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CONFERENCE: AUG. 14–17 EXHIBITION: AUG. 15–17 ST. LOUIS UNION STATION HOTEL, ST. LOUIS, MISSOURI



PROGRESS TOWARDS DATA-DRIVEN HIGH-RATE STRUCTURAL STATE ESTIMATION ON EDGE COMPUTING DEVICES

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Methodology

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Experimentation

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Results and Discussion

Future work

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Outline

Methodology:

- DROPBEAR experimental testbed
- Long short-term memory model development
- Real-time edge implementation

Experimentation:

- Signal prediction test
- Real-time execution test

Results and discussion:

- LSTM model performance
- Timing accuracy

Future work:

- Prediction accuracy
- Model throughput rate







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Introduction

- High-rate dynamics framework
- Advances enabling high-rate structural health monitoring (HR-SHM)
- Long short-term memory (LSTM)
- Data-driven state estimation













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Methodology

Contributions of this work

Long short-term memory real-time

Experimental validation method to

state estimation framework

gauge LSTM performance.

Experimentation



Future work

Results and Discussion









- The Dynamic Reproduction of Projectiles in Ballistic Environments for Advanced Research (DROPBEAR) was used to generate the experimental data in this work.
- Cantilever beam with controllable roller to alter the state.
- Acceleration and roller location are recorded.







Future work

Experimentation

entation 🛛 🔪 Results and Discussion

Recurrent neural network that propagates

through long- and short-term memory

SNRdB and RMSE are used to evaluate

forms to make a state prediction.

LSTM network is trained offline.

prediction accuracy.

Experimentation

Results and Discussion

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echnical Conferences gineering Conference Long short-term memory model development СШ igineering mation in E ullet2 esign nationa put











Long short-term memory model development

- Grid search of execution time and performance vs. number of hidden units.
- Four LSTM architectures with varying number of hidden units were explored.







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Long short-term memory model development

- Model was chosen according to execution time ulletthreshold of 2.5ms.
- Network shape is 30-30-15-15. ullet
- Output rate of 400 S/s ullet







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Deployment of LSTM network to real-time operating system results in significant model constraints.

Methodology

Real-time edge implementation

- Acceleration data is sampled at 400 S/s.
- LSTM makes a prediction every 2.5 ms.
- Hardware device is a cRIO-9035 running NI-Linux RT utilizing PREEMPT RT patch.
- Trained model is deployed on edge device and executed in real-time.



target







Experimentation

Results and Discussion

Future work

Signal prediction and timing tests

- The experimental setup consisted of two subsystems:
 - Data synthesis device reproduces the DROPBEAR dataset using a digital to analog converter.
 - The real-time system digitizes the analog voltage and feed the input into the LSTM architecture.
- A prediction is made every 2.5 ms.
- State predictions are returned via a first-in-first-out buffer to the host PC.
- SNRdB, RMSE, and timing report are generated.





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Experimentation

Results and Discussion

Future work

LSTM model performance results

- SNRdB of 43.2 dB
- RMSE of 12.8 mm
- LSTM traces reference roller location closely.

Timing accuracy results:

- Execution-time jitter in observed.
- Timing follows a normal distribution.
- A result of non-determinism in the Linux real-time system.

Algorithm execution timing report.

Mean	2.5 ms
Standard deviation	0.004 ms
Max overshoot	0.019 ms







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Algorithm execution timing report.	
Mean	2.5 ms
Standard deviation	0.004 ms
Max overshoot	0.019 ms



Results and Discussion

 The prediction results demonstrate that a data-driven approach using LSTMs has potential in HR-SHM applications.

Methodology

 LSTMs can achieve accurate state estimations at moderately consistent latency.

Experimentation

roller location (m)



Experimentation

Future work will revolve around:

- Enhance prediction accuracy by altering training method.
- Increase model throughput and minimize hardware latency.









Thank you Questions?



The ARTS-Lab
University of South Carolina
Progress towards data-driven high-rate structural state
estimation on edge computing devices



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> https://github.com/ARTS-Laboratory/Paper-Progress-towardsdata-driven-high-rate-structural-state-estimation-on-edgecomputing-devices

