Leak Detection in Pipelines Using Acoustic Sensors and System Identification

Arne Dankers
Hifi Engineering Inc.

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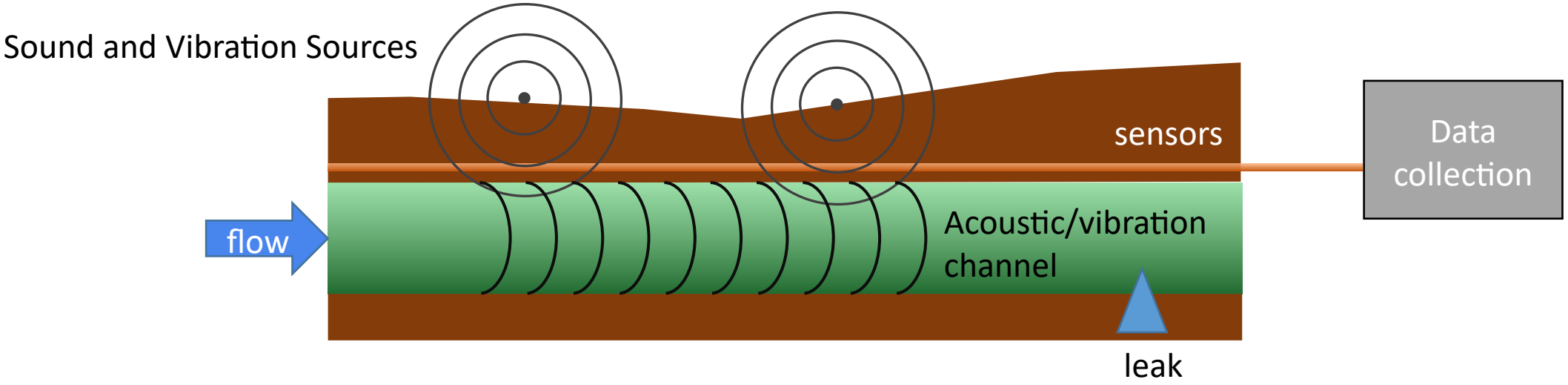
TransCanada Keystone Pipeline leak in South Dakota, USA, Nov. 17, 2017. Image: https://www.ctvnews.ca/business/transcanada-s-keystone-pipeline-spill-cleanup-on-schedule-1.3807061

Leak Detection and Pipeline Monitoring System



Effects of Leaks:

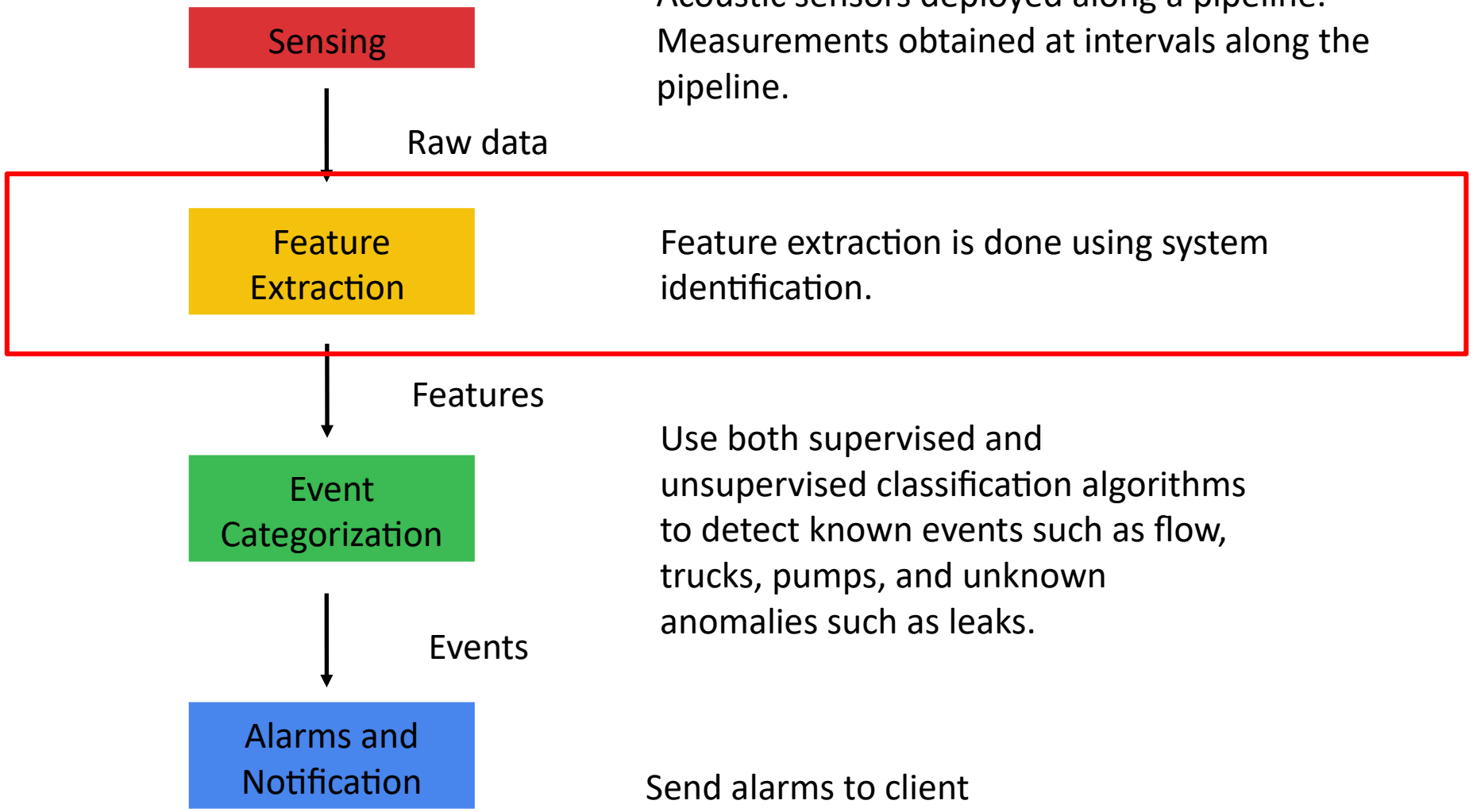
- Drop in pressure in pipeline
- Drop in mass flow rate
- Change in properties of material surrounding pipeline (temperature, conductivity, density, etc. of material)
- Acoustic hiss
- Pressure exerted on surrounding material
- Vibrations along pipeline

Causes of Leaks:

- Corrosion in pipeline
- Strikes to pipeline
- Buckling of pipeline due to slope erosion
- High pressure inside pipeline (due to blockage for instance)
- Loose or cracked joints

Objective: Detect as many causes and effects of leaks

Monitoring Systems



Acoustic sensors deployed along a pipeline. Measurements obtained at intervals along the pipeline.

Feature extraction is done using system identification.

Use both supervised and unsupervised classification algorithms to detect known events such as flow, trucks, pumps, and unknown anomalies such as leaks.

Send alarms to client

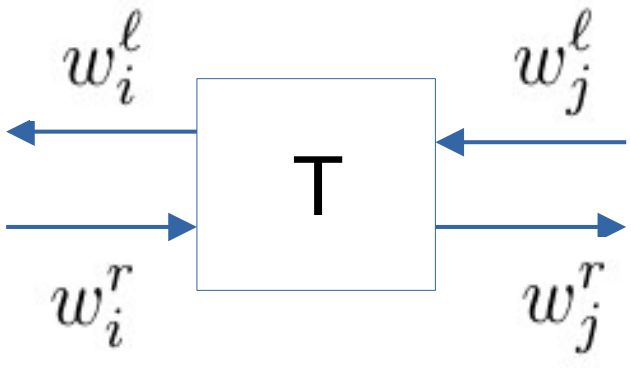
Outline

1)From Physics-based model to dynamic network
2) Small Case Study
3) Field Experiment

Main objective: see how network system identification can be applied in practice.

Acoustic Two-Port Models

Can be used to model acoustic pressure waves moving through a wave guide

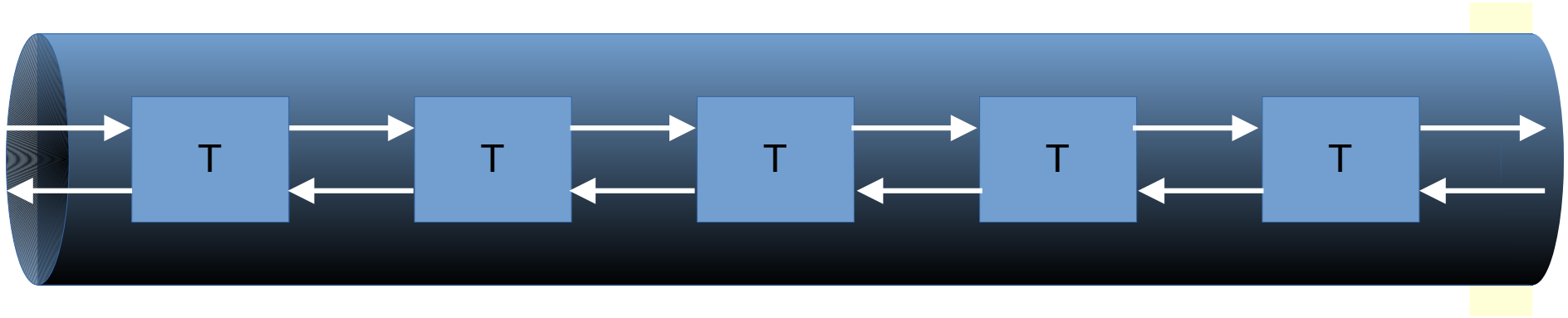


w_i^ℓ - air pressure of acoustic waves moving to the left, leaving the channel

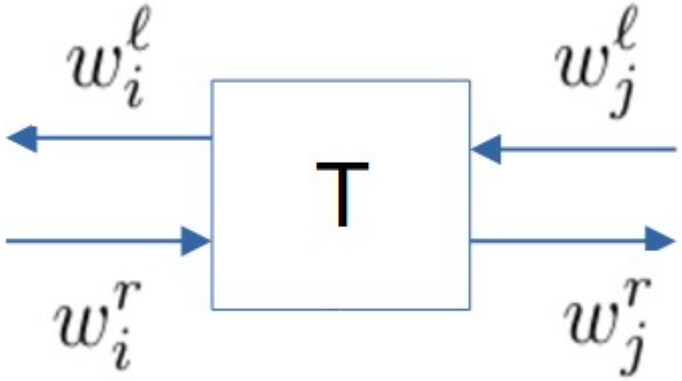
w_i^r - air pressure of acoustic waves moving to the right, entering the channel

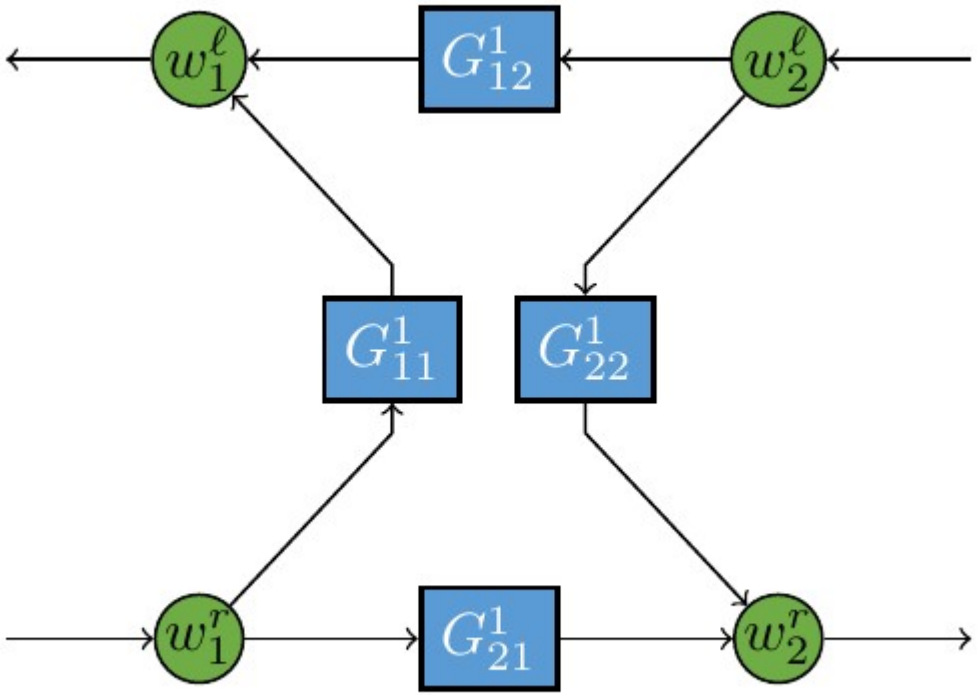
w_j^ℓ - air pressure of acoustic waves moving to the left, entering the channel

w_j^r - air pressure of acoustic waves moving to the left, leaving the channel

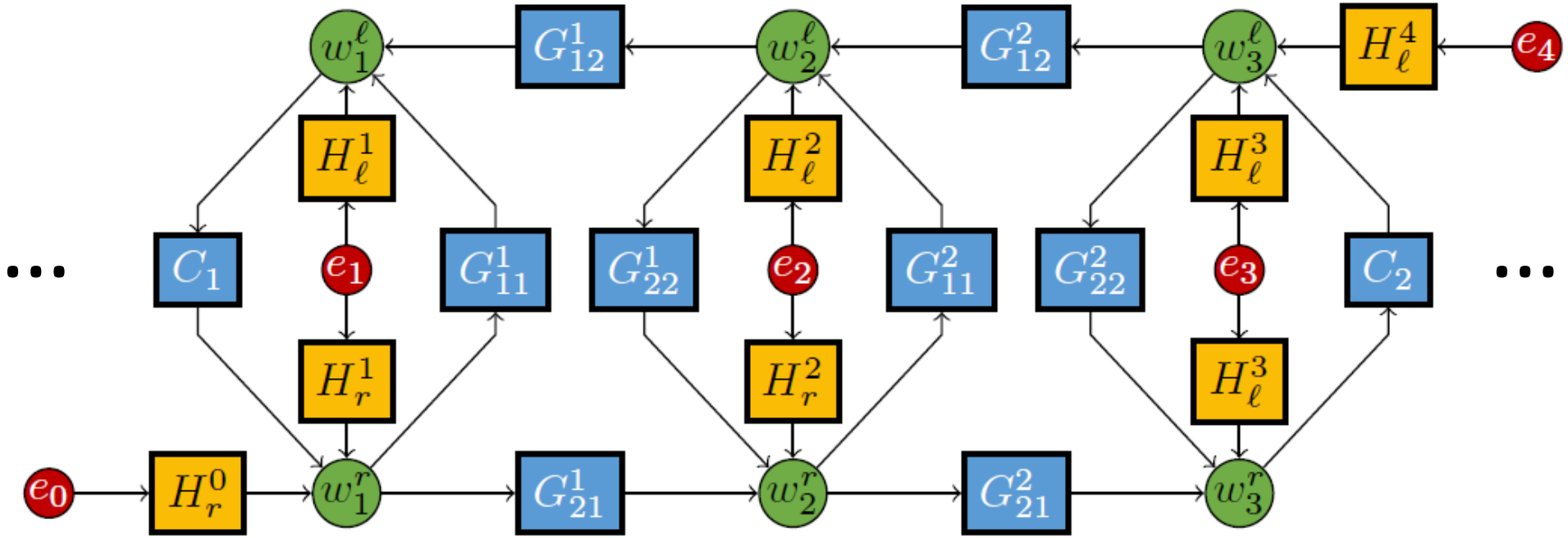


Acoustic Two-Port Models



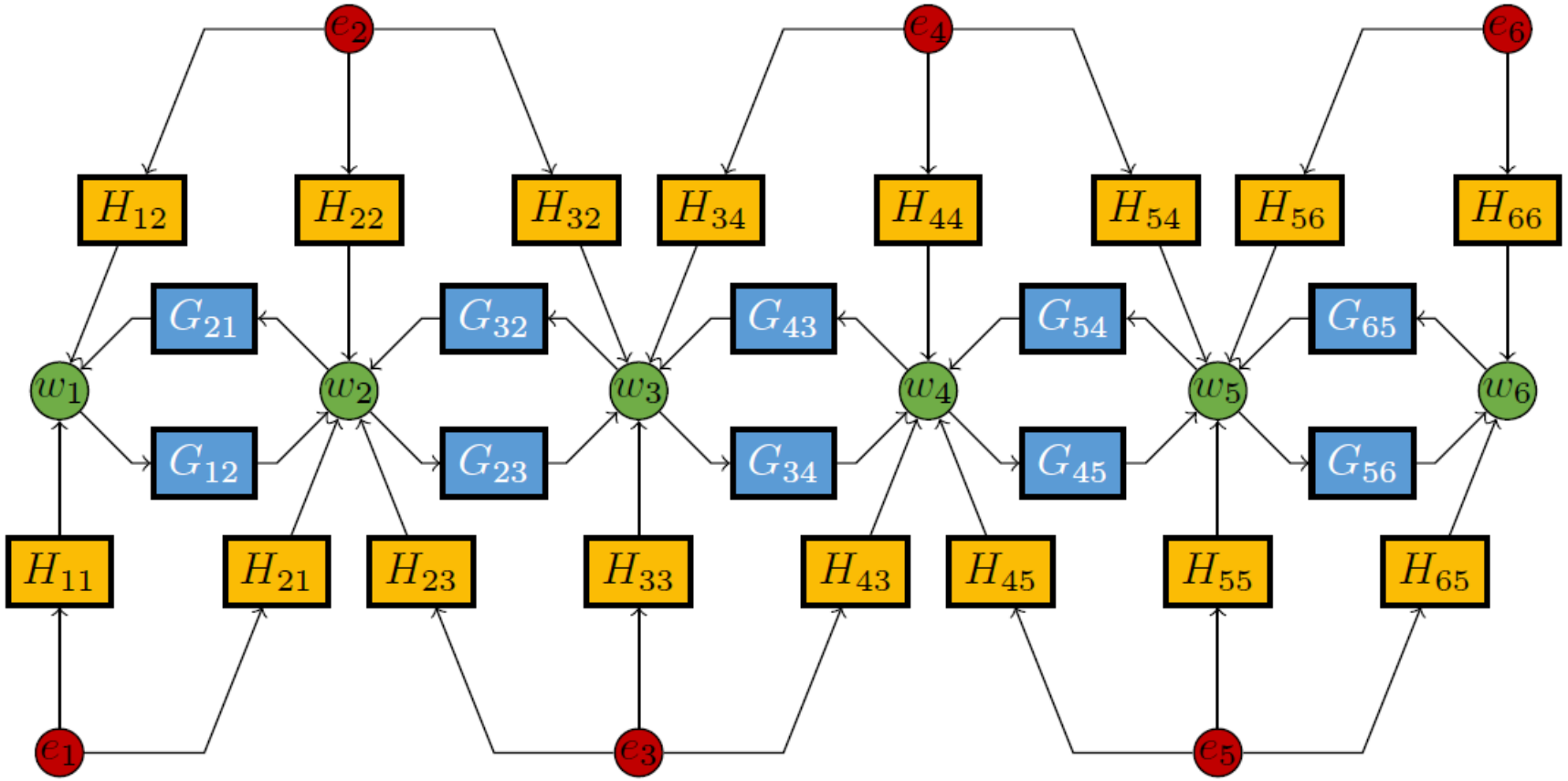


Model for Acoustic Wave Propagation Along 1D Wave Guide



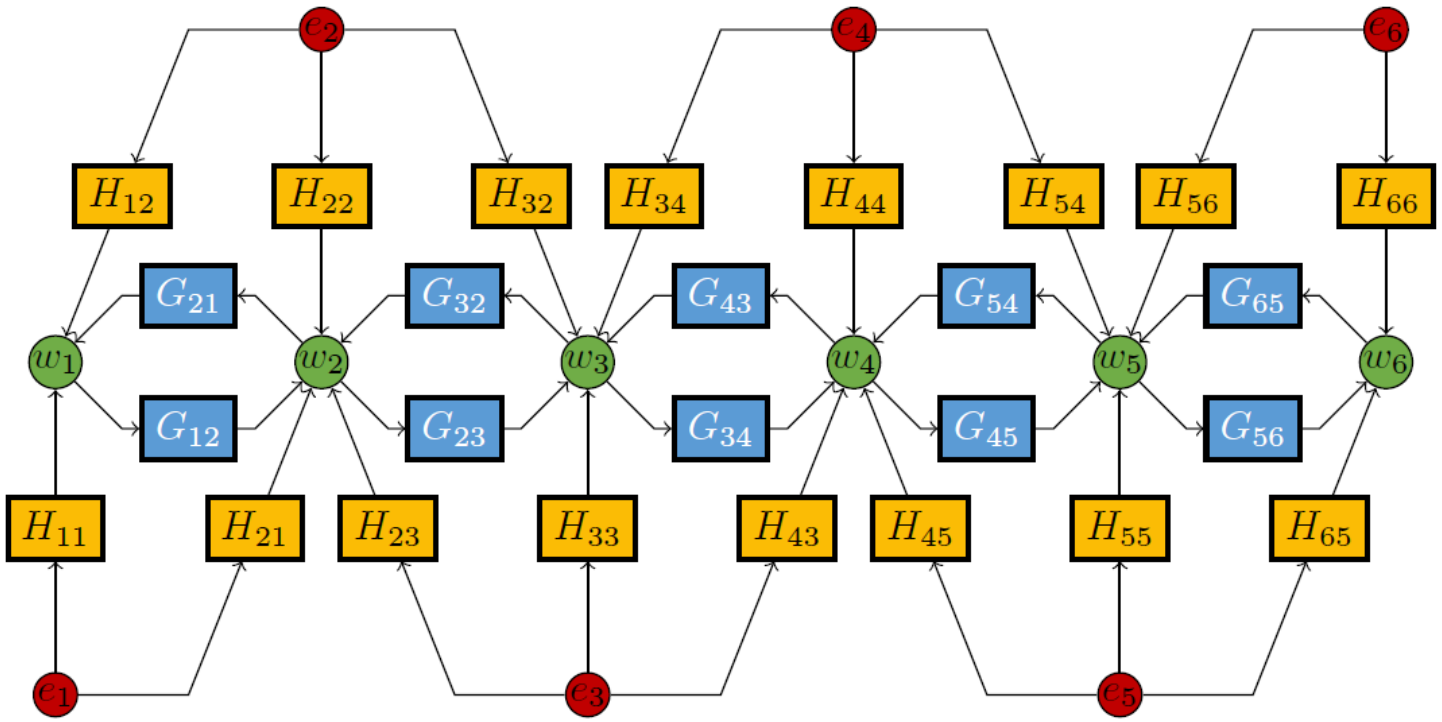
Measured signal is: $w_i = w_i^\ell + w_i^r$

Identifiable Model of Acoustic Propagation Along 1D Waveguide



Every transfer function in this model is identifiable.

Objective



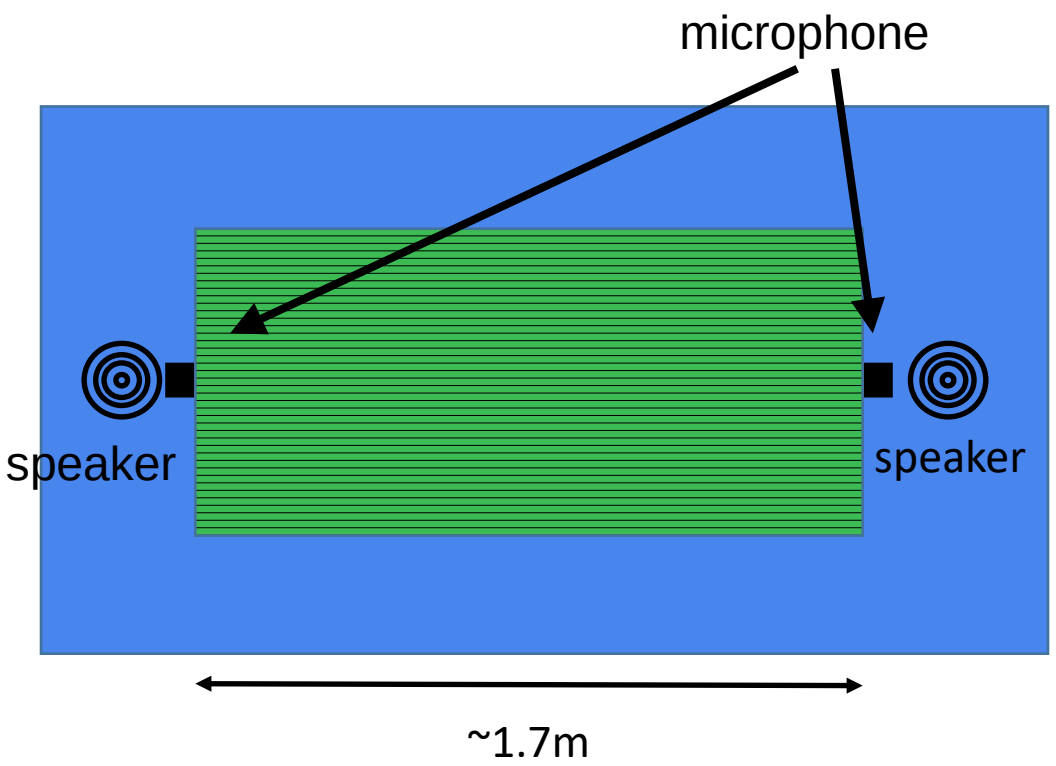
Monitor G's for changes. A change in G could indicate:

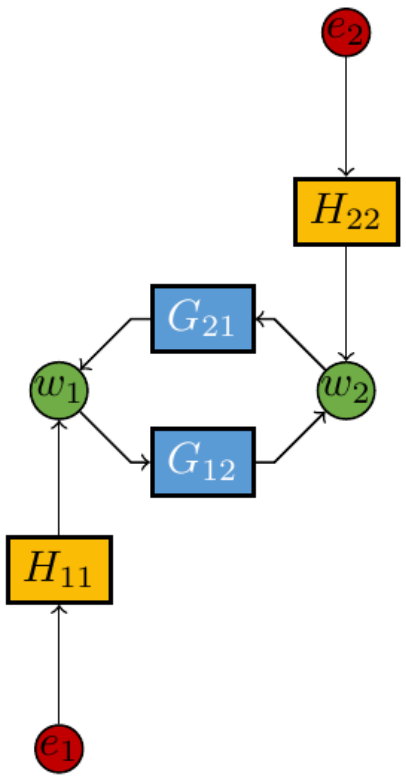
- Change in pressure in the pipeline
- Dent in the pipeline
- Change in moisture content surrounding the pipeline
- Blockage in the pipeline

Key Point: A change in frequency content of external sounds will not affect G.

Small Scale Lab Experiment

Small Scale Experimental Validation of Sound Propagation Model





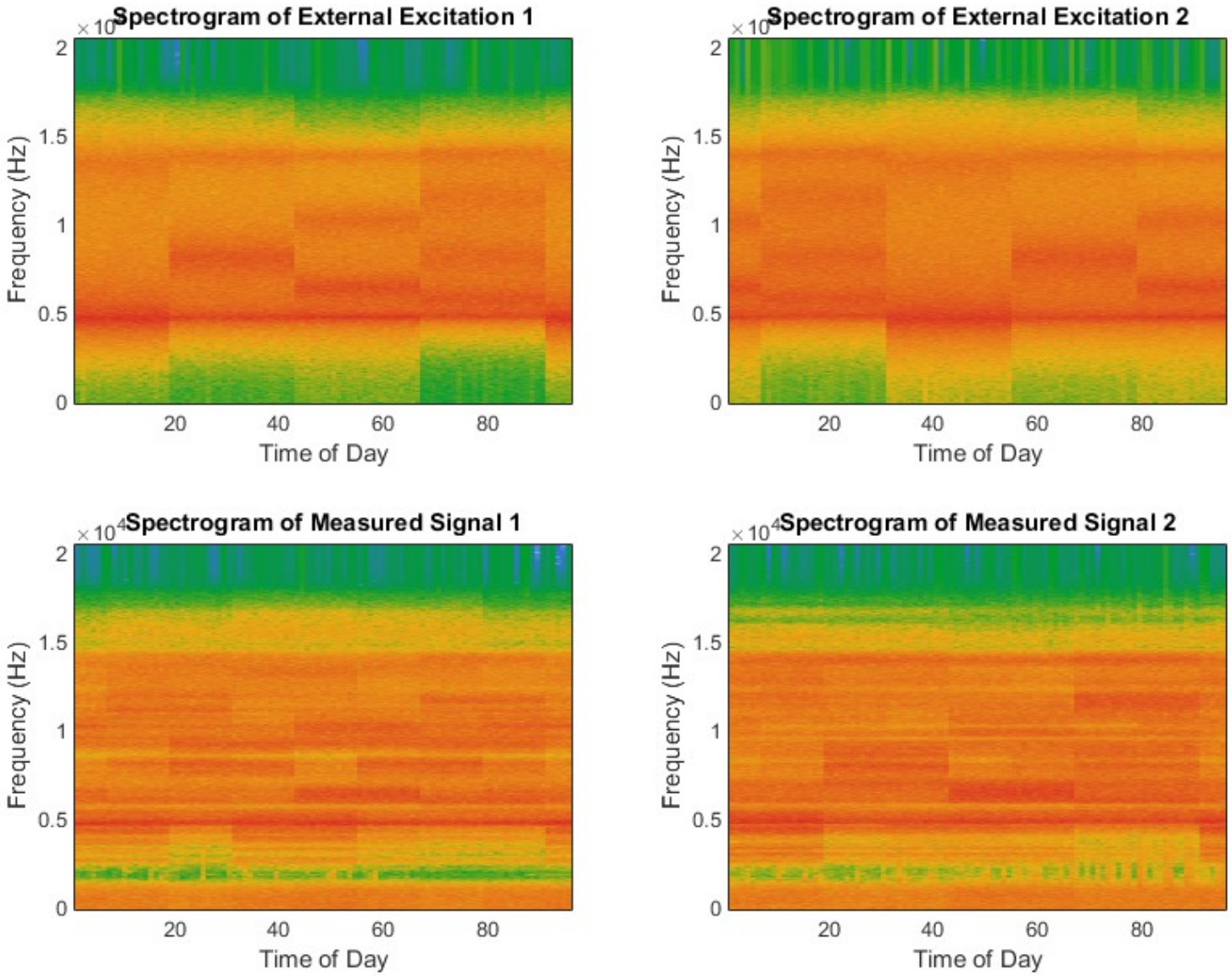
Objective of experiment: determine when frequency content of the speakers changed, and when the acoustic channel response changed.

Small Scale Experimental Validation of Sound Propagation Model

During the experiment:

- Both speakers continuously playing sounds
- Change frequency content of sound playing on speaker 1
- Change frequency content of sound playing on speaker 2
- Change the acoustic channel response by placing a foam block in the middle of the room

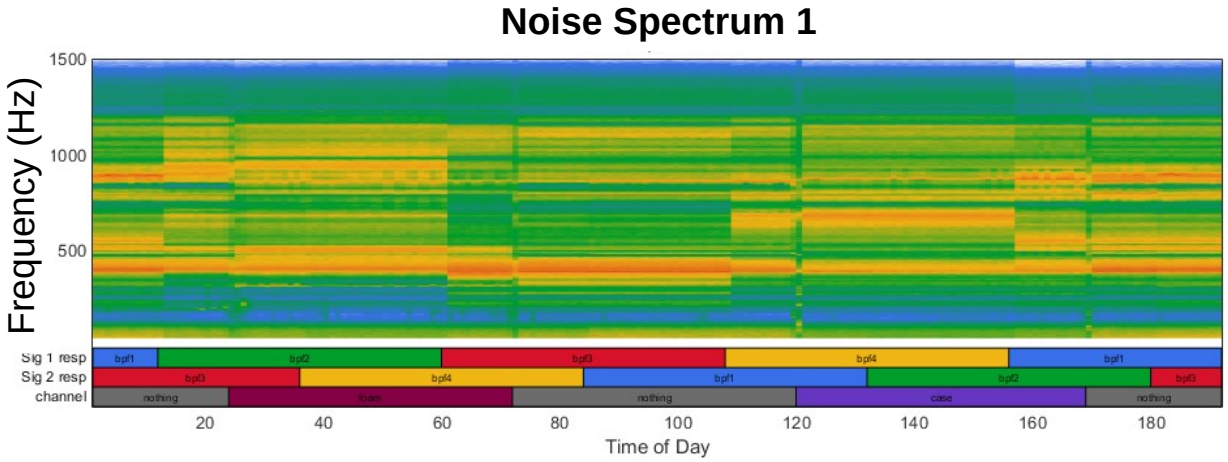
External Excitation Signals and Measured Data

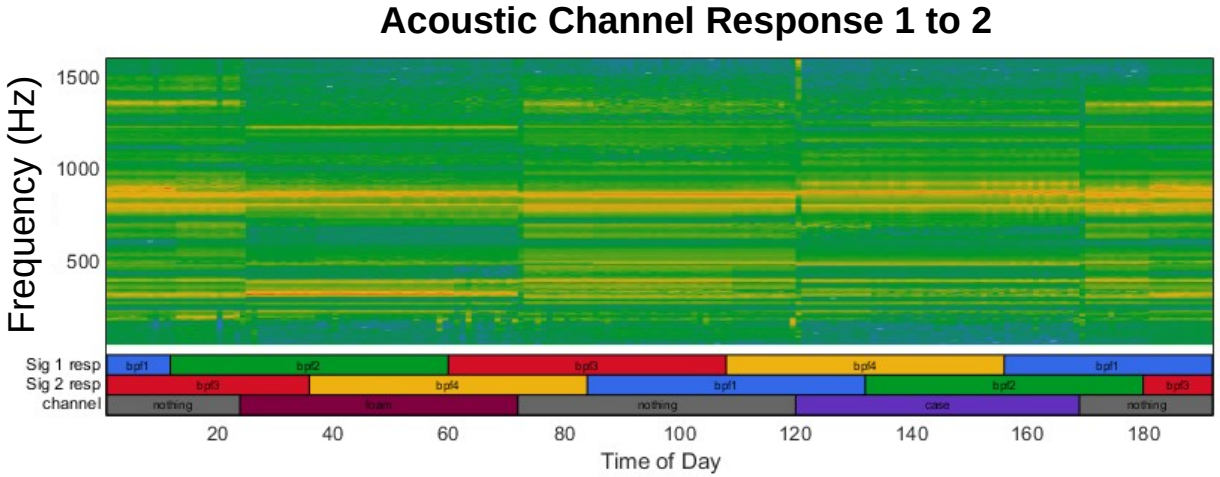


Frequency content of signals played on each speaker

Frequency content of measured signals

Estimated Acoustic Channel Response and External Signal Frequency Content



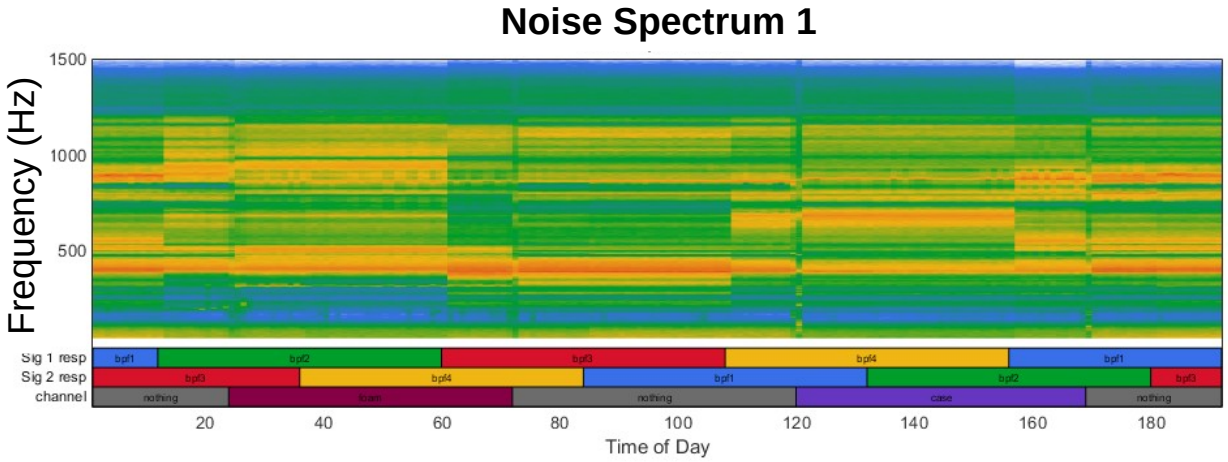


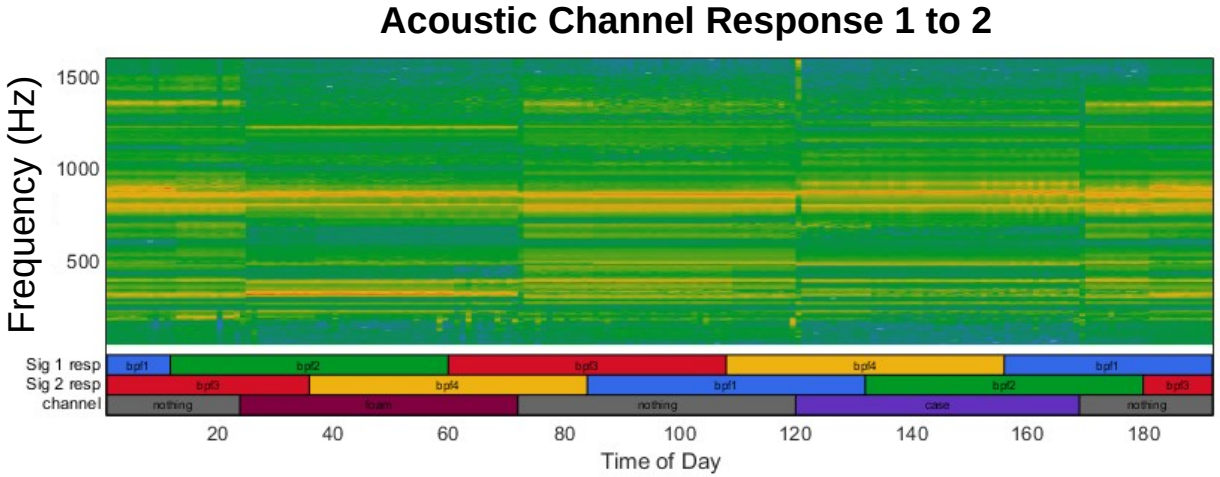
Results are a bit disappointing.

Each estimate has a variance that is related to frequency content of predictor inputs.

Are changes in estimated transfer functions due to changing physics, or changes in variance of the estimates?

Estimated Acoustic Channel Response and External Signal Frequency Content

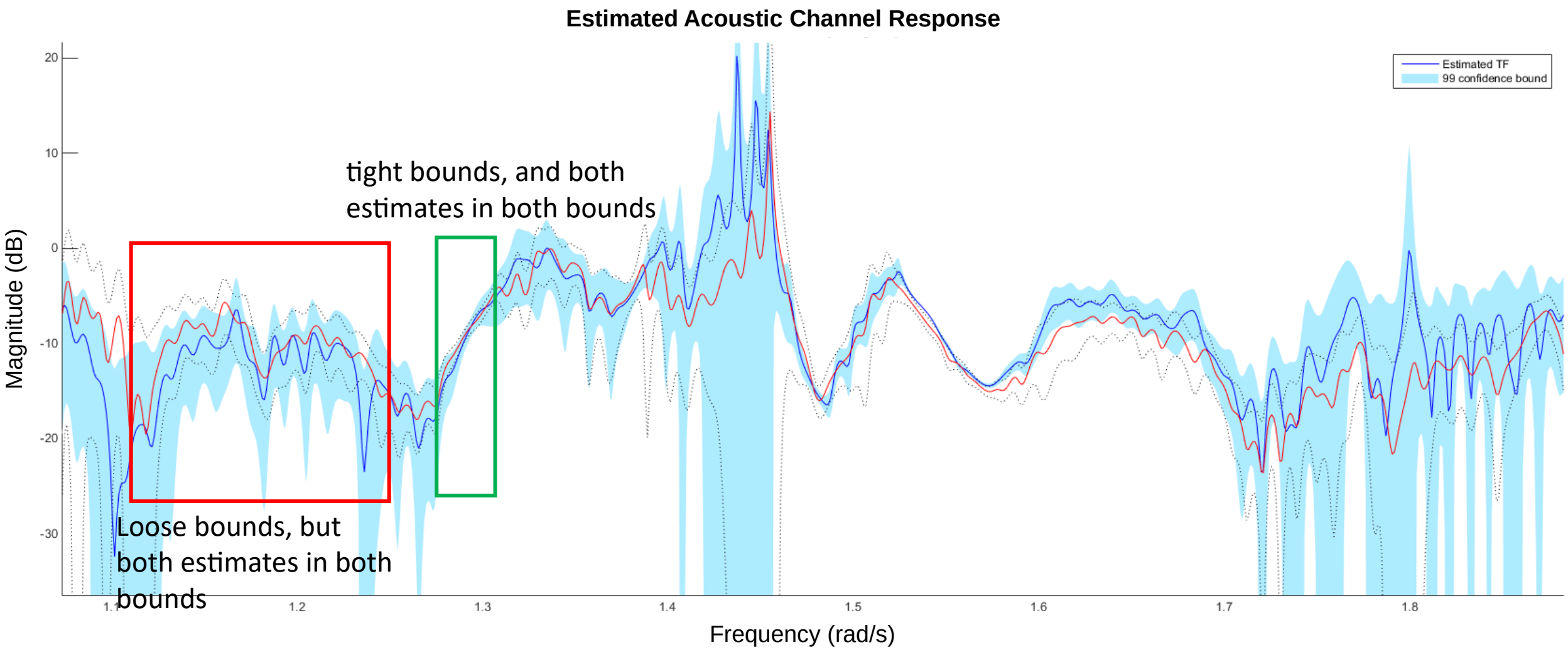




Idea: attempt to quantify whether the estimated frequency response at time *t* is statistically the same as the estimate at time *t-1.*

Should be able to detect changes in the frequency responses.

Confidence Bounds

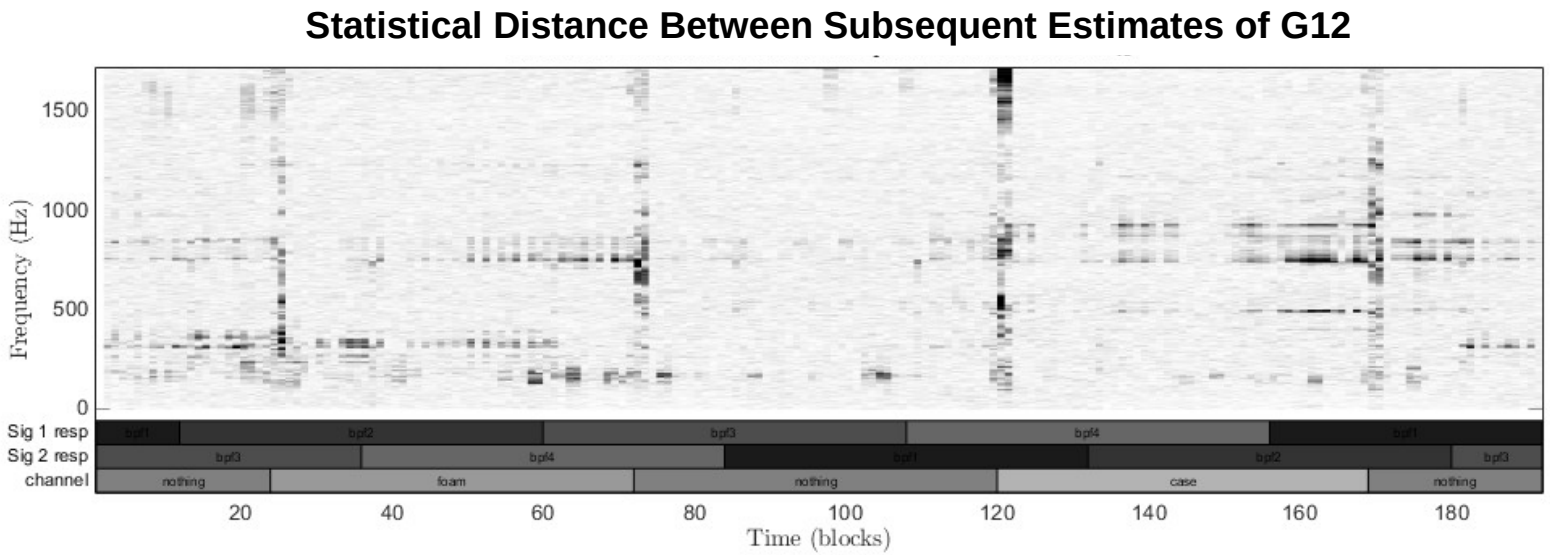


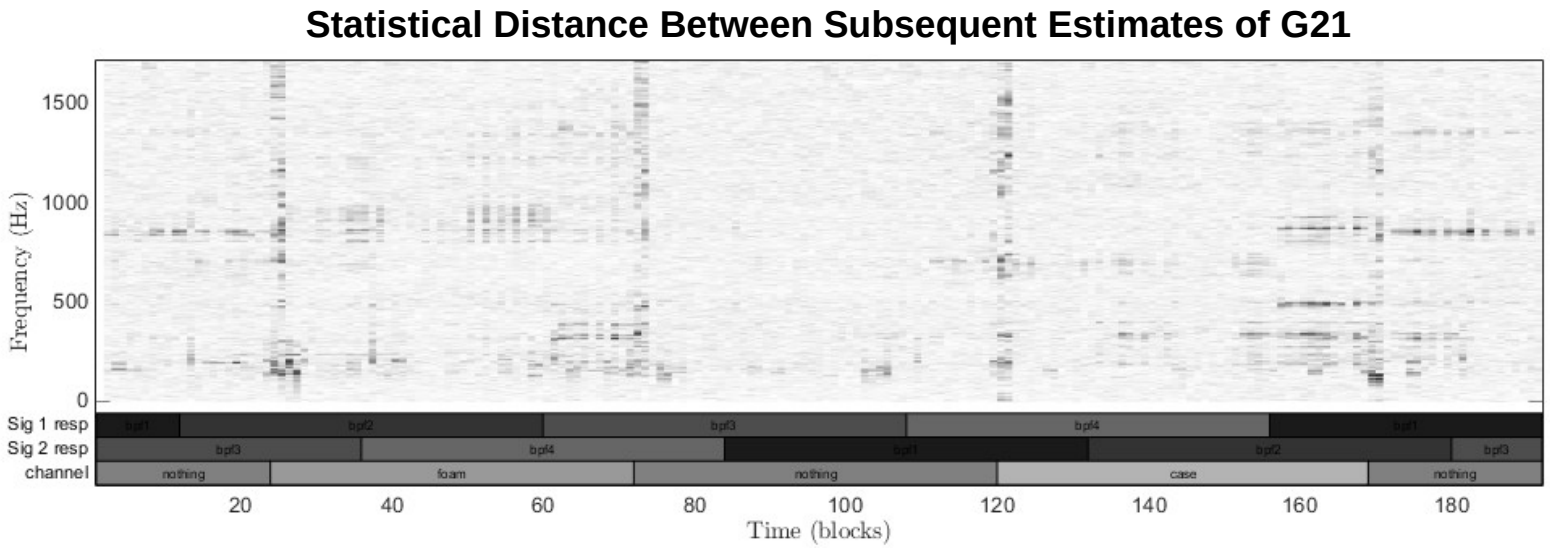
Statistical Distance

To compute how statistically similar two frequency responses are:

$$d_{12}(\omega) = \frac{\hat{G}_{12}^{t_1}(\omega) - \hat{G}_{12}^{t_2}(\omega)}{\mathrm{var}(\hat{G}_{12}^{t_1}(\omega)) - \mathrm{var}(\hat{G}_{12}^{t_2}(\omega))}$$

Statistical Distance

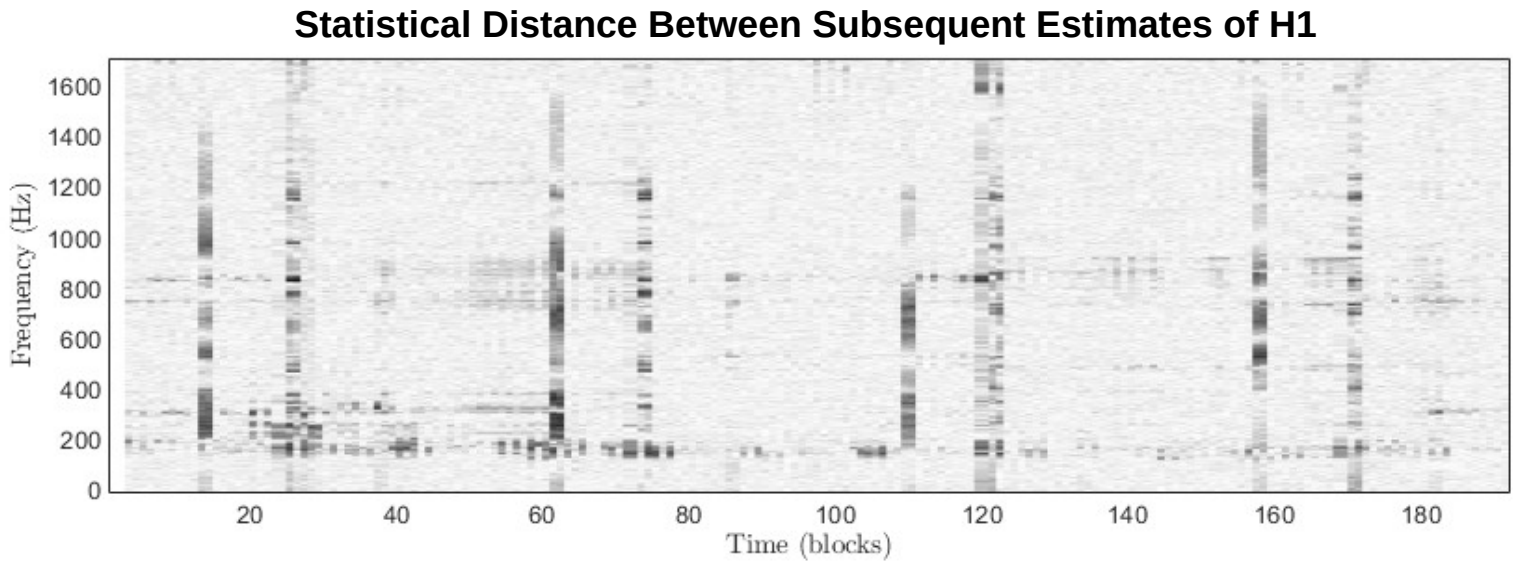


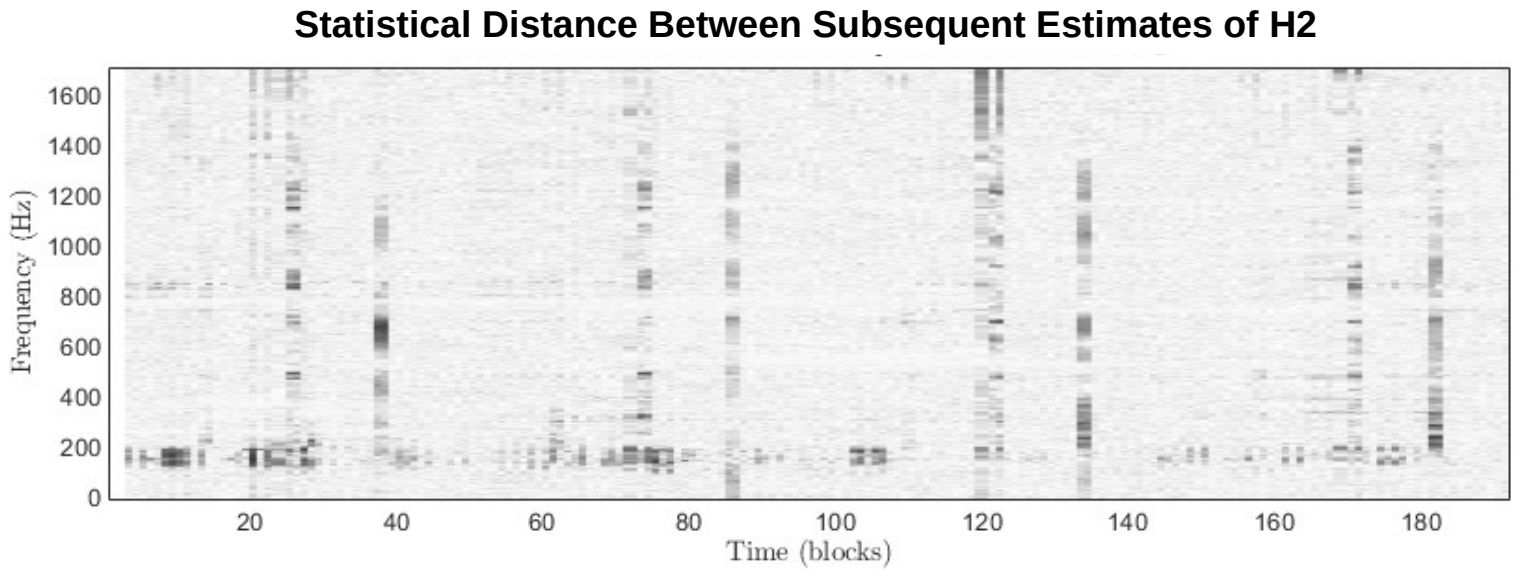


Dark vertical lines denote when there is a large statistical distance between two consecutive estimated frequency responses.

The dark lines correspond exactly to when the foam block was placed or removed from the room.

Statistical Distance





The dark lines correspond exactly to when the frequency content of a speaker was changed, and when I walked into the room to place the foam block.

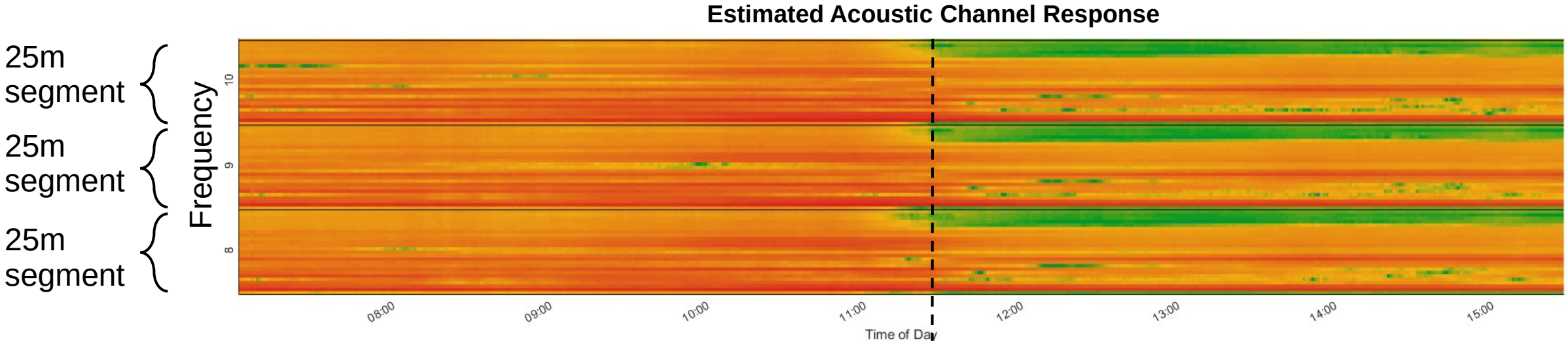
Conclusions of Experiment

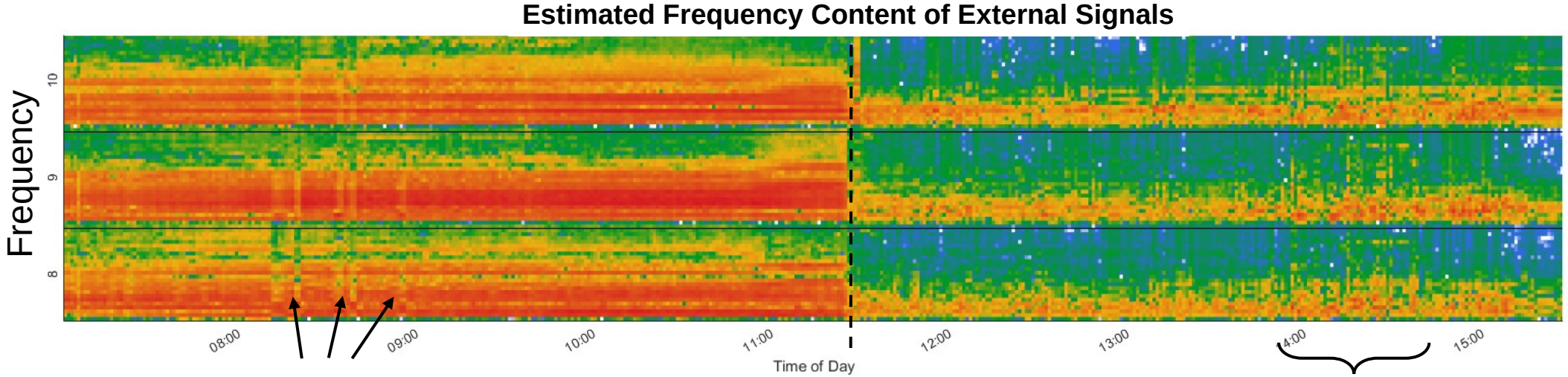
Can distinguish between changes in the acoustic channel response between two speakers, and changes in the frequency content of external sources.

Field Study

- Identification algorithm was implemented on an operational pipeline.
- 39 acoustic sensors were deployed along the pipeline.

Estimated Transfer Functions





Trucks (do not affect acoustic channel response, but does affect frequency content of sources)

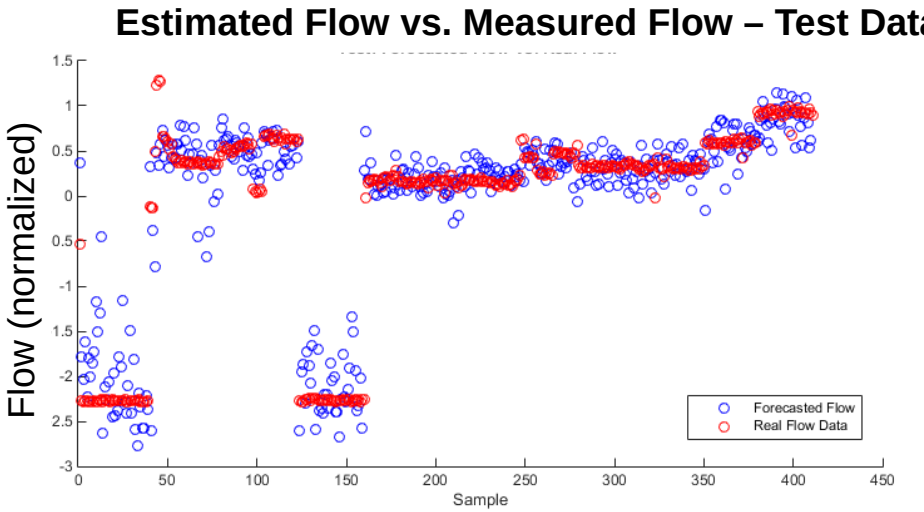
End of flow (affects both acoustic channel response and frequency content of sources)

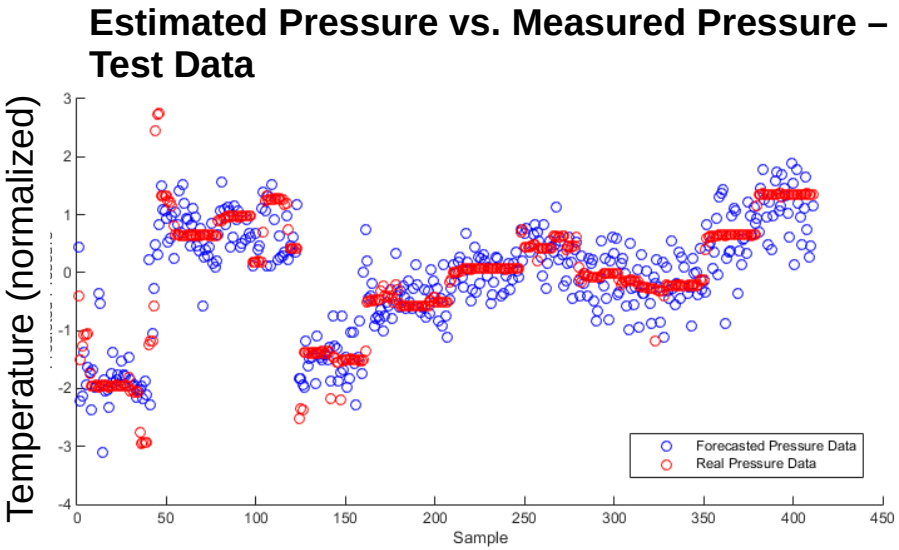
Trucks

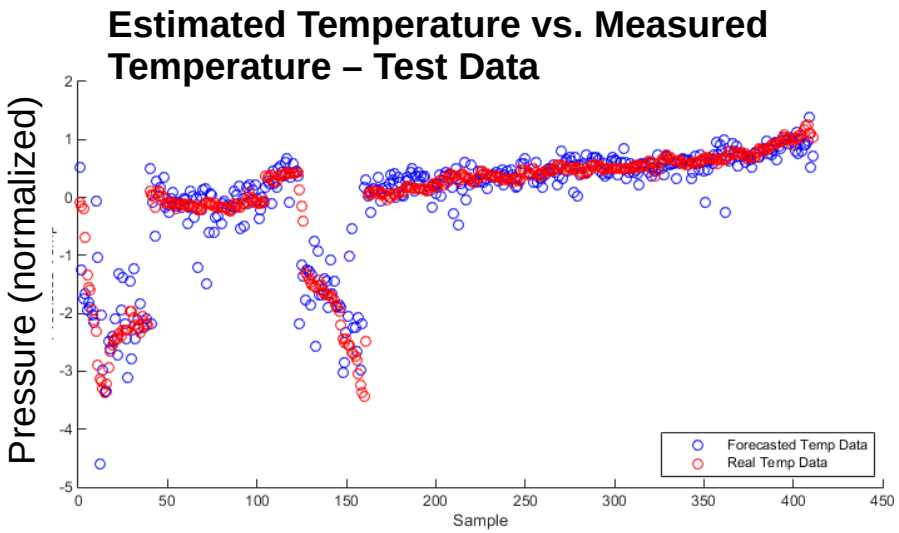
Processing of Acoustic Channel Response

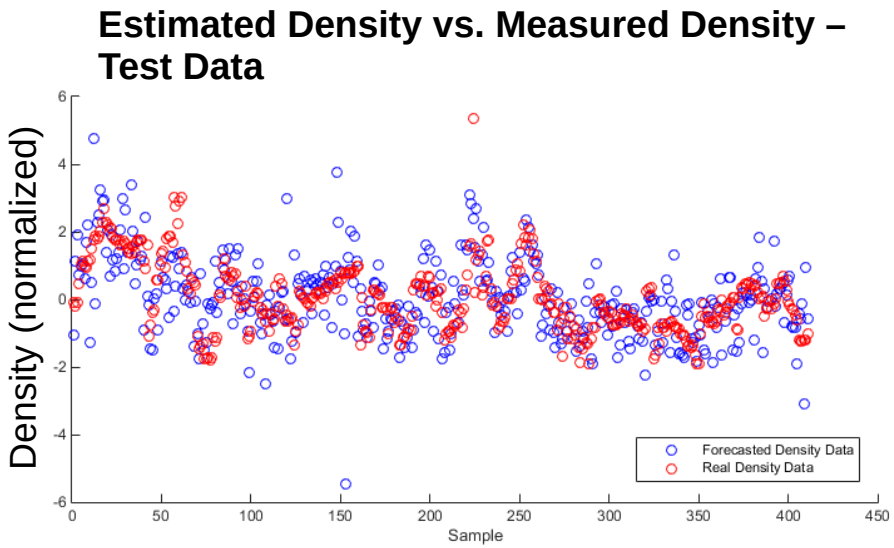
- Monitoring algorithm must run in **real time** (acoustic data can be up to 500Mb every 4s for long pipelines)!
- Parameterized all transfer functions as FIR. Designed algorithm to obtain estimates using only a sequence of linear regressions.
- **Unable** to implement algorithm to estimate **variance** of estimates (cannot calculate statistical distance to detect changes in acoustic channel response).
- Use **Machine Learning** to estimate **operational data** given estimated acoustic channel response.

Post-processing of Acoustic Channel Response









Conclusions

1) Using network system identification it is possible to estimate the acoustic channel response of a pipeline.
2) The estimated acoustic channel response can be effectively incorporated into a health monitoring algorithm

Future Work

More controlled field study to determine if causes of leaks (such as large dents, corrosion, buckling) can be distinguished from normal conditions.