A non-linear vibration signal compensation technique for UAV-deployable sensor packages with edge computing

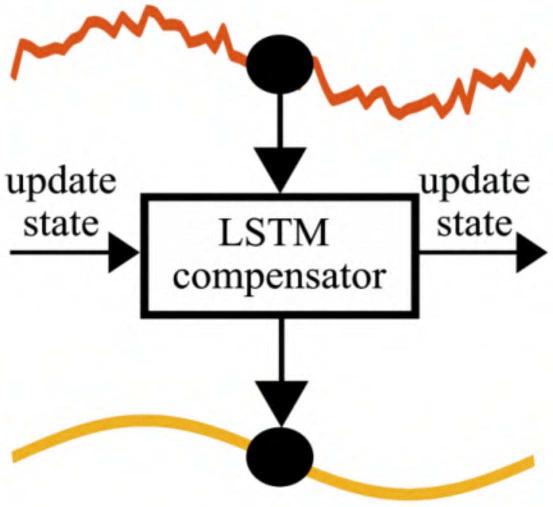
Joud Satme; Department of Mechanical Engineering
Daniel Coble; Department of Mechanical Engineering
Hung-Tien Huang; Department of Computer Science and Engineering
Austin R.J. Downey; Department of Mechanical, Civil and Environmental Engineering
Jason D. Bakos; Department of Computer Science and Engineering

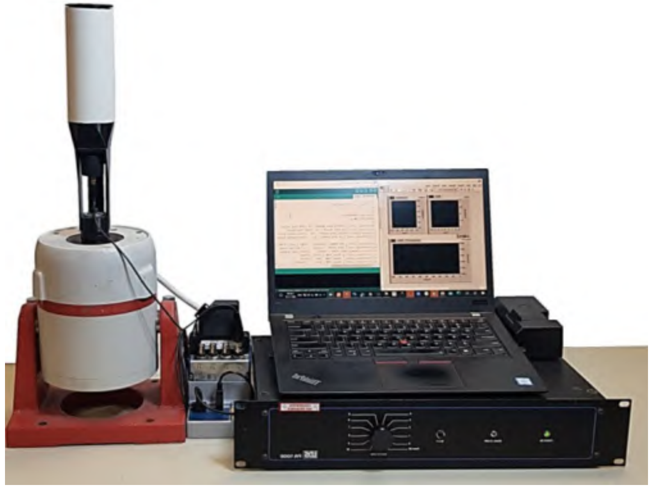
UNIVERSITY OF SOUTH CAROLINA

Methodology → Experimentation → Results and Discussion → Future work

Outline

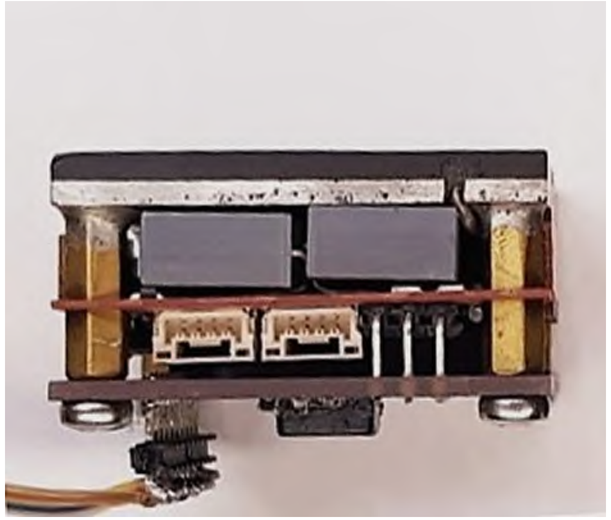
- Methodology:
  - Minimal invasiveness sensors
  - Long short-term memory networks
  - Error compensator model
- Experimentation:
  - Bench-top experiment
  - Model training procedure
  - Performance metrics
- Results and Discussion:
  - LSTM compensator performance
  - Hardware implementation
- Future work:
  - Improve model parameters
  - Embedded system implementation





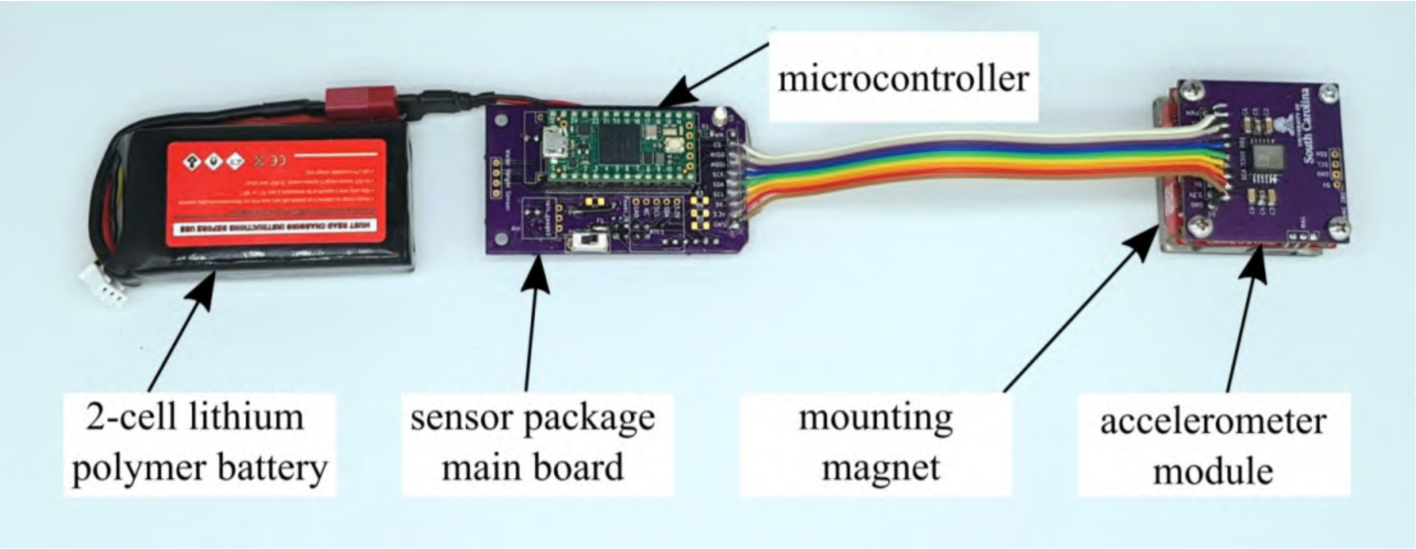
Introduction

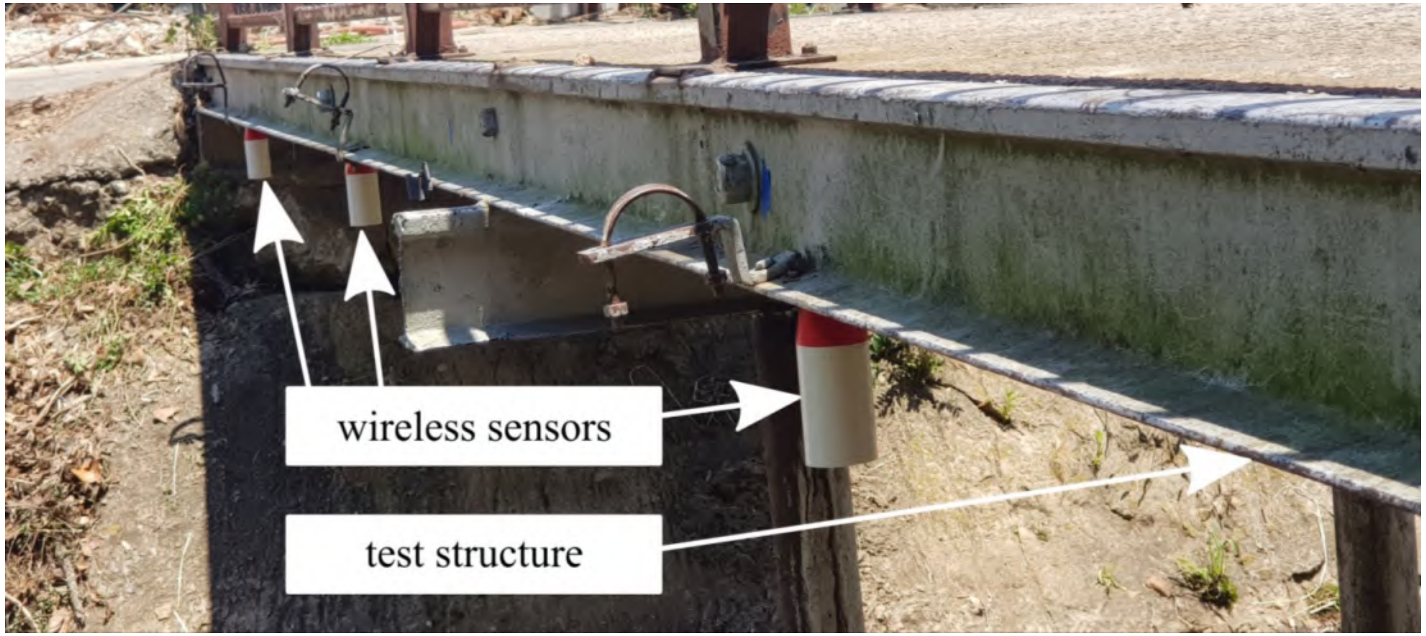
- Rapid structural health monitoring
- Wireless sensor UAV-deployment
- Mounting medium limitations
- Problem statement:
  - Transmissibility loss
  - Rapid SHM sensing
  - Limited-performance electronics
- Proposed approach:
  - Non-linear compensation method
  - Filter implementation on-the-edge
  - Develop a computationaly efficient filter



Minimal invasiveness sensors

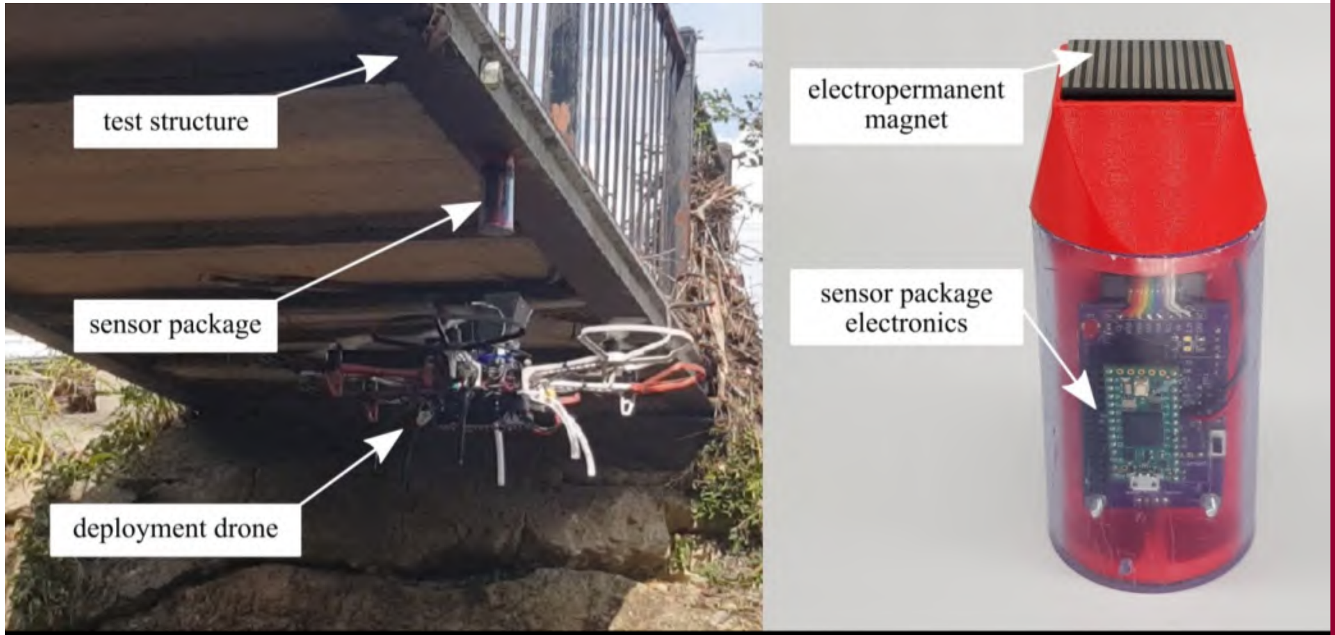
- Sensors that cause no alteration to the structure being examined
- Consists of:
  - Electropermanent magnet (EPM)
  - MEMS accelerometer
  - Microcontroller
  - Lithium polymer battery
  - Memory storage
  - RF wireless communication
- Rapidly deployed for modal-based structural health monitoring applications





Minimal invasiveness sensors

- Sensors are deployed via UAV to remote locations
- Using EPMs to secure package to UAV and to mount onto metal structures
- Sensors can be rapidly mobilized to multiple points on the structure
- Low-cost alternative to permanent hardwired systems



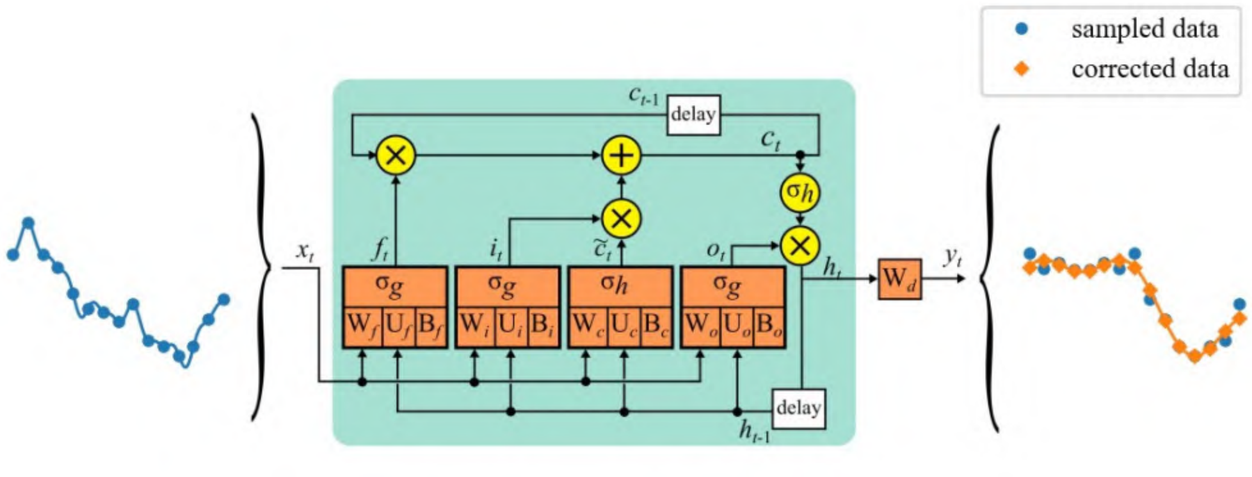
Long short-term memory networks

- Type of recurrent neural networks
- Using feedback to pass state information to future timesteps
- Data enters the network as a singleton vector
- Internal states of the network are updated
- The network then produces an output
- The output is fed into a dense layer to make a prediction

$$f_t = \sigma(W_f x_t + U_f h_{t-1} + b_f)$$
$$i_t = \sigma(W_i x_t + U_i h_{t-1} + b_i)$$
$$o_t = \sigma(W_o x_t + U_o h_{t-1} + b_o)$$
$$\tilde{c}_t = \tanh(W_c x_t + U_c h_{t-1} + b_c)$$
$$c_t = f_t \circ c_{t-1} + i_t \circ \tilde{c}_t$$
$$h_t = o_t \circ \tanh(c_t)$$
$$y_t = W_d^T h_t + b_d$$

Error compensator model

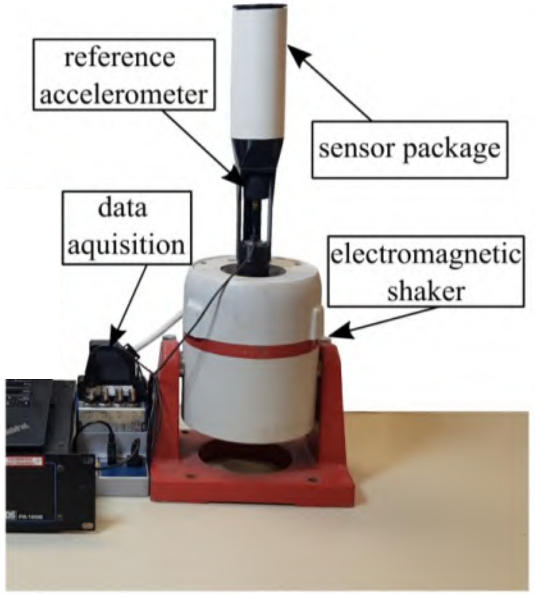
- LSTMs are ideal for processing temporal data
- Identify high nonlinear anomalies that linear functions perform poorly with
- Use an input output relationship between two sensors to train
- LSTM models recognize false sensor measure
- Compensators mitigate undesirable sensor noise or inaccurate gain measurement
- Large memory footprint and computation load compared to linear transfer functions
- Model chosen is a single-layer 50 units with a dense final layer

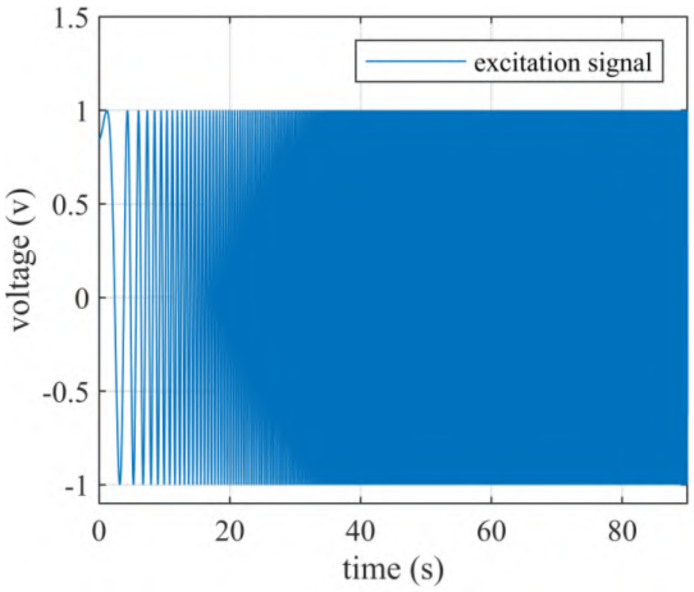


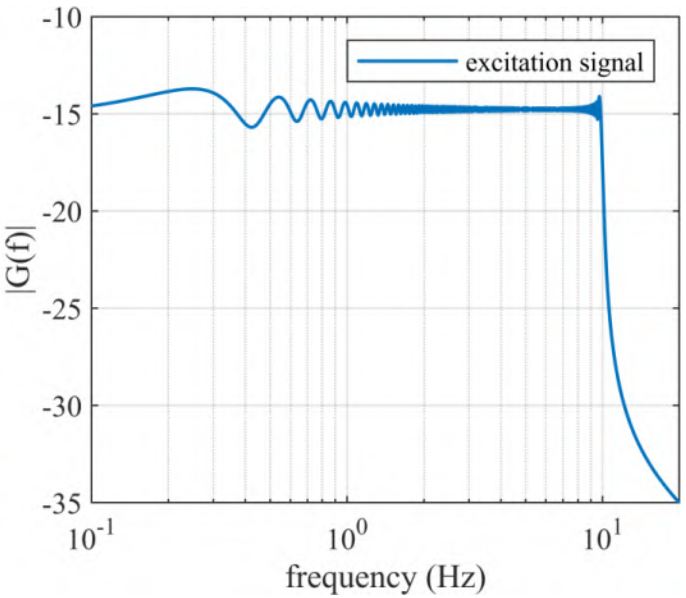
Bench-top experiment

- Bandwidth: 0-10Hz
- Excitation signal: frequency sweep
- Training datasets focused on the lower frequency scale (<5Hz)
- Model trained best when one frequency was presented at a time
- The synthetic waveform is converted to an analog signal for excitation

$$x(t) = \sin\left(2\pi\left(\frac{f_{\text{end}} - f_{\text{start}}}{2(\text{test time})}t^2 + f_{\text{start}}t\right)\right)$$

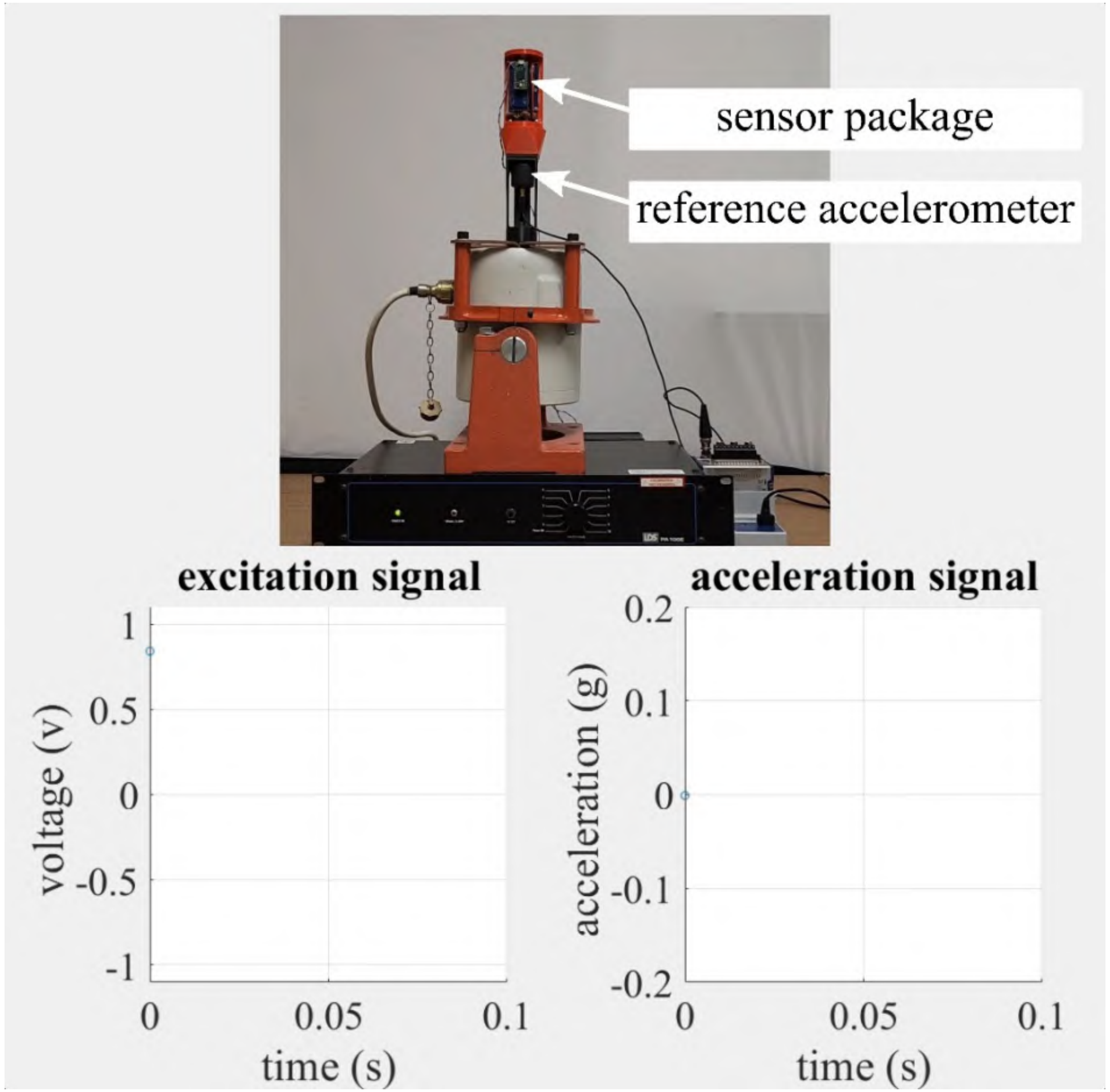






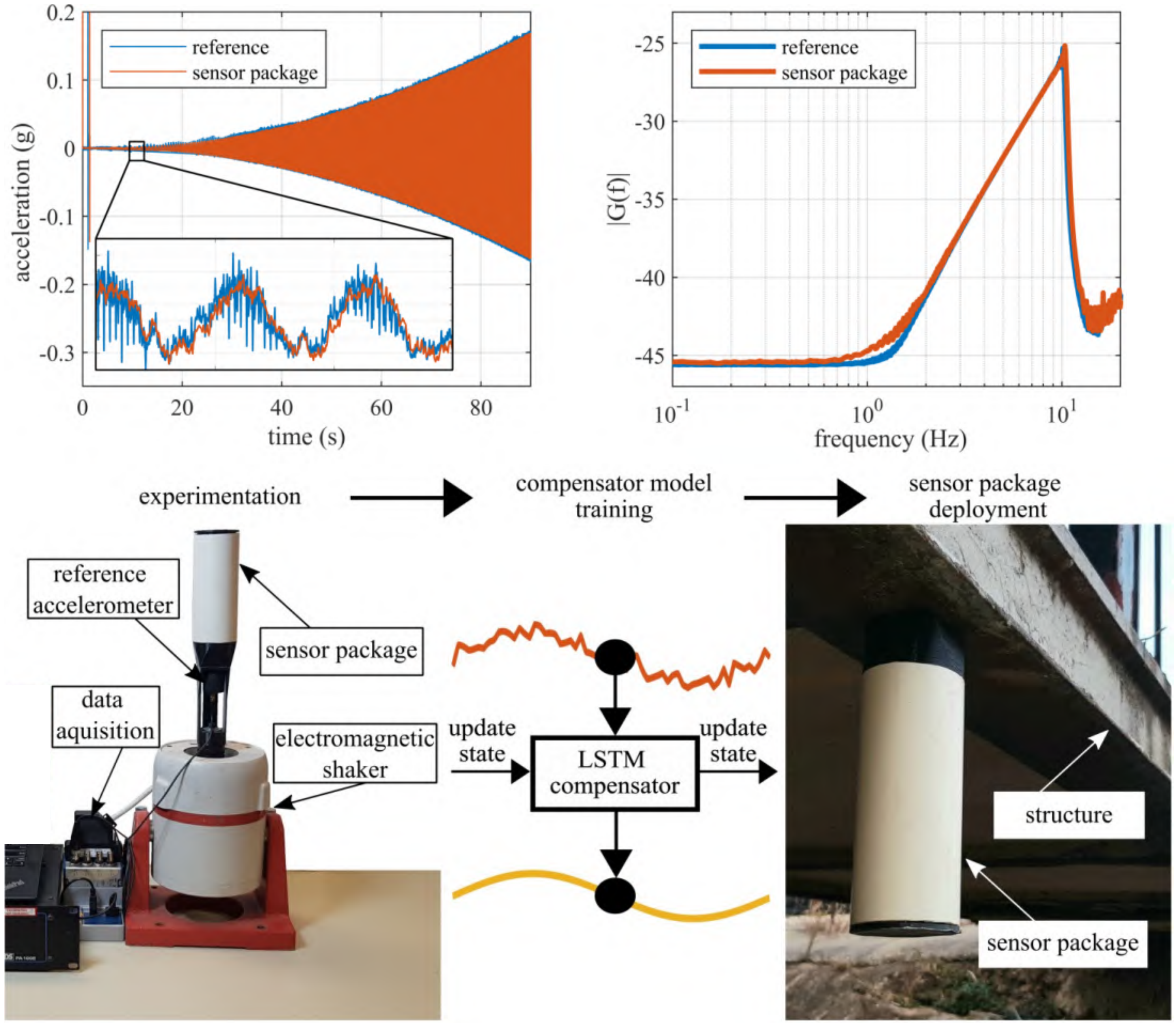
Bench-top experiment

- Chirp excitation is fed into the electromagnetic shaker using an analog output module
- A data acquisition is used to record reference acceleration
- A digital trigger is set to synchronize both the reference accelerometer and sensor package
- Various dynamic ranges were used to expand the training range of the LSTM model



Model training procedure

- Supervised learning method
- Assumptions:
  - Sampling rates were set equal (400 S/s)
  - Zero phase between the two sensors
  - Bandwidth of interest to be < 10 Hz
- Model chosen is a single-layer 50-unit LSTM
- Backpropagation is done online every 400 datapoints (1 second)



Performance metrics

- Network performance is examined in time-domain
  - SNR_{dB}
  - RMSE
- In the frequency domain using a frequency response function
- Goal is to compare sensor package measurement to the LSTM error-compensator prediction

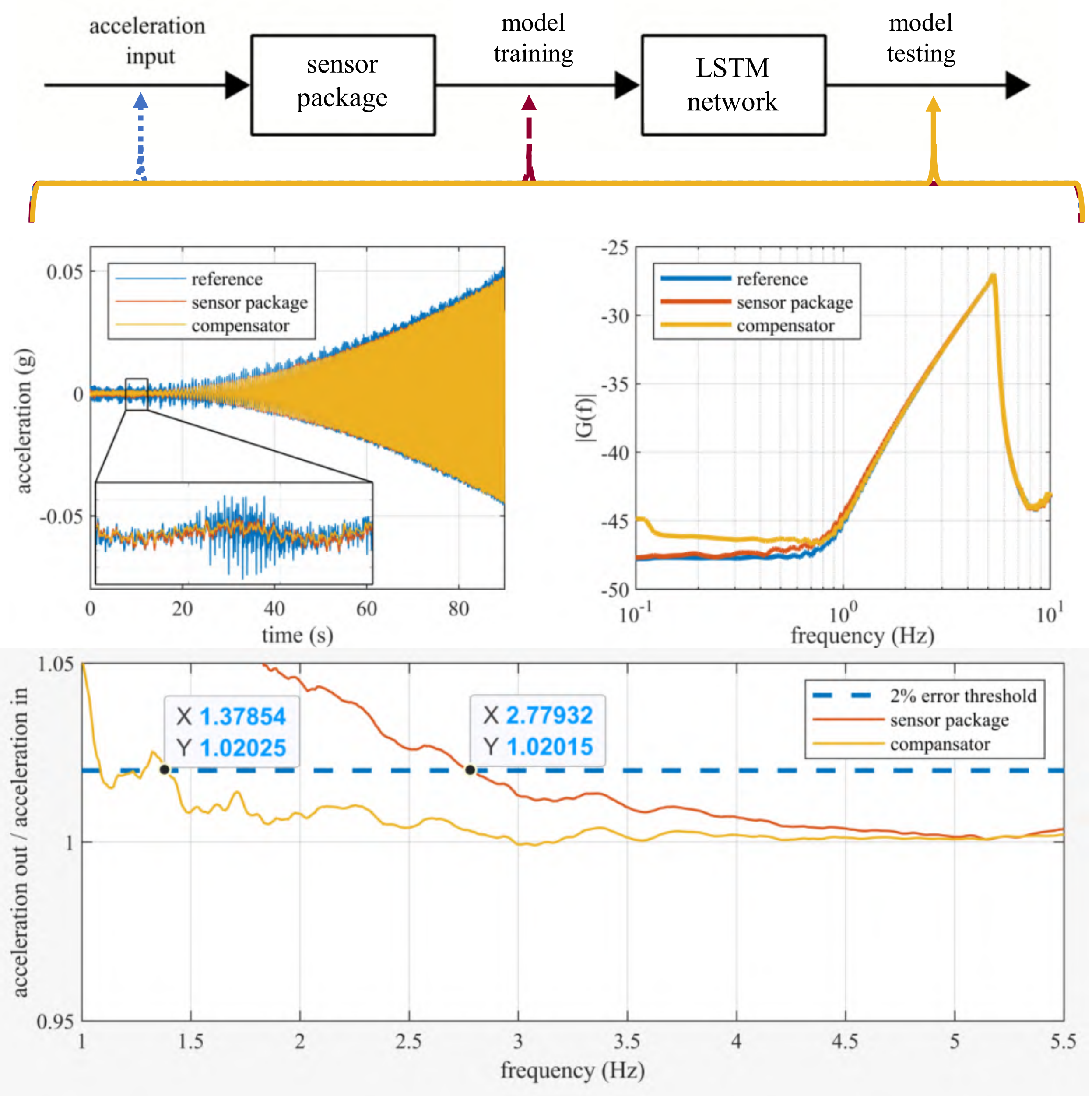
$$\mathrm{SNR}_{\mathrm{dB}} = 10\log_{10}\left(\frac{\sum_{i=1}^{\text{data length}}(\text{signal}(i))^2}{\sum_{i=1}^{\text{data length}}(\text{noise}(i))^2}\right)$$

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{\text{data length}}(\text{truth(i)} - \text{prediction(i)})^2}{\text{data length}}}$$

LSTM compensator performance

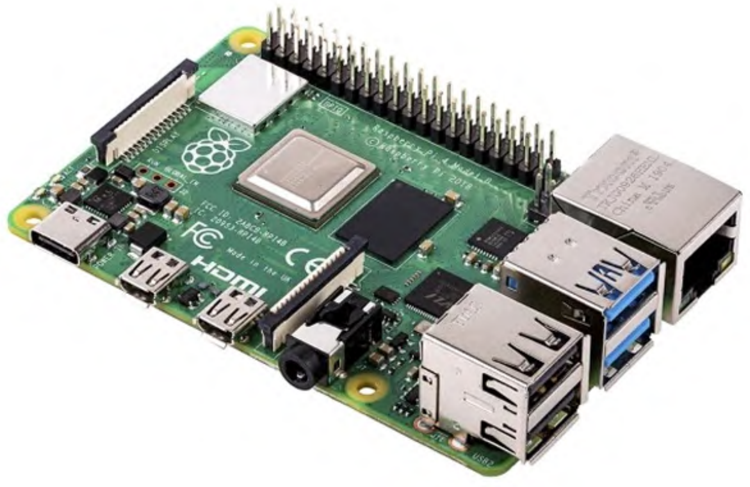
- For testing a chirp excitation in 0-5 Hz is used
- SNR_{dB} enhancement of 9.34%
- RMSE reduction of 19.66%
- Usable bandwidth (< ±2%) is shown to increase form 2.78 Hz to 1.34 Hz
- An overall increase in gain below 0.9 Hz due to training bias

testing	SNR_{dB}	RMSE
sensor package	17.26 dB	1.795×10^{-3}
LSTM compensator	18.88 dB	1.442×10^{-3}
% improvement	9.34%	19.66%



Hardware implementation

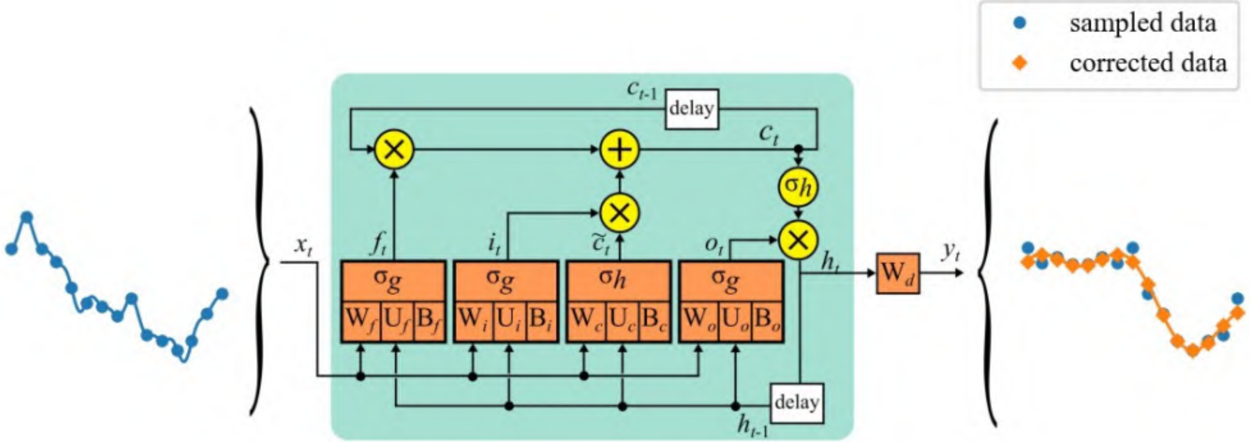
- Hardware: Raspberry Pi 4 with 2 GB of RAM running Ubuntu Mate 20.04
- 32-bit precision
- Compensator model size is 5.1 MB
- Runtime memory consumption 36.8 MB
- Forward pass average 10 μs per prediction
- Throughput rate 10 kS/s



"Raspberry pi 4 B 4GB: Raspberry Pi," *RS Components* . [Online]. Available: https://ae.rsdelivers.com/product/raspberry-pi/raspberry-pi-4-4g-model-b/raspberry-pi-4-b-4gb/1822096. [Accessed: 27-Feb-2023].

Future work

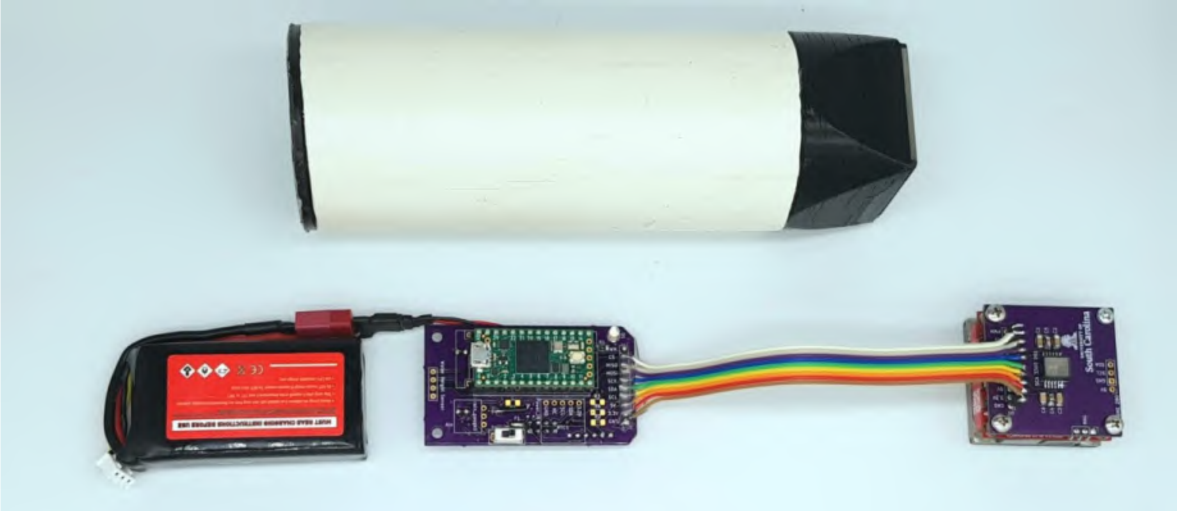
- Expanding training range to increase usable bandwidth
- Improve model performance and memory footprint
- Full-scale embedded system implementation



Open-source UAV-deployable vibration sensor package

Open-Source hardware Designs

https://github.com/ARTS-Laboratory/Drone-Delivered-Vibration-Sensor



ACKNOWLEDGEMENT:

This material is based upon work supported by the Air Force Office of Scientific Research (AFOSR) through award no. FA9550-21-1-0083. This work is also partly supported by the National Science Foundation Grant numbers 1937535, 1956071, 2152896, and 2237696.

Thank you

Questions?

Author Information
Name: Austin R.J. Downey
Email: austindowney@sc.edu

References:

[1] Noel, A. B., Abdaoui, A., Elfouly, T., Ahmed, M. H., Badawy, A., and Shehata, M. S., “Structural health monitoring using wireless sensor networks: A comprehensive survey,” IEEE Communications Surveys & Tutorials 19(3), 1403–1423 (2017).
[2] Bernardini, L., Benedetti, L., Somaschini, C., Cazzulani, G., and Belloli, M., “SHM campaign on 138 spans of railway viaducts by means of OMA and wireless sensors network,” in [Lecture Notes in Civil Engineering], 15–25, Springer International Publishing (aug 2022).
[3] Ierimonti, L., Cavalagli, N., Venanzi, I., Garc´ıa-Mac´ıas, E., and Ubertini, F., “A bayesian-based inspectionmonitoring data fusion approach for historical buildings and its post-earthquake application to a monumental masonry palace,” Bulletin of Earthquake Engineering 21, 1139–1172 (Dec. 2022).
[4] Carroll, S., Satme, J., Alkharusi, S., Vitzilaios, N., Downey, A., and Rizos, D., “Drone-based vibration monitoring and assessment of structures,” Applied Sciences 11(18) (2021).
[5] Zhou, H., Lynch, J., and Zekkos, D., “Autonomous wireless sensor deployment with unmanned aerial vehicles for structural health monitoring applications,” Structural Control and Health Monitoring 29 (mar 2022).
[6] Sreenath, S., Malik, H., Husnu, N., and Kalaichelavan, K., “Assessment and use of unmanned aerial vehicle for civil structural health monitoring,” Procedia Computer Science 170, 656–663 (2020). The 11th International Conference on Ambient Systems, Networks and Technologies (ANT) / The 3rd International Conference on Emerging Data and Industry 4.0 (EDI40) / Affiliated Workshops.
[7] Whelan, M. J., Gangone, M. V., Janoyan, K. D., and Jha, R., “Real-time wireless vibration monitoring for operational modal analysis of an integral abutment highway bridge,” Engineering Structures 31(10), 2224–2235 (2009).
[8] Krishnamurthy, V., Fowler, K., and Sazonov, E., “The effect of time synchronization of wireless sensors on the modal analysis of structures,” Smart Mater. Struct. 17, 055018 (Oct. 2008).
[9] Bocca, M., Eriksson, L. M., Mahmood, A., J¨antti, R., and Kullaa, J., “A synchronized wireless sensor network for experimental modal analysis in structural health monitoring,” Computer-Aided Civil and Infrastructure Engineering 26(7), 483–499 (2011).
[10] Takeuchi, K., Masuda, A., Akahori, S., Higashi, Y., and Miura, N., “A close inspection and vibration sensing aerial robot for steel structures with an epm-based landing device,” 101692U (04 2017).
[11] Takeuchi, K., Masuda, A., Akahori, S., Higashi, Y., and Miura, N., “An aerial robot landing on a steel structure for vibration measurement: -elimination of an influence of airframe vibration-,” The Proceedings of the Symposium on Evaluation and Diagnosis 2016.15, 209 (01 2016).
[12] Boehme, B., Roellig, M., and Wolter, K.-J., “Moisture induced change of the viscoelastic material properties of adhesives for shm sensor applications,” in [2010 Proceedings 60th Electronic Components and Technology Conference (ECTC)], 1885–1892 (2010).
[13] Liu, X., Xu, Y., Wang, X., Ran, Y., and Zhang, W., “Effect of adhesive and its aging on the performance of piezoelectric sensors in structural health monitoring systems,” Metals 10, 1342 (Oct. 2020).
[14] Tanaka, A., Masuda, A., Akahori, S., Higashi, Y., and Miura, N., “A clinging device for structural inspection aerial robot,” The Proceedings of JSME annual Conference on Robotics and Mechatronics (Robomec) 2018, 1A1–B11 (12 2018).
[15] Zhu, L., Fu, Y., Chow, R., Spencer, B., Park, J., and Mechitov, K., “Development of a high-sensitivity wireless accelerometer for structural health monitoring,” Sensors 18, 262 (jan 2018).
[16] Bedon, C., Bergamo, E., Izzi, M., and No`e, S., “Prototyping and validation of MEMS accelerometers for structural health monitoring—the case study of the pietratagliata cable-stayed bridge,” Journal of Sensor and Actuator Networks 7, 30 (jul 2018).
[17] Latt, W. T., Tan, U.-X., Riviere, C. N., and Ang, W. T., “Transfer function compensation in gyroscopefree inertial measurement units for accurate angular motion sensing,” IEEE Sensors Journal 12, 1207–1208 (May 2012).
[18] Satme, J., Smith, C., Downey, A. R. J., Bakos, J. D., Vitzilaios, N., and Rizos, D., “Compensation technique for accurate acceleration measurements using a UAV deployable and retrievable sensor package,” in [Sensors and Smart Structures Technologies for Civil, Mechanical, and Aerospace Systems 2022], Zonta, D., Su, Z., and Glisic, B., eds., SPIE (apr 2022).
[19] Ward, P. and Liu, D., “Design of a high capacity electro permanent magnetic adhesion for climbing robots,” in [2012 IEEE International Conference on Robotics and Biomimetics (ROBIO)], 217–222 (2012).
[20] Satme, J. N., Yount, R., Vaught, J., Smith, J., and Downey, A. R., “Modal analysis using a uav-deployable wireless sensor network,” Society for Experimental Mechanics, International Modal Analysis Conference (2023).
[21] Satme, J. and Downey, A., “Drone delivered vibration sensor.” GitHub (2022).
[22] Hochreiter, S. and Schmidhuber, J., “Long short-term memory,” Neural Computation 9, 1735–1780 (nov 1997). [23] Gers, F., “Learning to forget: continual prediction with LSTM,” in [9th International Conference on Artificial Neural Networks: ICANN '99], IEEE (1999).