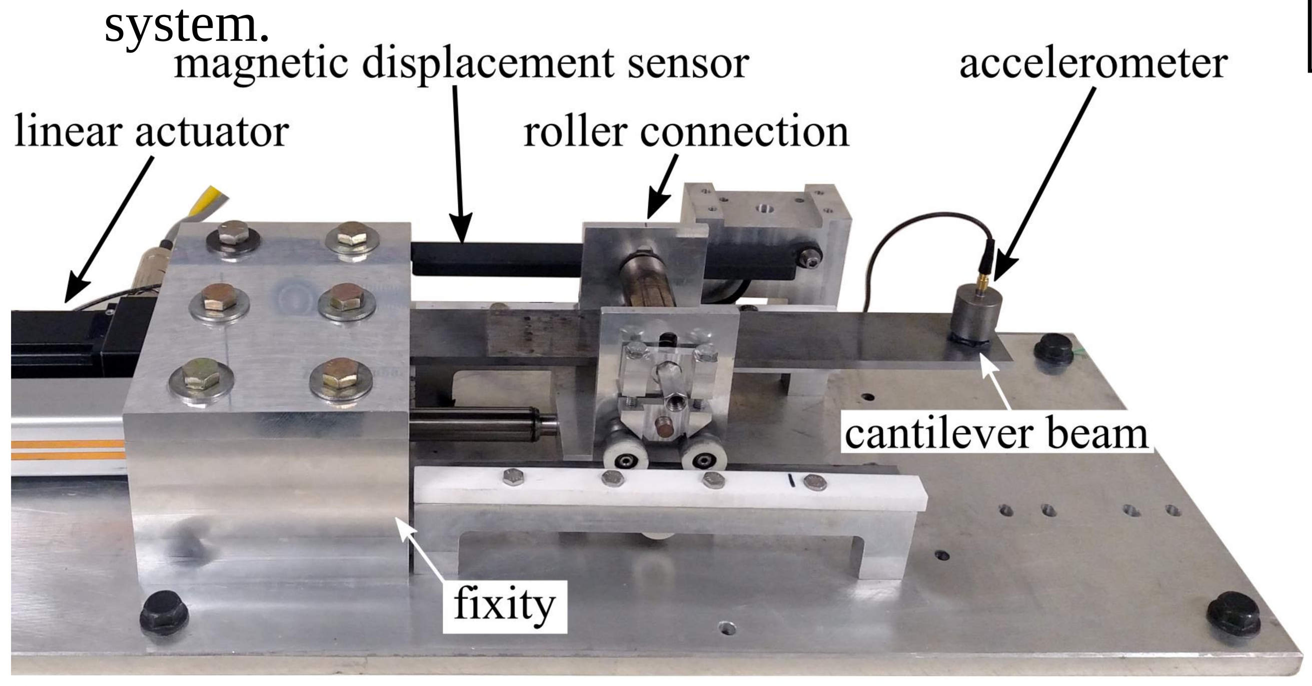
Introduction

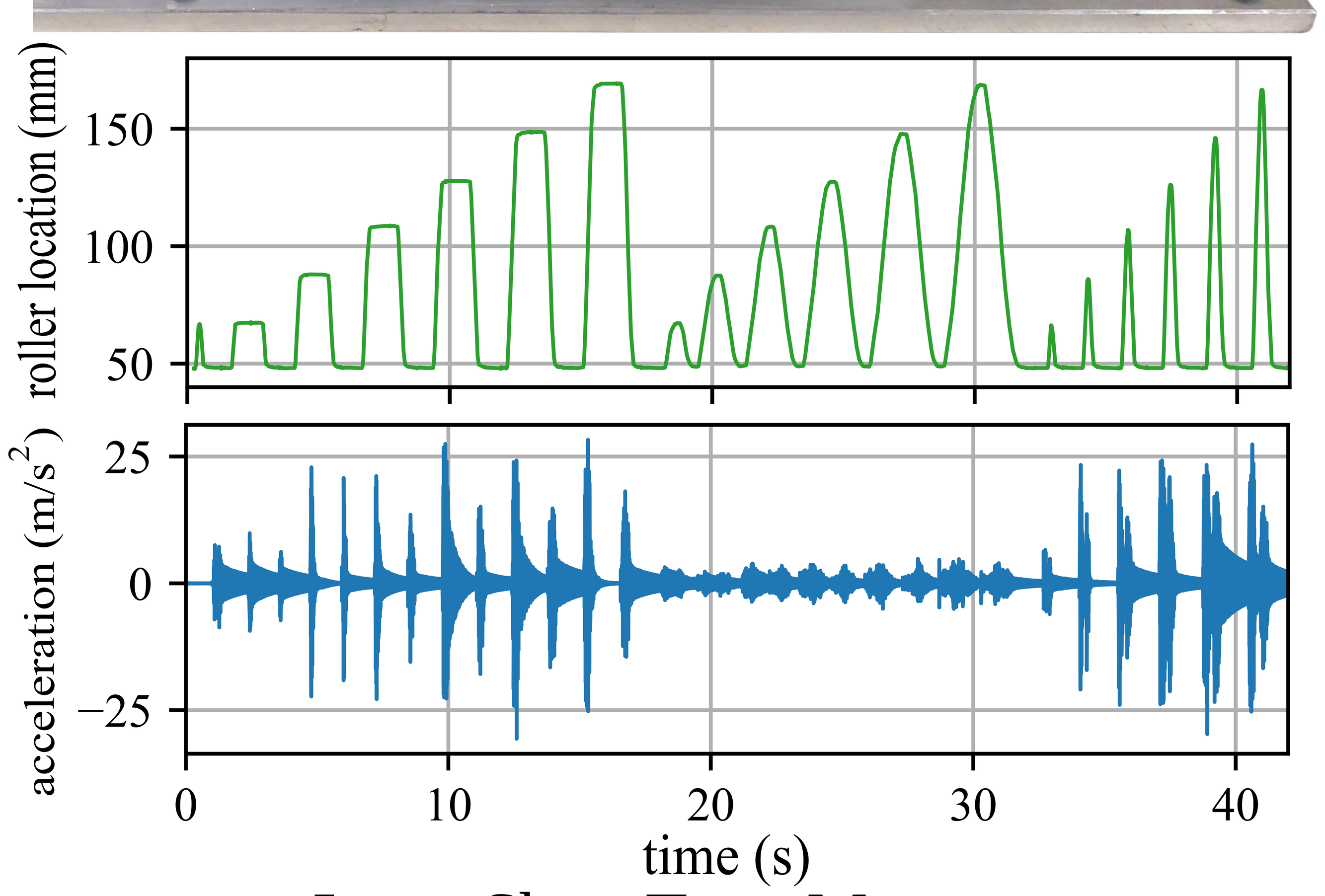
- High-rate dynamics consists of structures subjected to impact loading that results in accelerations greater than 100 g during time periods of less than 100 milliseconds.
- Physics-based models cannot provide event detection within 1 millisecond timing deadlines.
- Goal: create a data-driven model capable of producing low-latency state prediction from a time-domain signal.

Background

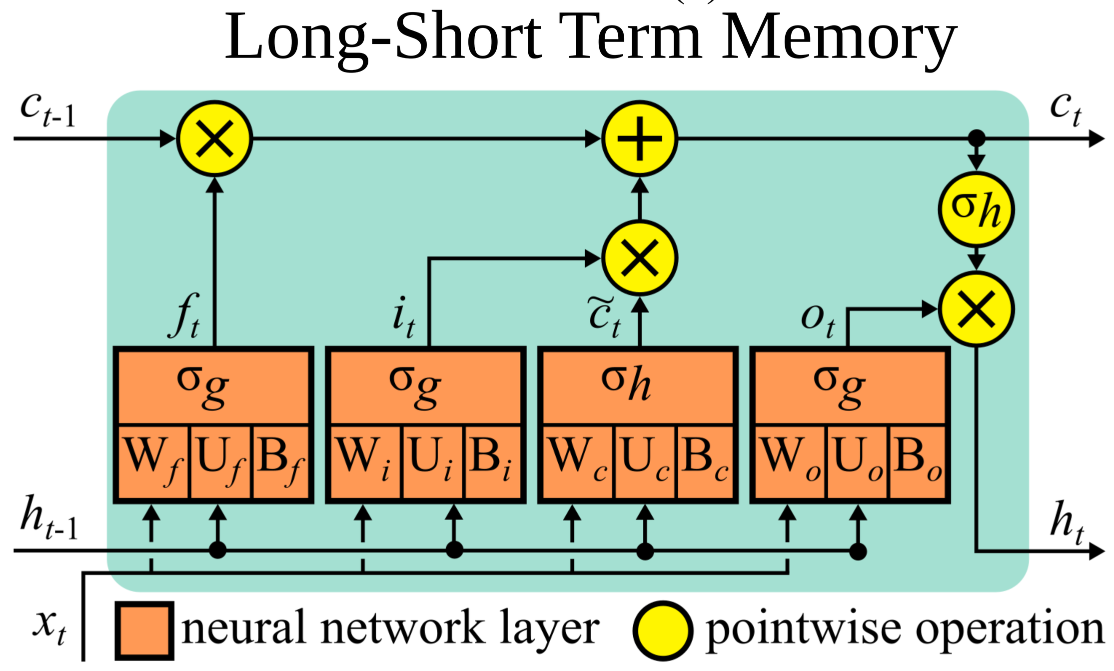
DROPBEAR Testbed

- The DROPBEAR testbed consists of cantilever beam with a controllable roller to alter "state" of the system.





Long-Short Term Memory

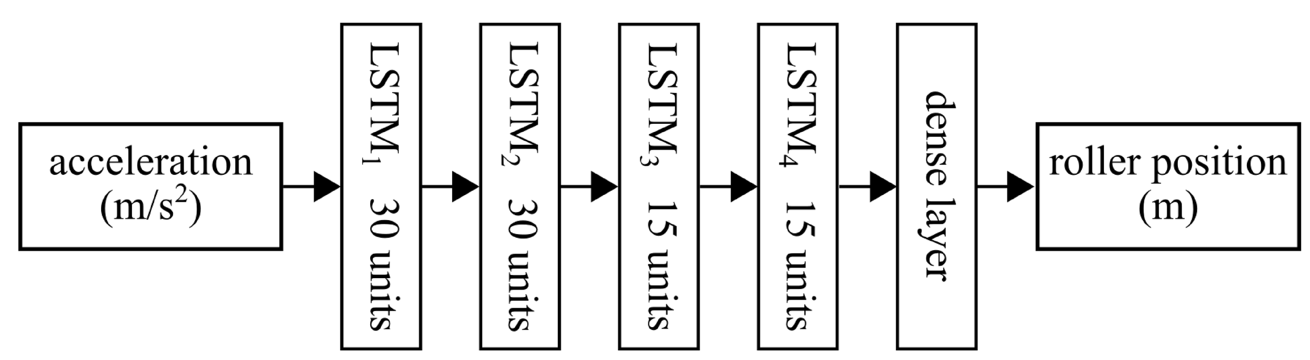


- Recurrent neural networks (RNNs) propagate memory forward through time while receiving a series of inputs.
- The long-short term (LSTM) cell, is a type of RNN that propagates two forms of memory—long- and short-term.
- *The natural agreement between the returned cell state and structural states makes LSTMs an obvious fit for structural health monitoring.*

Methods

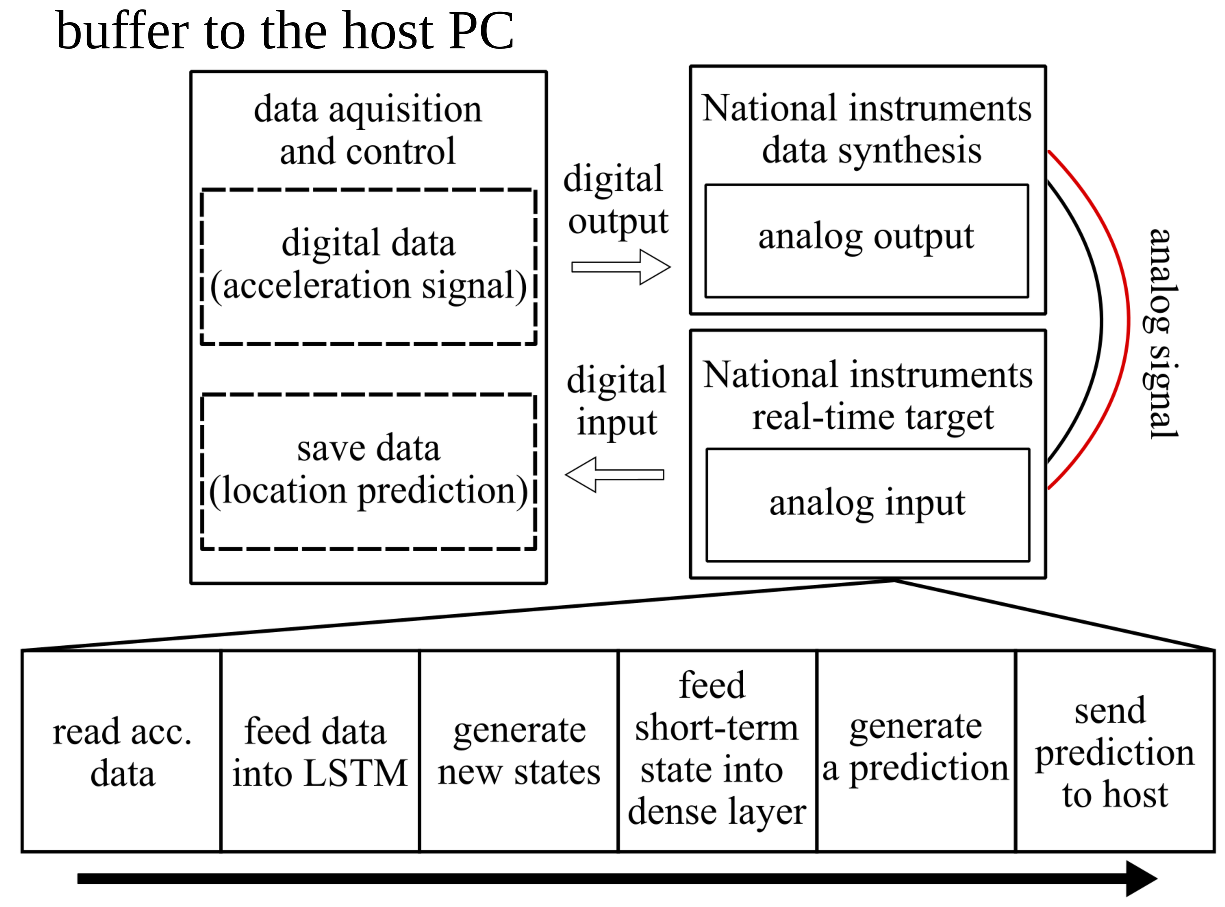
LSTM Model Development

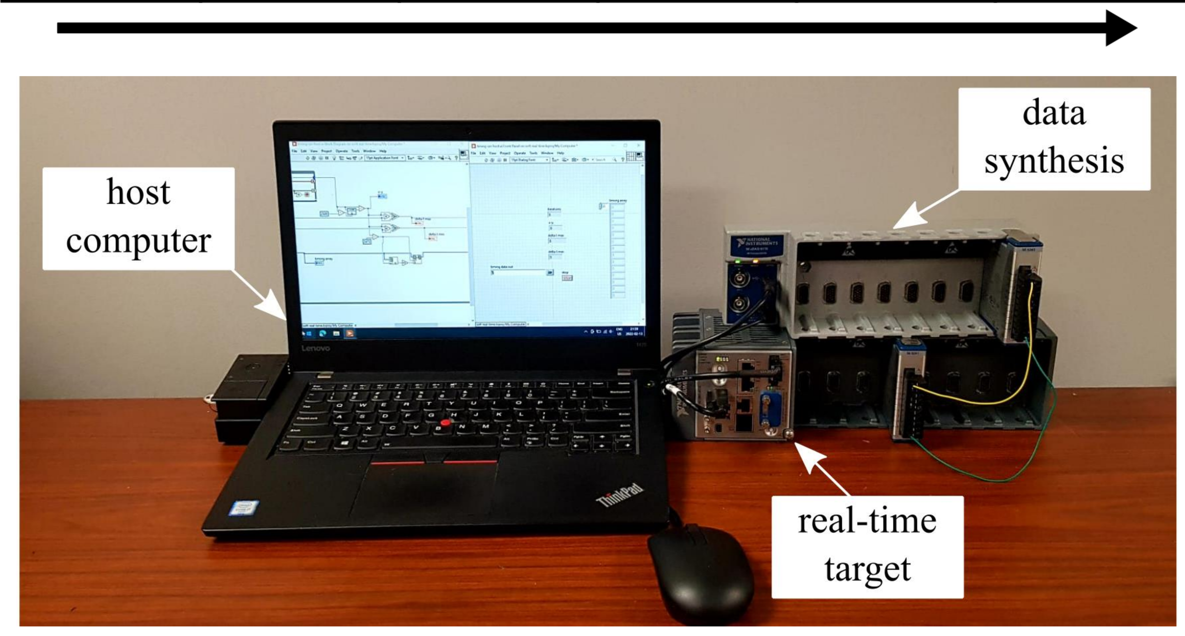
- The deployment of LSTMs to edge computing devices results in significant constraints in the size of the model.
- A down-sample factor of 64 to the 25.6 kS/s acceleration data reduces computational load and creates a 2.5 ms deadline for the edge implementation.
- An ad-hoc investigation produced a stacked LSTM sequence with high accuracy while still maintaining an efficient model size.



Real-time Implementation

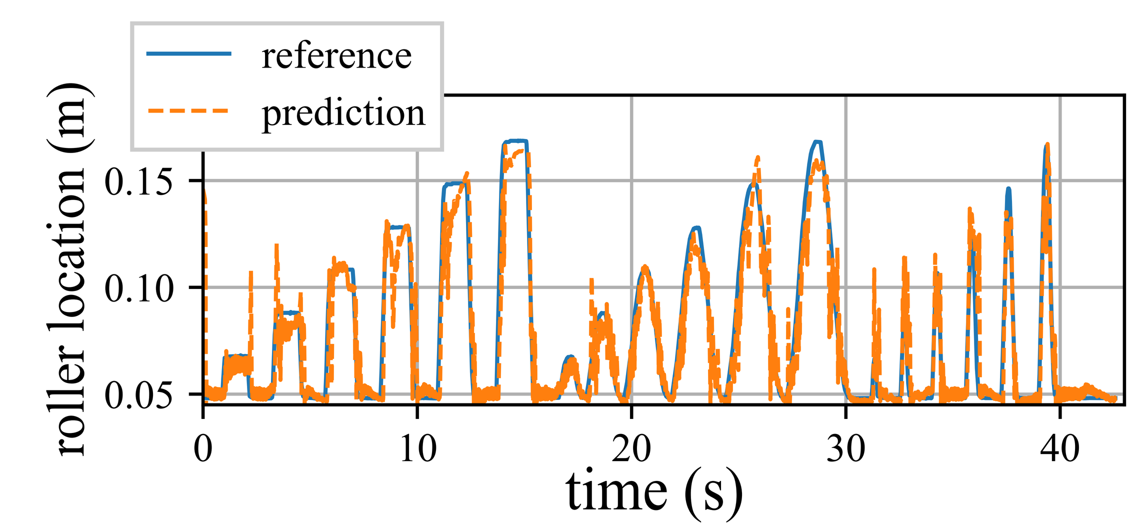
- To gauge the model's performance in a real-time environment, an experiment is constructed with two subsystems:
  - A data synthesis device reproduces the DROPBEAR dataset as an analog voltage to simulate a direct connection to the accelerometer sensor.
  - The real-time system digitizes the analog voltage and feed the inputs into the LSTM architecture deployed onboard the real-time processor.
- Downsampling is then done by altering the rates of data synthesis and data acquisition.
- State predictions are returned via a first-in-first-out buffer to the host PC



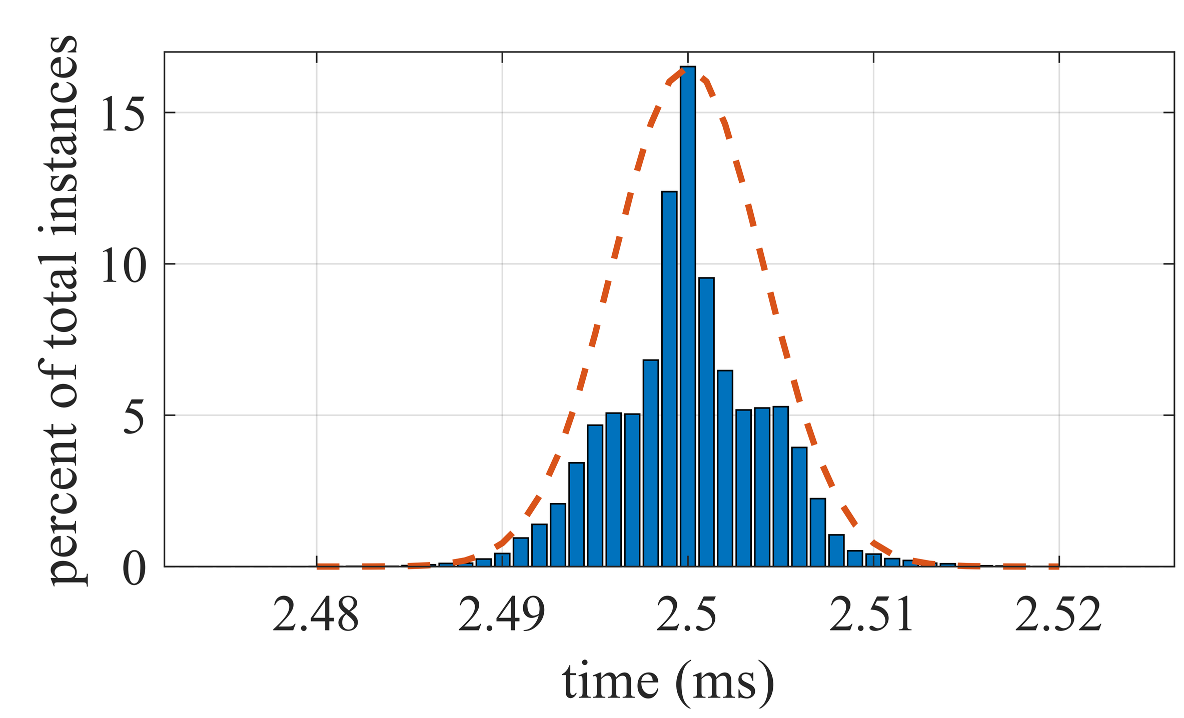


Results

- Performance was examined using signal-to-noise ratio (SNR_{dB}), RMSE, and execution time.



- Results demonstrate a SNR_{dB} of 43.2 and an RMSE of 12.8 mm.



- Execution-time jitter is a result of non-determinism in the Linux real-time system.
- A time-step of 2.5 ms produces a maximum overshoot of 19 μs.

Conclusion

- The accuracy demonstrated by the model for state estimation shows the promise of data-driven approaches for tracking system health.
- LSTMs offer a viable path forward for high-rate state estimation as they can achieve accurate state estimations for structures subjected to dynamic environments.
- Future work will revolve around validating the accuracy of signal replication and decreasing prediction latency.

Dissemination

[1] Progress Toward Data-Driven High-Rate Structural State Estimation on Edge Computing Devices. *Proceedings of the ASME 2022 International Design Engineering Technical Conferences & Computers and Information in Engineering Conference.*

[2] All code and models have been made publicly available via a GitHub repository.