SEISMIC SIGNAL PREDICTION USING ACCELEROMETER ARRAYS FOR ONLINE NEWTONIAN-NOISE MITIGATION ON FPGA

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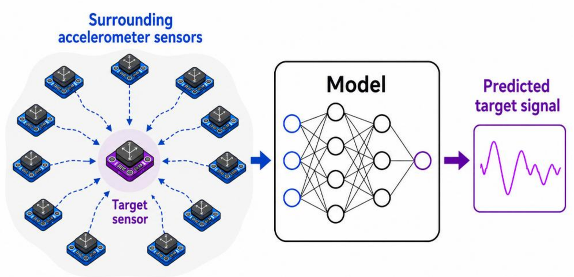
1. NEWTONIAN NOISE PREDICTION

Newtonian noise is gravitationally coupled into interferometer mirrors and caused by various seismic activity. Accelerometer arrays can monitor the surrounding seismic field and provide input data for predicting this noise. Currently, this is done offline on recorded data [1]. Our goal is to predict it in real-time (online).

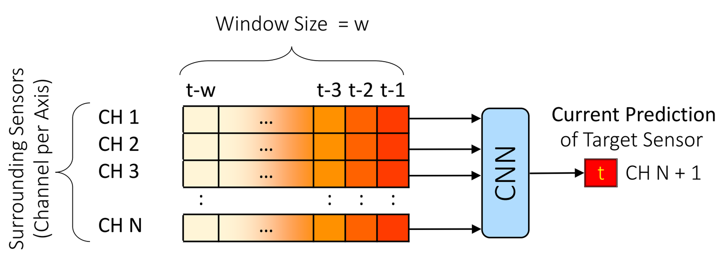
1.1 MOTIVATION FOR ONLINE PREDICTION

- **Multi-messenger** observation triggering requires online noise mitigation and signal analysis
- Low-latency input for **active mirror stabilization**
- Our **proxy**: prediction of the target sensor from the others



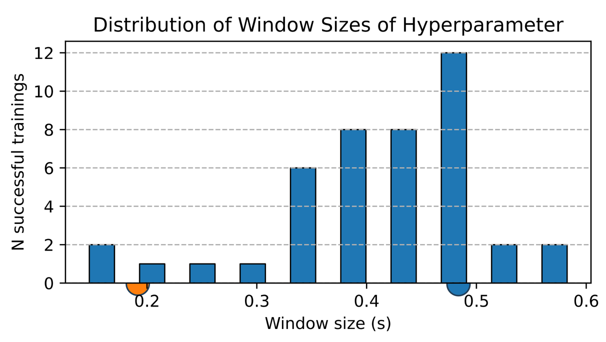
1.2 FPGA-BASED ARCHITECTURE

- Neural-network interface on FPGA
- Deterministic low-latency
- Streaming sensor input



2. MODEL SEARCH

Fixed parameters
- Epoch 1000
- Early stopping patience 10



Data set Recorded at ETpathfinder Lab

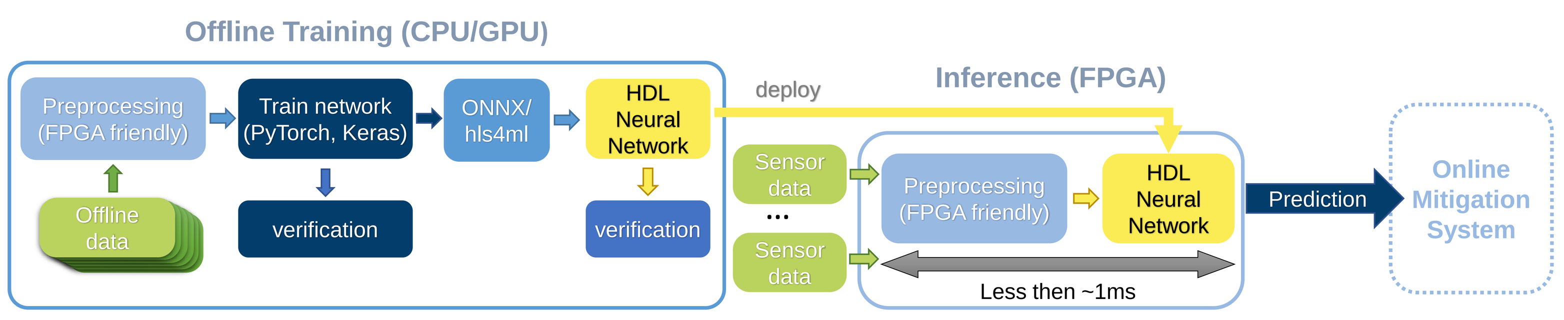
Selected Model Hyperparameters [3]

Hyperparameter		Model A	Model B	Search space
Window size		240	87	64–300 samples*
Learning Rate		6.37×10^{-4}	1.00×10^{-4}	$5 \times 10^{-5} – 10^{-3}$
Batch		64	16	1 – 128
Optimizer		Adam	RMSprop	—
Dropout		0.283	0.067	0.0 – 0.6
Conv. Layers		1	2	1 – 4
Channel	L0	256	64	4 – 256
Kernel size	L0	32	2	1 – 128
ReLU	L0	False	True	—
Channel	L1	—	16	4 – 256
Kernel size	L1	—	2	1 – 128
ReLU	L1	—	False	True/False
Hidden	L2	16	32	4 – 256

*sampling rate: 500 Hz

- Size: 30 hours at 500 Hz/sample
- 13x **vertical** (Innoseis GRAVITON 0-20) sensors
- Data set from [2]: not shown but its Hyperparameter optimization yields Model B

3. TRAINING AND FPGA DEPLOYMENT FLOW



Resource Utilization for Model B
(Model A pending due to ONNX issues)

Input channels	BRAM (18K)	DSP	FF (K)	LUT (K)
1	402	71	91	73
4	409	70	95	73
8	417	70	101	76
11	422	71	105	77
13	426	71	108	78
22	444	73	119	82
ZCU216	2160	4272	850	425

- **Offline Training:** PyTorch model optimization
- **Conversion:** PyTorch → ONNX → HLS4ML → HDL
- **Target:** sub-ms FPGA inference
- **Driver for Search:**
  - prediction quality,
  - model size / FPGA deployment ability

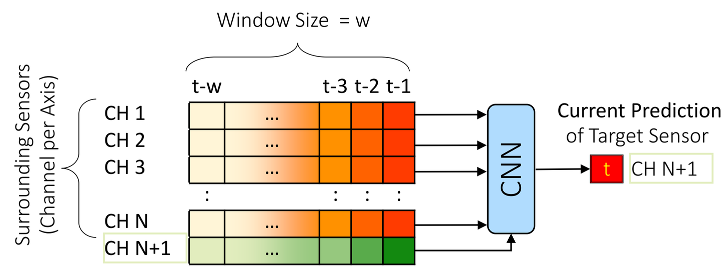
4. IDEALIZED BASELINE STUDY

Injected ground truth (**GT**), *i.e.* target sensor data, among the input channels for model testing (upper bound baseline). Analysis done in python, respecting FPGA limits.

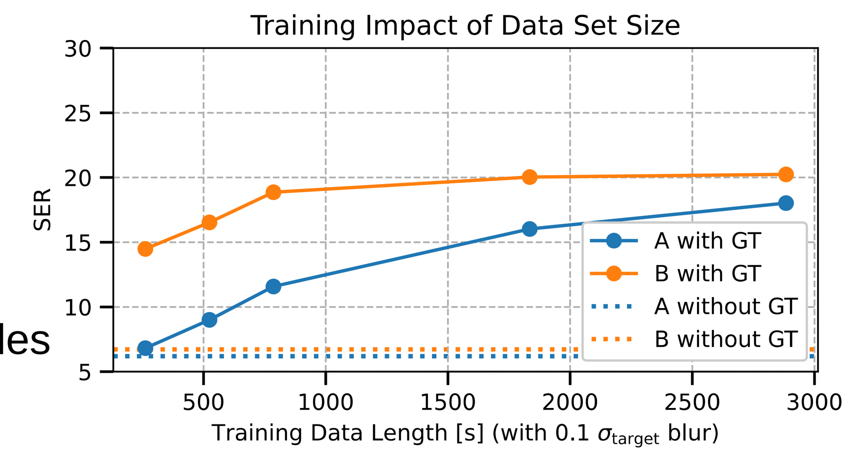
Signal to Error Ratio (higher is better)

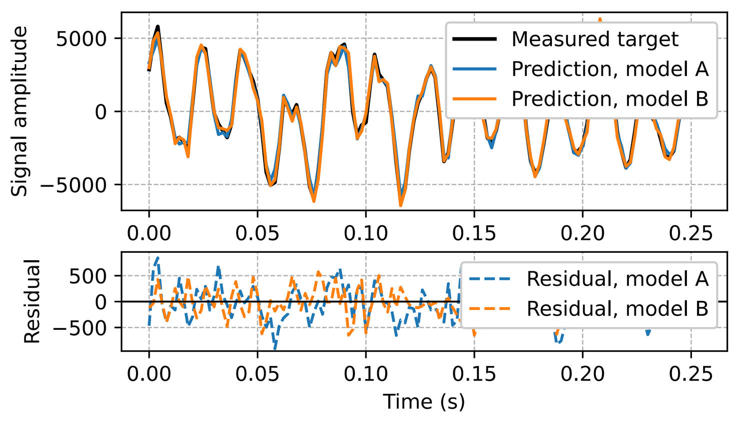
$$\mathrm{SER} = 10 \times \log_{10} \frac{\sum_{i=1}^{N} y_i^2}{\sum_{j=1}^{N} (y_i - \tilde{y}_i)^2}$$

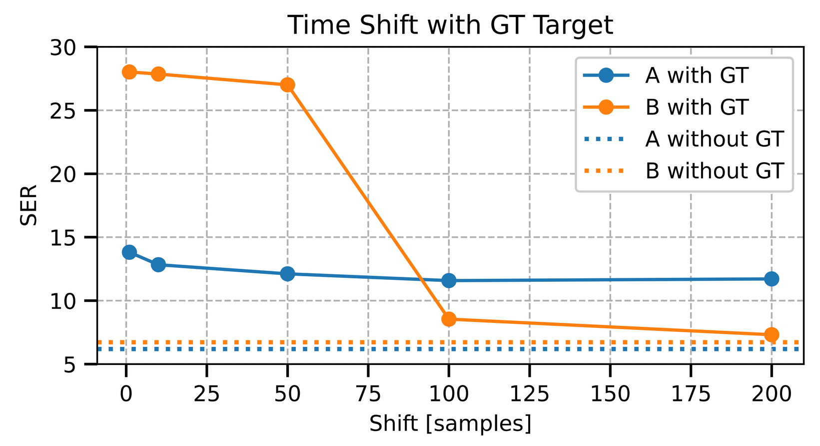
SER is the ratio between target-signal power and residual power, expressed in dB

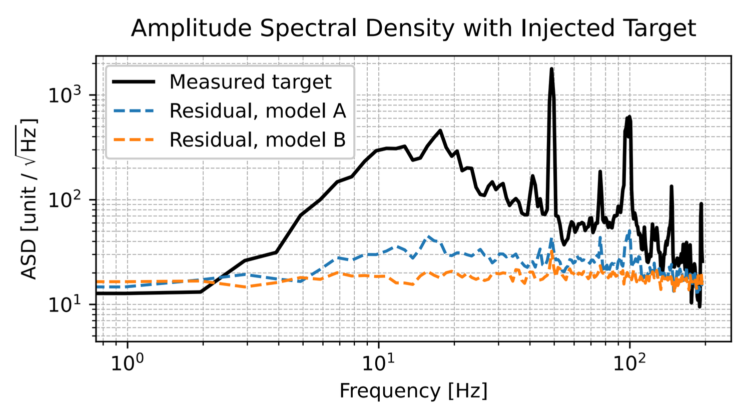


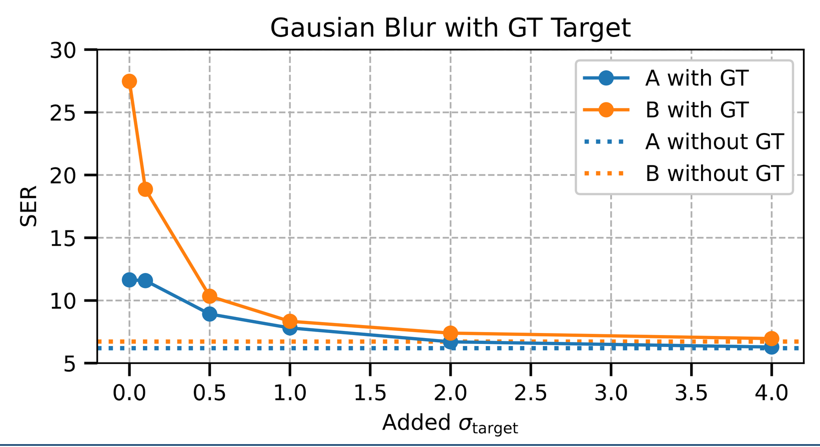
- Training data length at least 1800 s
- Arrival Δt shift ok if within window
  - *e.g.* Model B window = 87 samples
- Adding noise reduces accuracy
  - Nominal ~ 4 sigma blur



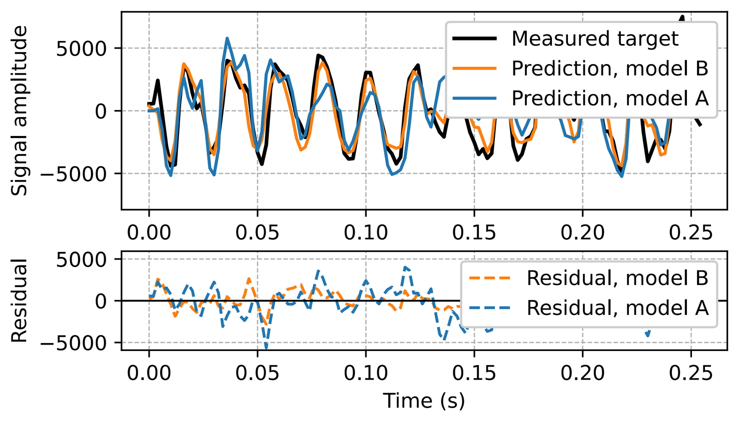


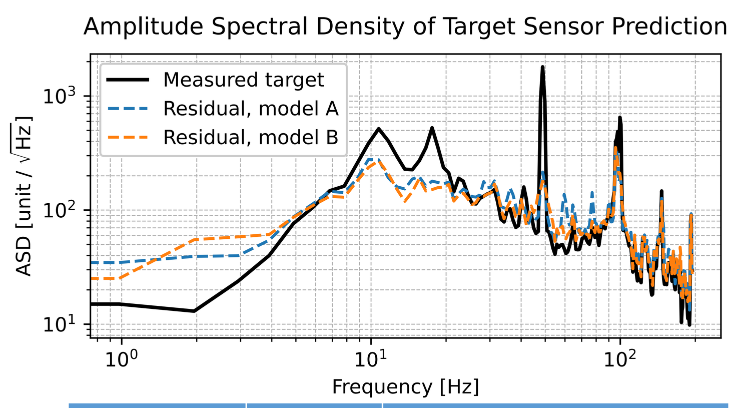






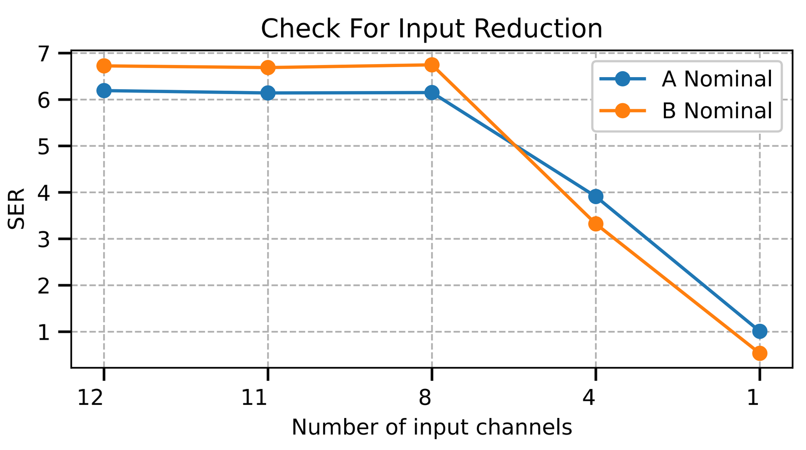
5. VALIDATION RESULTS





Model	RMS_e	Residual / measured
Model A	353.5	0.120
Model B	268.6	0.093

The performance of both models (A,B) is evaluated by comparing the predicted signal with the measured target sensor signal. The residual qualifies unpredicted seismic component.



Residual RMS Compared with Measured Signal

$$(2) \quad RMS = \sqrt{\int_1^{220} ASD^2(f)\, df}$$

- Reduction of ~90% of initial measured signal for target sensor
- Model deployable on ZCU216 evaluation board
- Model B hyperparameters suitable for Model A data, similar performance

CONCLUSION AND OUTLOOK

An accelerometer array prediction pipeline was developed using measured **ETPathfinder** data. Neural network models were trained and validated for seismic target sensor prediction achieving 90% amplitude mitigation while staying under idealized potential. Analysis over other datasets as well as simulated data needs to be performed in order to investigate optimal model hyperparameters.
Future work will focus on improving prediction accuracy, estimating real-time latency, optimizing FPGA resource usage, and testing the complete online system.

შოთა რუსთაველის საქართველოს ეროვნული სამეცნიერო ფონდის მხარდაჭერით [GHZ-25-005] / This work was supported by Shota Rustaveli National Science Foundation of Georgia (SRNSFG) [GHZ-25-005]
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[1] doi.org/10.1088/1361-6382/acf3c8 [2] doi.org/10.1016/j.dib.2024.110174 [3] doi.org/10.48550/arXiv.1907.10902