Deep neural network for gravity-gradient background subtraction

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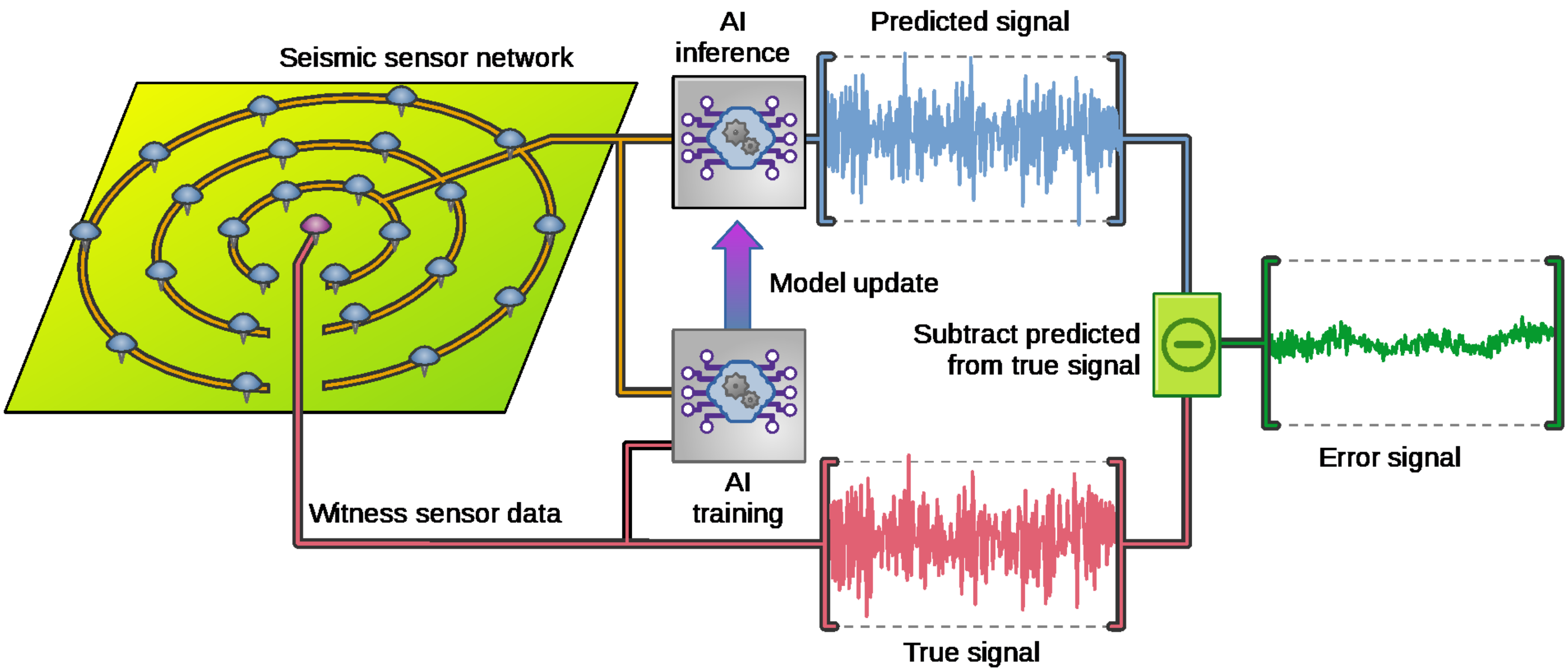
Seismic-sensor signal prediction by using DNNs

A neural network is applied to a seismic sensor network to predict the response of a seismic sensor

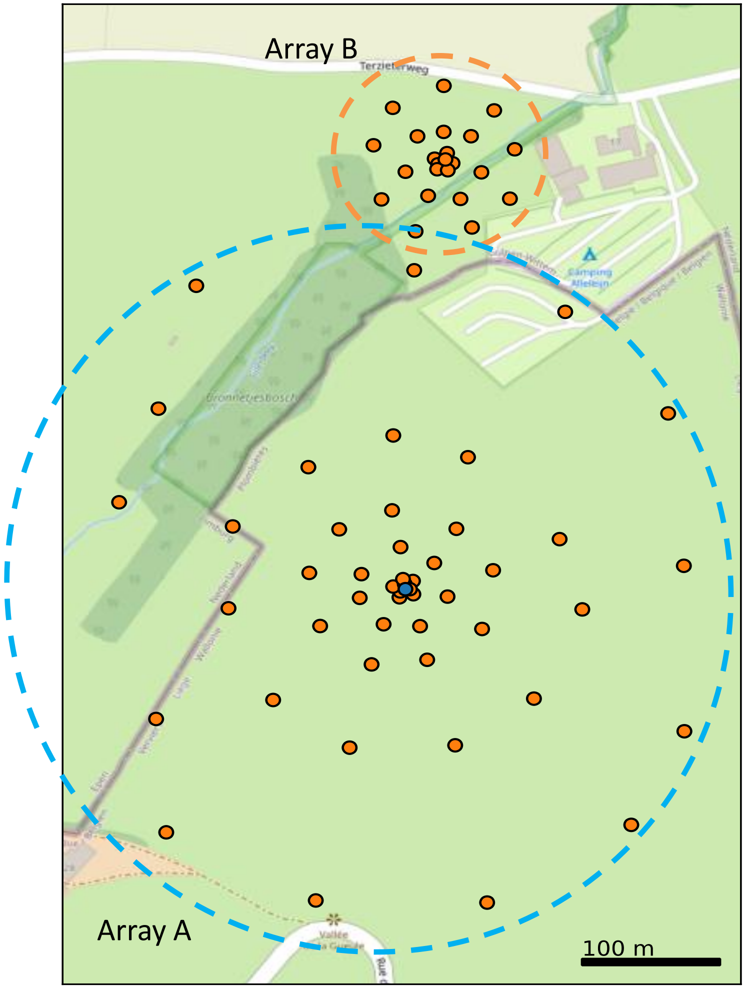
A study was done to demonstrate the applicability by predicting the response of a witness node in the centre of a seismic sensor network based on the sensors surrounding it

The error signal is the difference between the predicted signal and the true signal



Prediction of surface-sensor response

For surface-level sensor prediction data from the 2017 survey in Terziet, NL was used. The dense network ensures it is sensitive for frequencies up to about 10 Hz



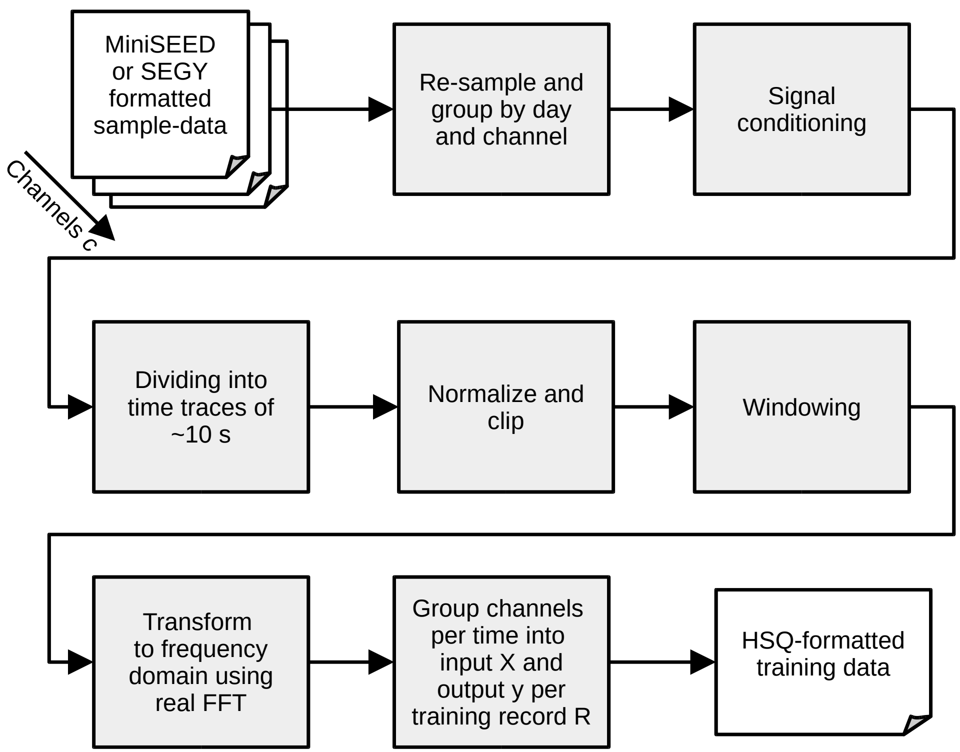
Terziet Array A (bottom) and B (top) sensors in orange, and witness (Z_{true}) sensor in blue

Overlooking castle Buesdaal and the survey area - credit: F. Fouarge

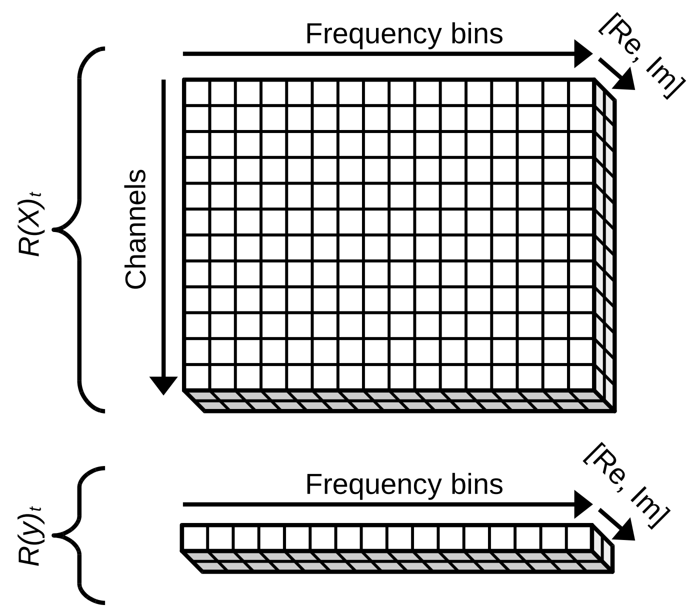
Seismic sensor data preprocessing

To make the seismic sensor data suitable for the DNN all channel data are transformed into the frequency domain: These are divided into traces of time of about 10 seconds with a sliding window and transformed to the frequency domain with an FFT. All frequency spectra at a specific time are combined into a single training record

Preprocessor pipeline



Single training record R_t



(Number of channels and frequency-bins illustrated not representative for actual training data)

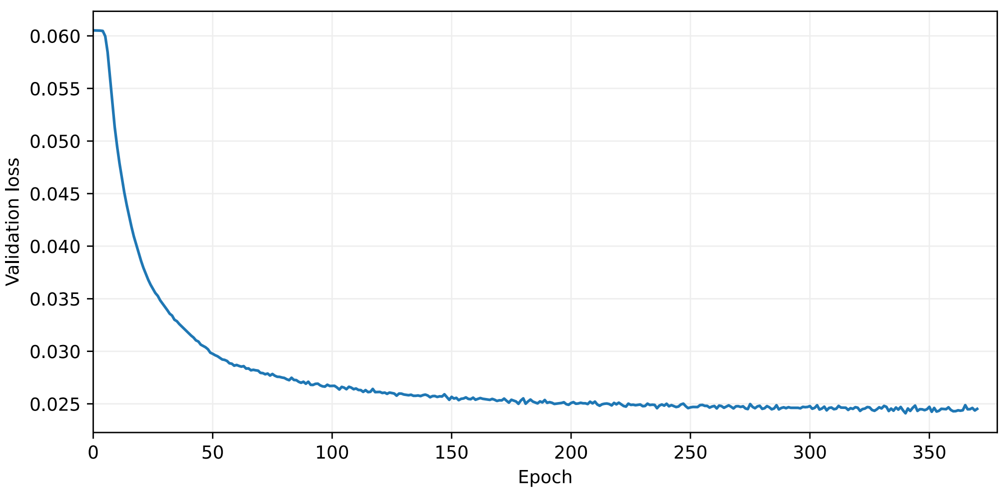
Deep neural network for seismic excitation prediction

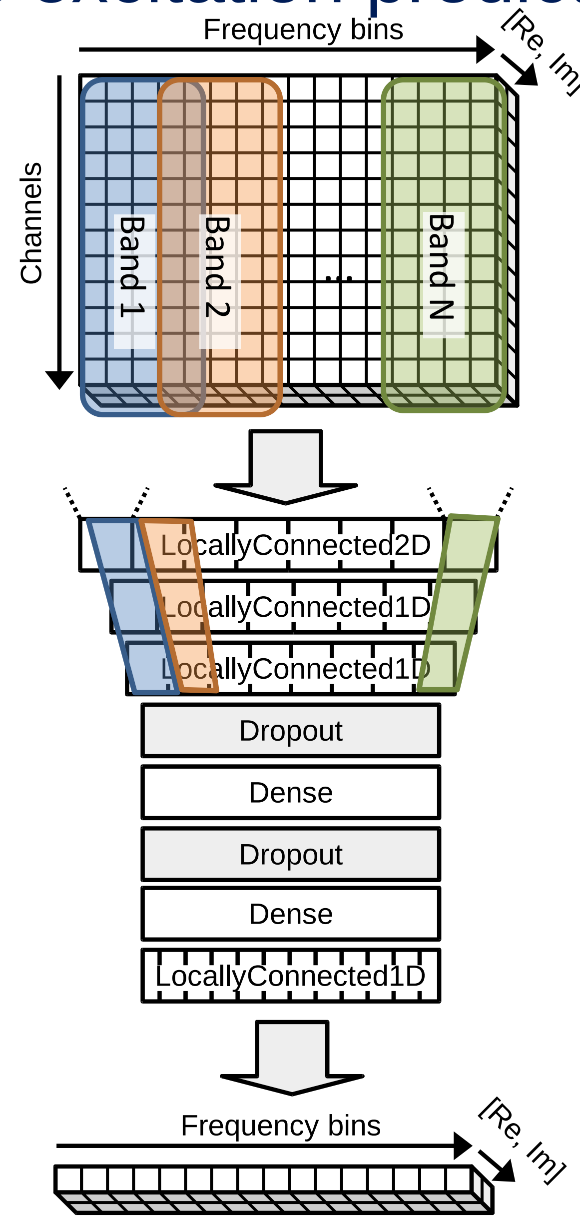
The DNN first processes the input data in 15 overlapping bands. In the last layers all bands are correlated by using a number of fully connected layers

Training parameters

Framework	: Google TensorFlow 2.5
GPU	: Nvidia Tesla V100
Dataset split	: 80% train, 20% verification
Optimizer	: Nadam (learning rate=1.5e-5)
Loss function	: absolute mean error
Activation function	: Exponential Linear Unit
End condition	: loss does not decrease for 30 epochs

Validation loss during training for surface excitation prediction

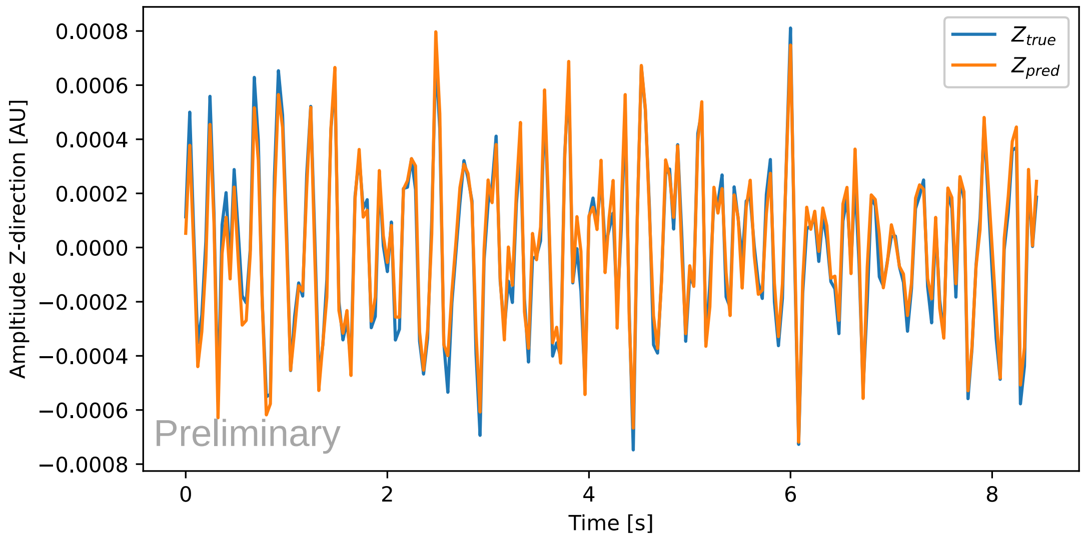




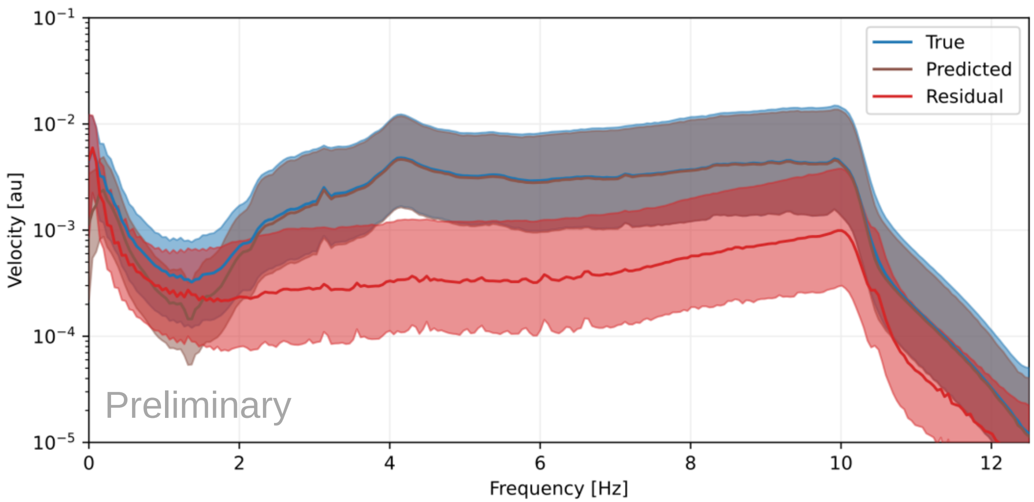
The DNN used for seismic excitation prediction. First 3 funnel shaped layers process the seismic X data per-band. The middle two layers allow cross-band correlations. The final layer is used for scaling, having a bias and no activation function

Results: surface excitation prediction

The DNN is capable of predicting seismic surface excitation with about 90% efficiency from 3 to 6.5 Hz



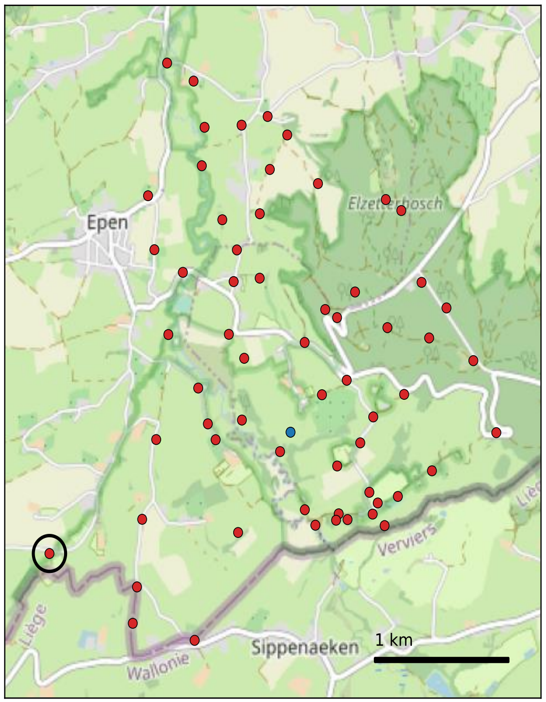
Time-trace record as recorded by the witness node (Z_{true}) and as estimated by the DNN (Z_{pred})



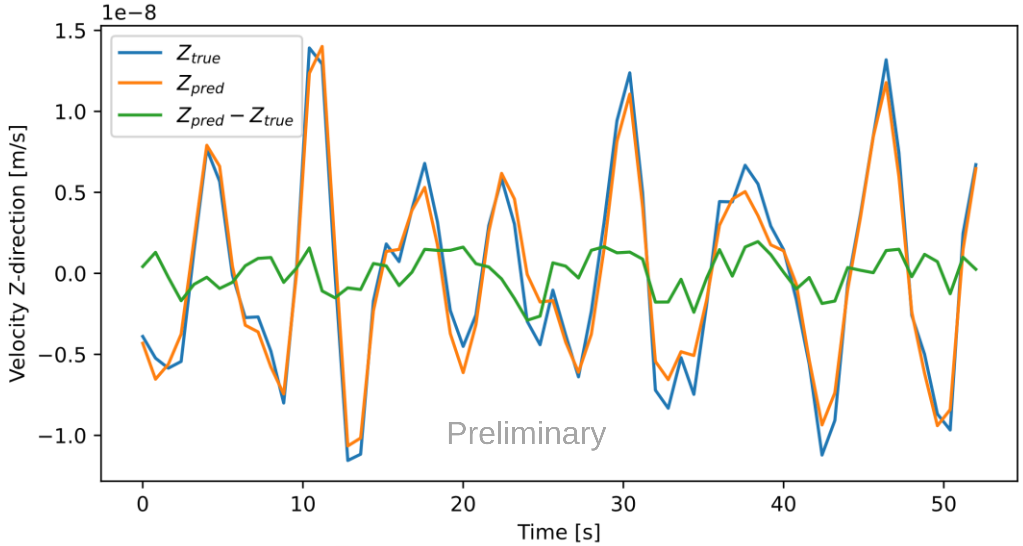
Median magnitude of the true signal, Predicted signal and the residual as provided to the DNN. Band represent the 10-90 %tile

Prediction of underground seismic activity

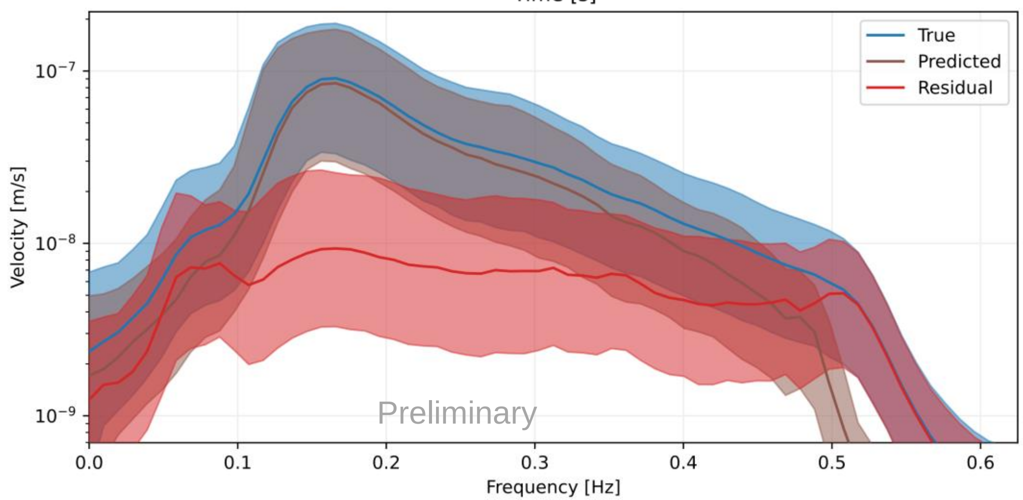
A sparse surface array in combination with a bore-hole (Terziet, NL) sensor was used to predict the subsurface seismic activity. With the same DNN the response at 250 meters depth can be predicted with about 80% accuracy between 150 to 400 mHz. Note that the one-sided sparse seismic network was not optimized for this study



Red circles indicate TN2 sensor nodes, the blue circle shows the Heimansgroeve sensor. The circled sensor is located above the Terziet borehole sensor.



Time-trace record for the subsurface seismometer (Z_{true}) and as estimated by the DNN (Z_{pred})



Median magnitude of the true signal, predicted signal and the residual. Band shows the 10-90 %tile.

NN subtraction from seismic-signal DNN inference

Data from a seismic sensor network are input to a DNN and the output the ET interferometer signal. The difference between the predicted interferometer signal and the true signal will be minimized by the neural network

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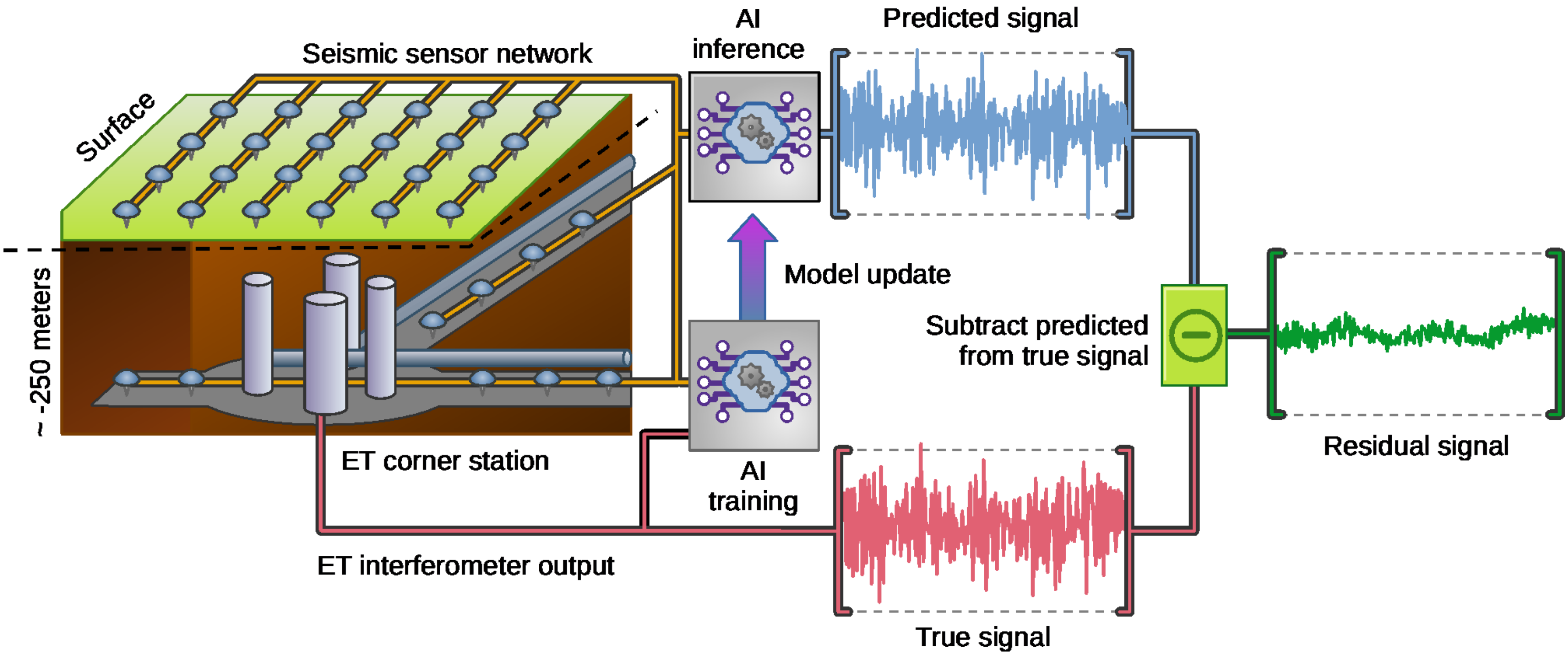


Overview of machine-learning solution for gravity-gradient noise background subtraction. The left shows a seismic-sensor network present both on the surface and underground at the ET site. The seismic network output and the interferometer output are used to train a machine learning algorithm for mapping seismic network output to the interferometer output. Once the model is trained it can be it can be used to predict the interferometer output given a seismic network output. This signal can be subtracted from the true output of the interferometer

Modeling is based on synthetic data

Model employs Limburg geology and seismic noise PSDs

See Koley et al
https://iopscience.iop.org/article/10.1088/1361-6382/ac2b08

Model is setup:

Surface excitations

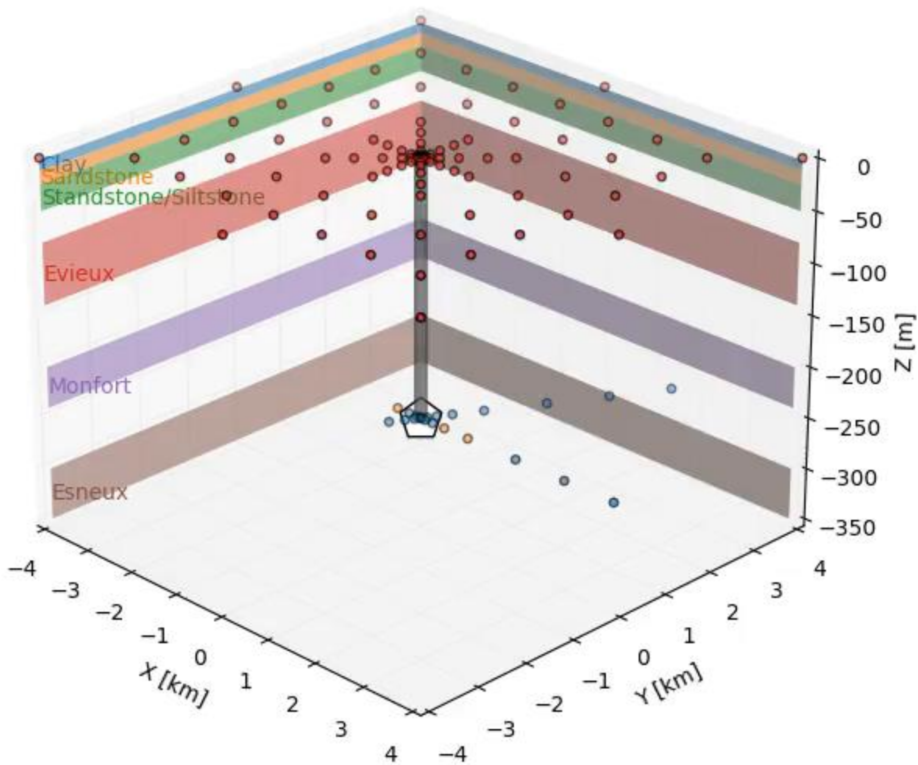
- Matlab EDT was used to calculate the displacement fields
- Surface excitations are isotropically distributed in a radius of 6 km around the borehole
- Sources have random direction, phase and Gaussian distributed amplitude
- Strength of the sources is matched to reproduce the mean PSD at the surface

Random body waves

- Described as plane waves, isotropic in displacement and in traveling direction. No rescattering, reflections, damping, and/or dispersion is included
- P-wave component traveling at 4 km/s and S-wave component at 2.8 km/s
- Body-wave background was estimated from the day-night variation in PSD at the surface and in the borehole

The model is used to generate 50,000 training records by adding 20 random surface sources and 4 random body waves. Each record contains seismic and NN noise in a limited amount of time (few seconds), for a single frequency for 136 sensor locations

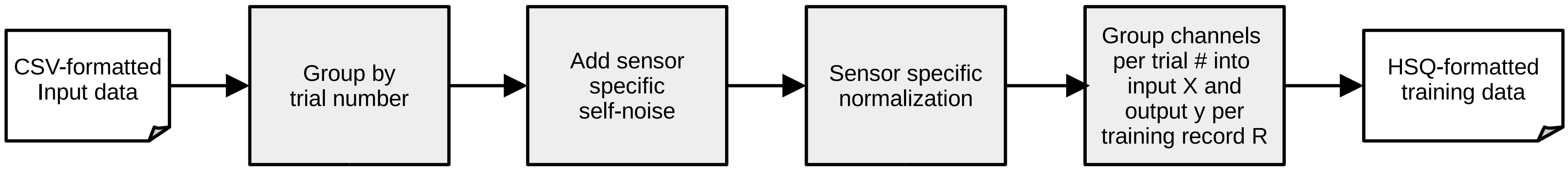
Synthetic network layout



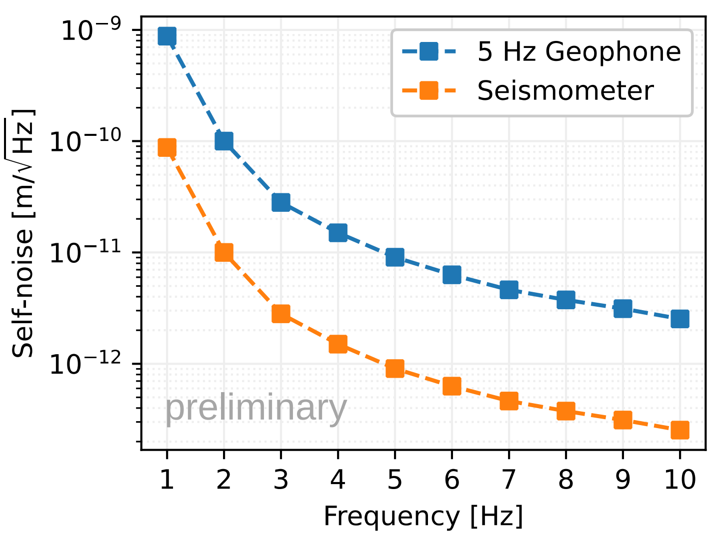
Circles represent 3C (X, Y and Z): seismic sensors: geophones on the surface (red) and 250 m underground (blue). Trilliums underground (orange) are modeled as having 10% of the noise compared to the modeled 5 Hz geophones. The pentagon shows the location of the mirror. The modeled soil layers are indicated. The gray cylinder represents the vertical ET tunnel boundary

Synthetic data preprocessing

The synthetic data must be preprocessed for suitability for a DNN by dividing by a sensor specific normalization factor. During preprocessing sensor-specific self-noise is added to the synthetic data. All data are in the frequency domain, and belong to a specific frequency band (1, 3, 5 and 10 Hz)

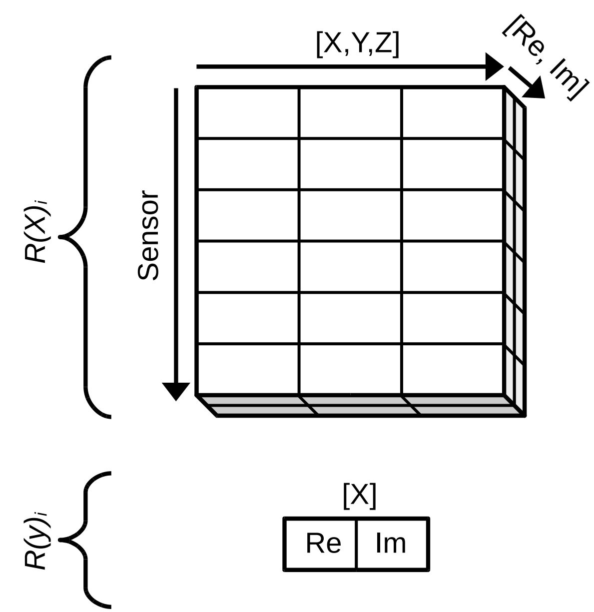


Synthetic data pre-processing pipeline. Data is first grouped per trial number (becomes one training record). All sensor values are divided through a scaled median value of that sensor data bringing it in a suitable range for the neural network. Lastly the training records are created and saved.



Seismic sensor self-noise. The 5 Hz geophone noise found by Bader et al. The seismometer noise is taken to be 10% of the geophone noise

DNN training record R_i. An input record consists of a number of sensors, each having 3 channels, X, Y and Z. Each channel is a complex vector (Re, Im)



Deep neural network for NN prediction

The network for NN prediction only operates on a single frequency band, resulting in a DNN with reduced complexity

Training parameters

Framework : Google TensorFlow 2.5
GPU : Nvidia Tesla V100
Dataset split : 80% train, 20% verification
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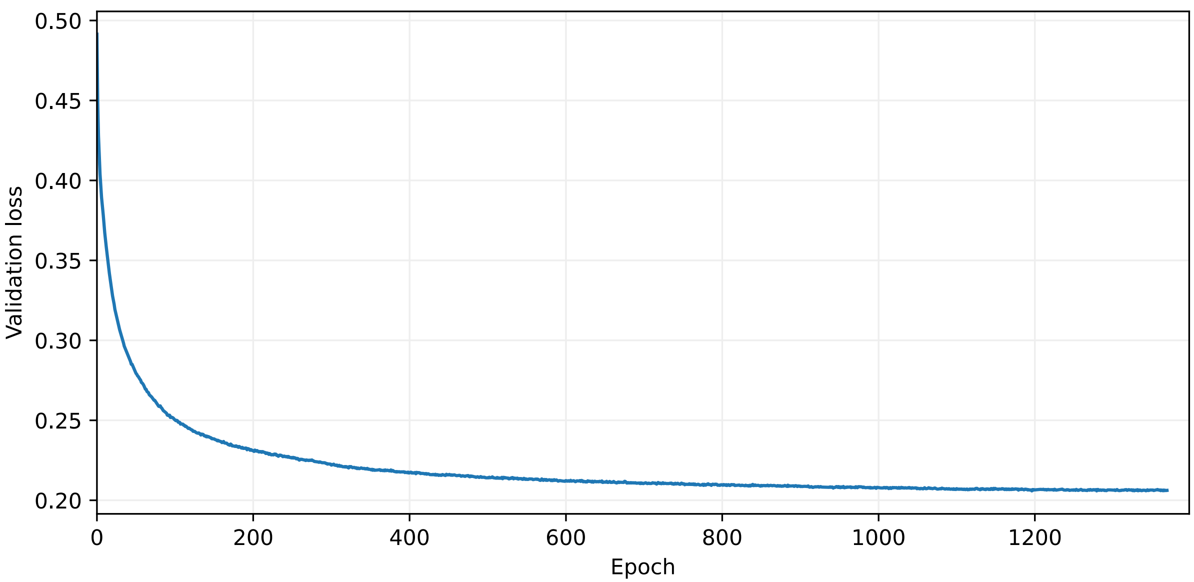
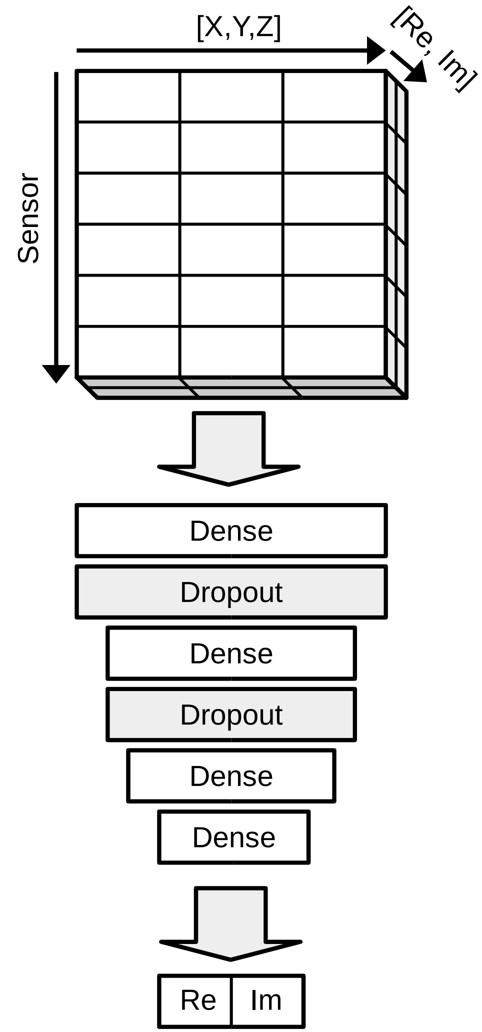
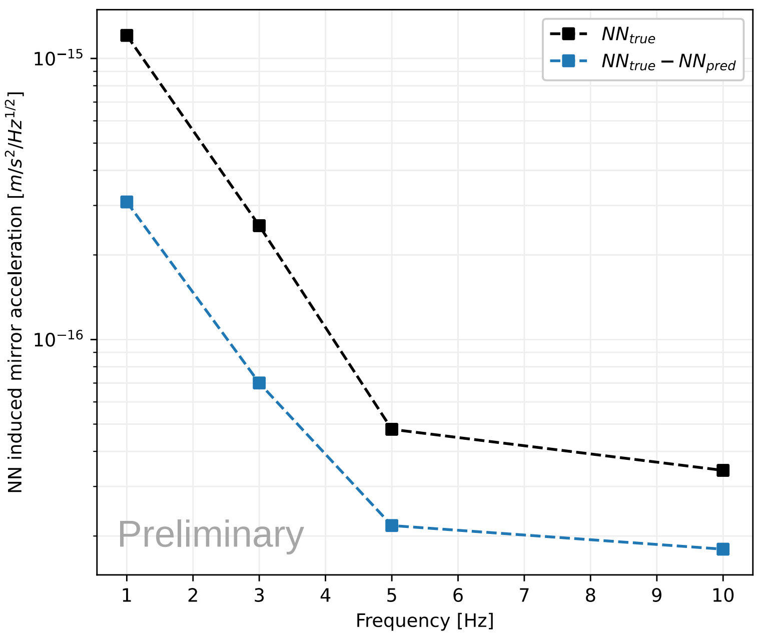


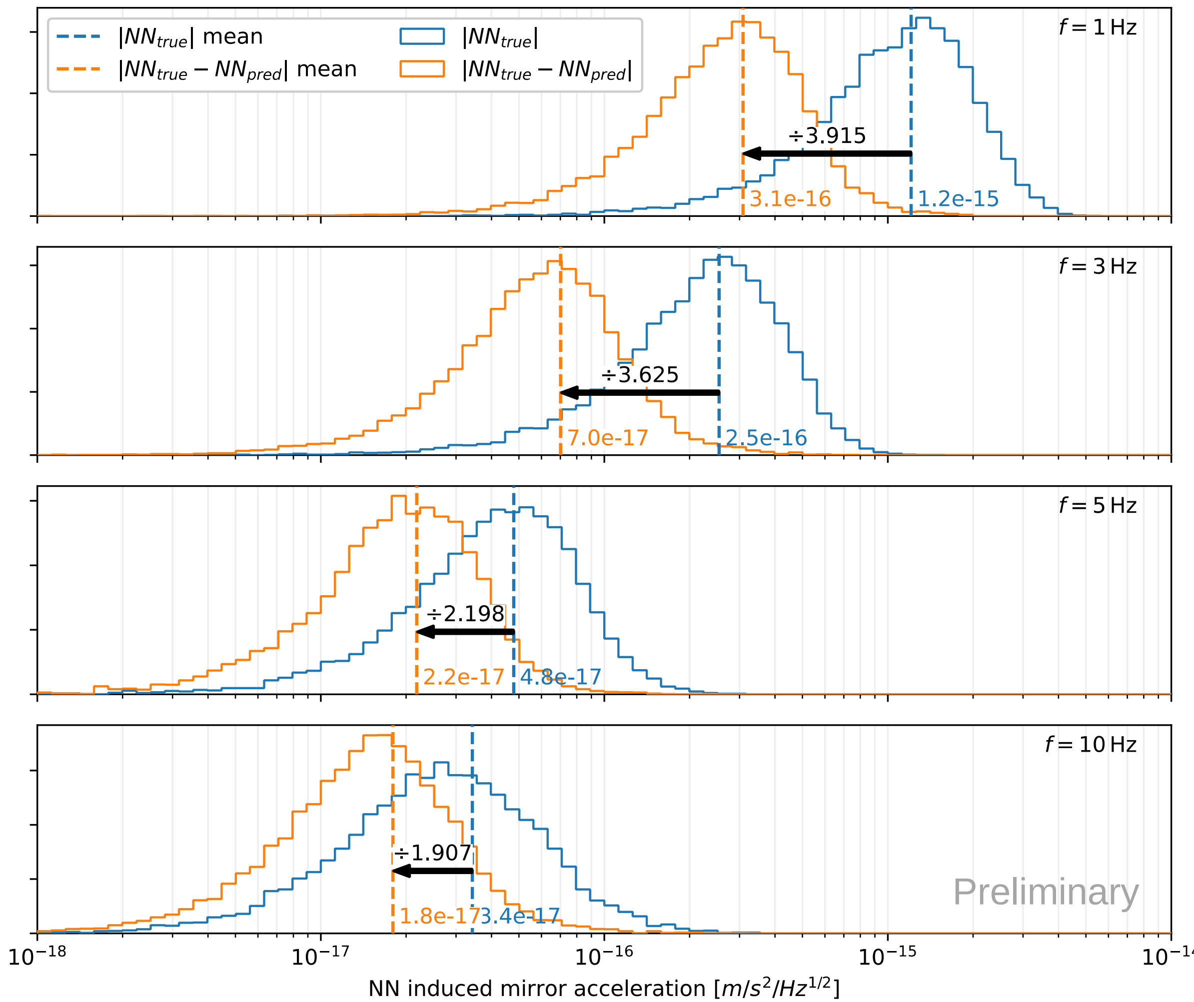


Results: NN subtraction efficiency

The DNN is capable of predicting (NN_{pred}) the gravity gradient noise with about 75% efficiency for 1 Hz to about 50% efficiency at 10 Hz. Subtracting NN_{pred} from the true acceleration NN_{true} reduces the NN noise on average about a factor 2 in amplitude

Left: NN as provided by the model, and NN after background subtraction of the predicted signal.





Summary and outlook

Modeling Newtonian noise

- Surface waves are a full solution of the elasto-dynamic wave equation: Rayleigh, Love, S-, P-waves, fundamental and higher-order modes, attenuation, dispersion, reflection, interference, mode conversion, …
- Better characterization of body waves
- Include more realistic layered (3D) geology

Seismic surveys

- Studies of underground geology and source distribution remain important
- Sensors: 3C, surface and borehole, non seismic: gradiometer, EM, borehole logging, …

Deep neural network

- Promising as a tool to subtract Newtonian noise
- Employs a network of surface and underground sensors