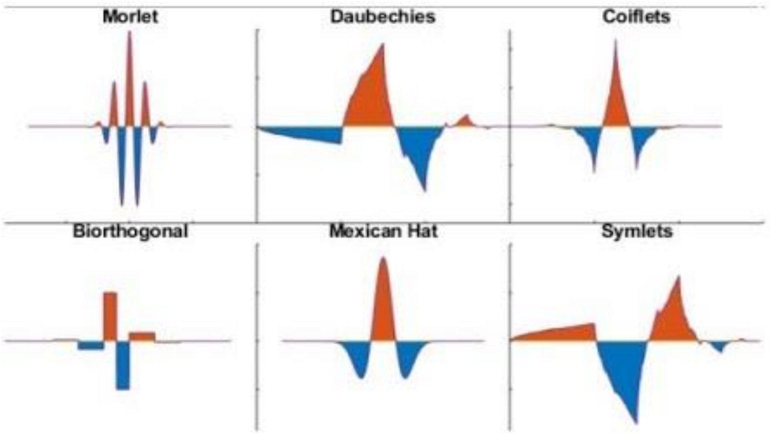
Wavelets – A Hidden Gem For Artificial Intelligence in Seismic Interpretations



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Key Takeaways

- Artificial Intelligence techniques when used in combination with Advanced Signal Processing algorithms can yield meaningful insights
- MATLAB can help you combine the best of AI and Signal Processing without requiring you to be an expert in either

Agenda

- Case study 1: Automated semantic segmentation of seismic images
  – Introduction to case study data
  – Challenges in developing AI models
  – How wavelet analysis helps

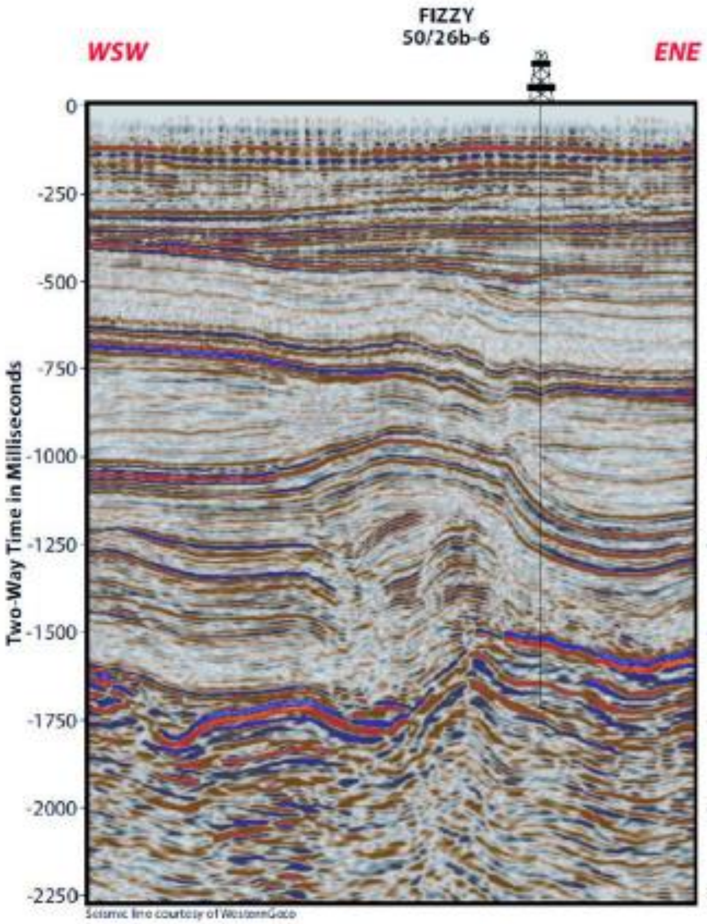
- Case study 2: Automated P- and S- waves arrival times detection in earthquake seismograms
  – Introduction to case study data
  – Challenges in developing AI models
  – How wavelet analysis helps

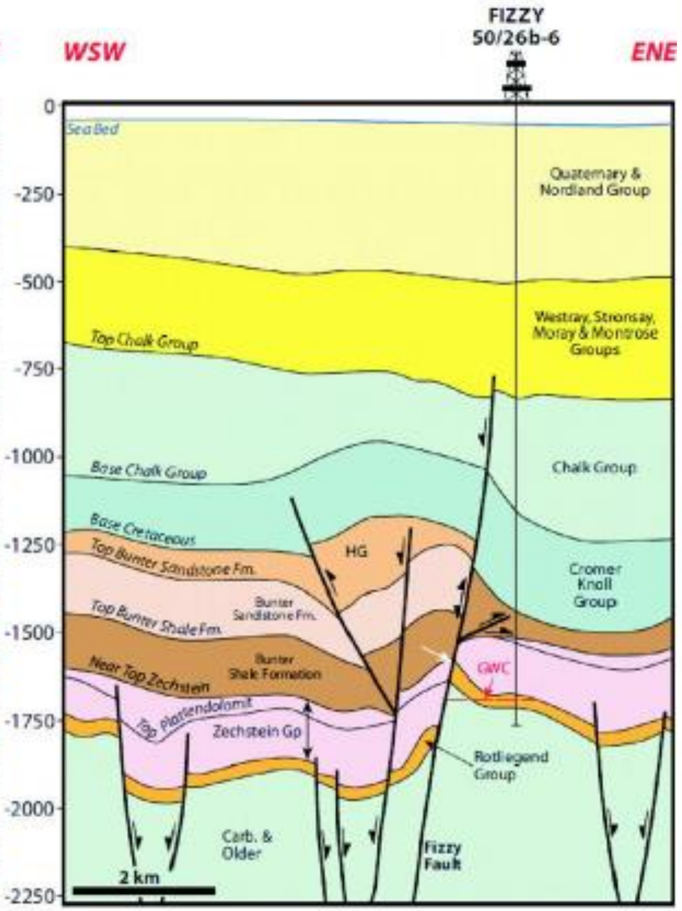
- Conclusion

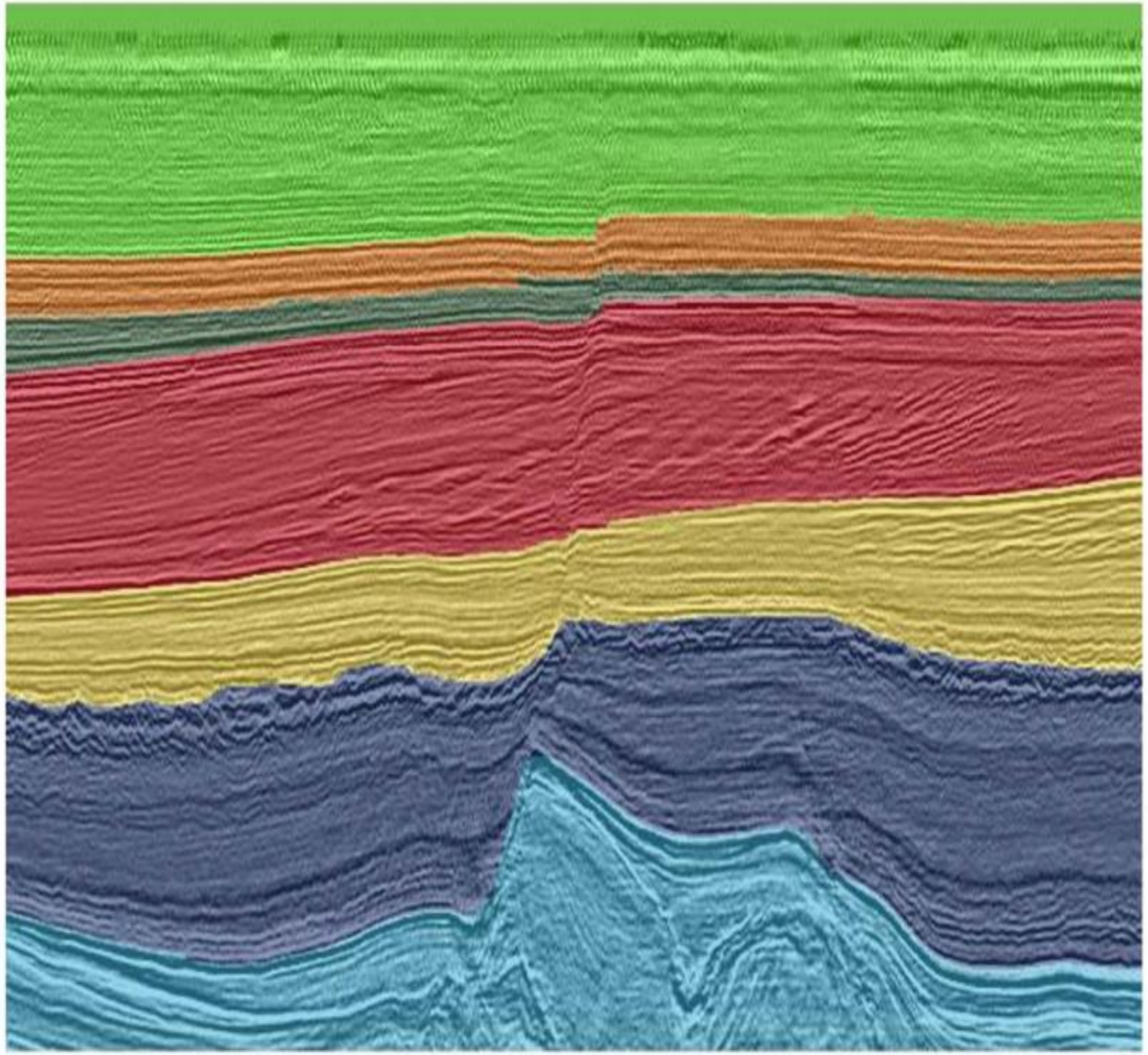
Case Study I :
Automated semantic segmentation of seismic images

Seismic semantic segmentation

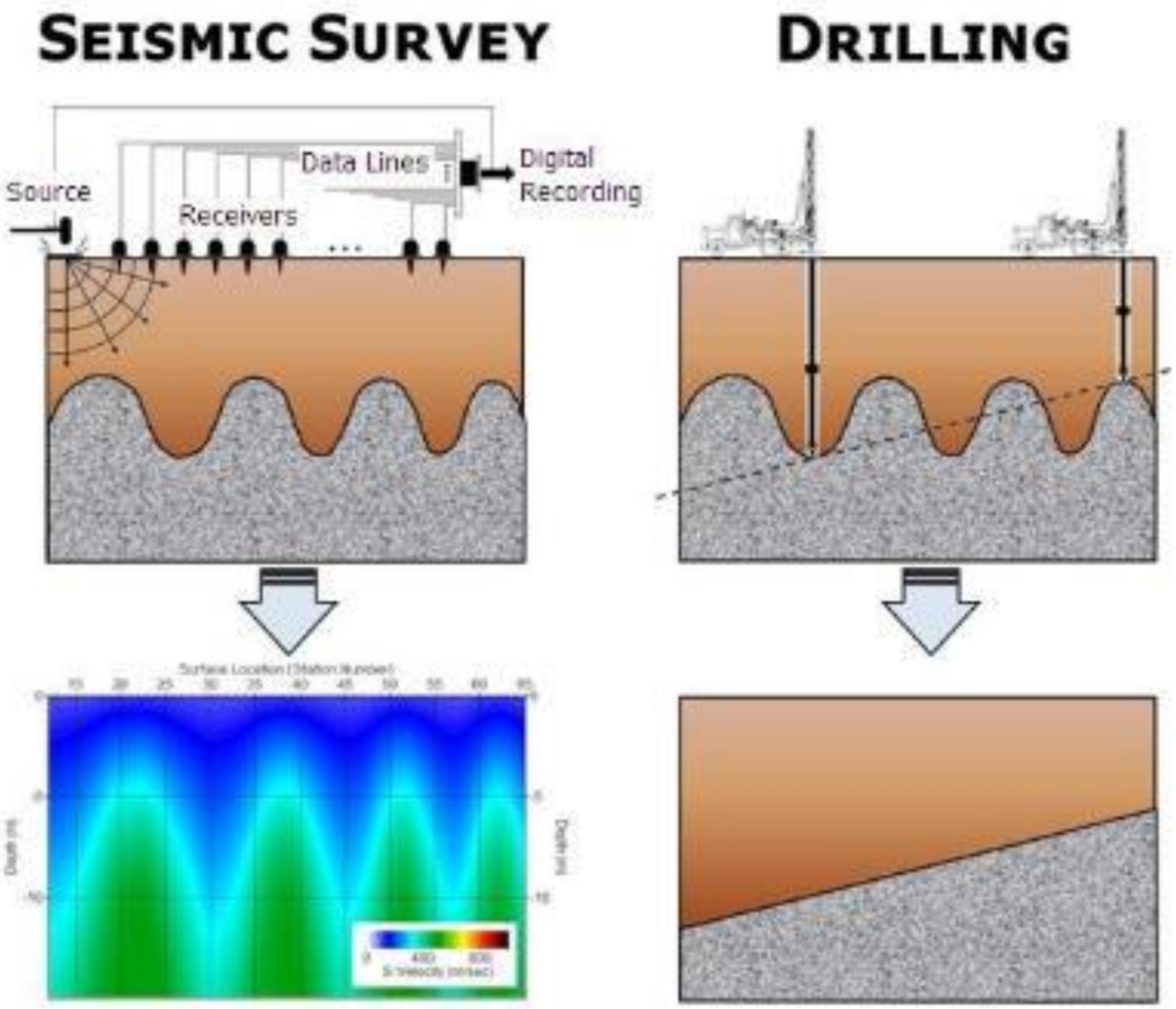
Automation of seismic facies labeling

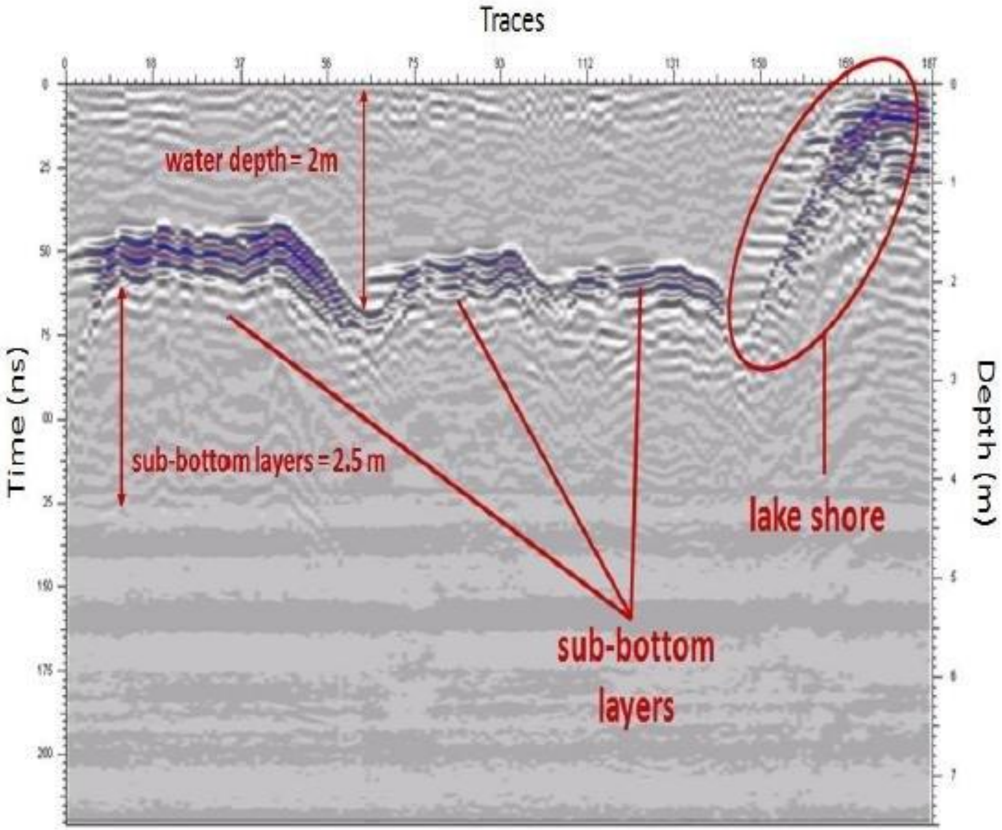






Seismic survey process

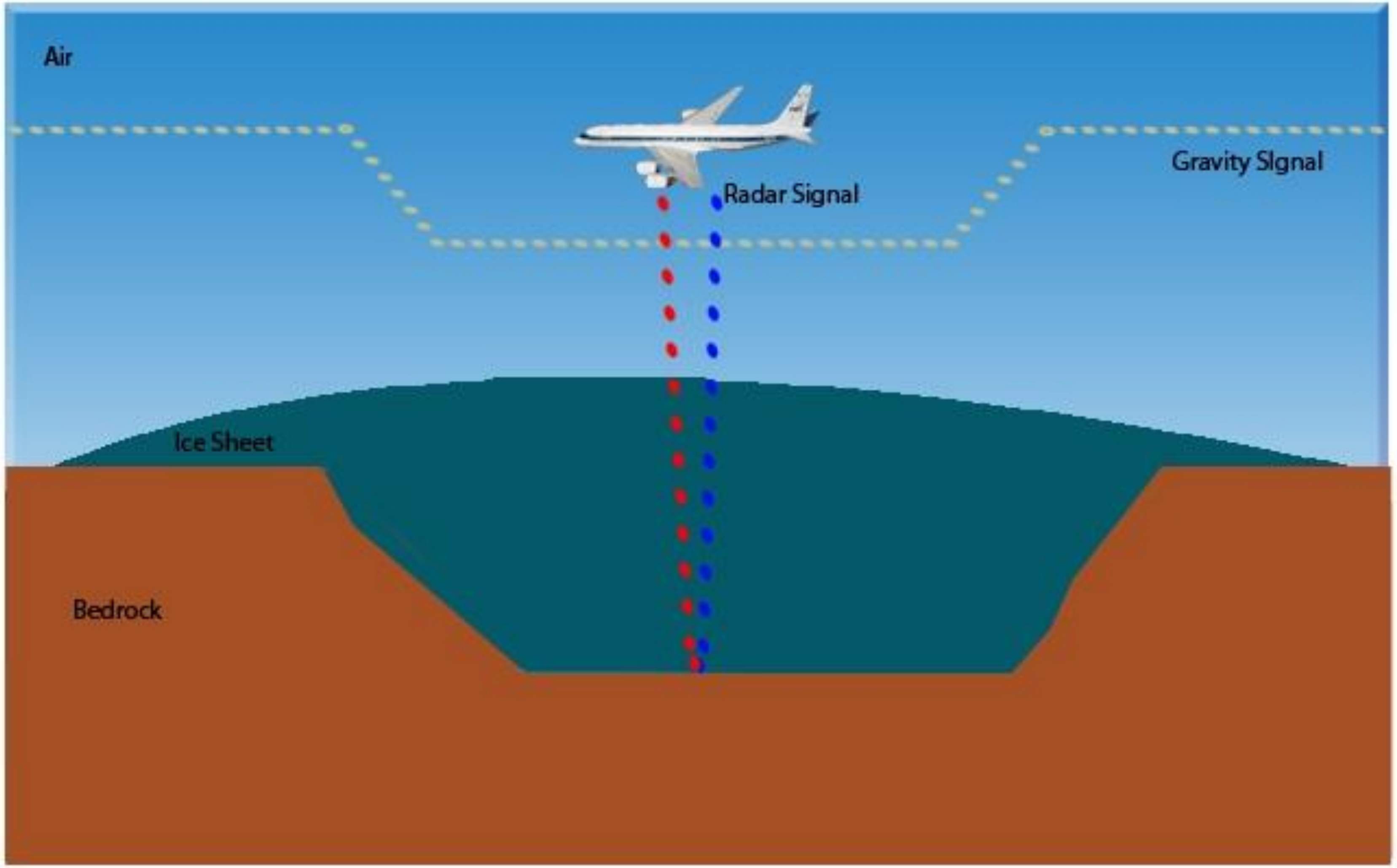




GPR profiling of lake sub-bottom layers

Case study data

Survey of polar icesheets



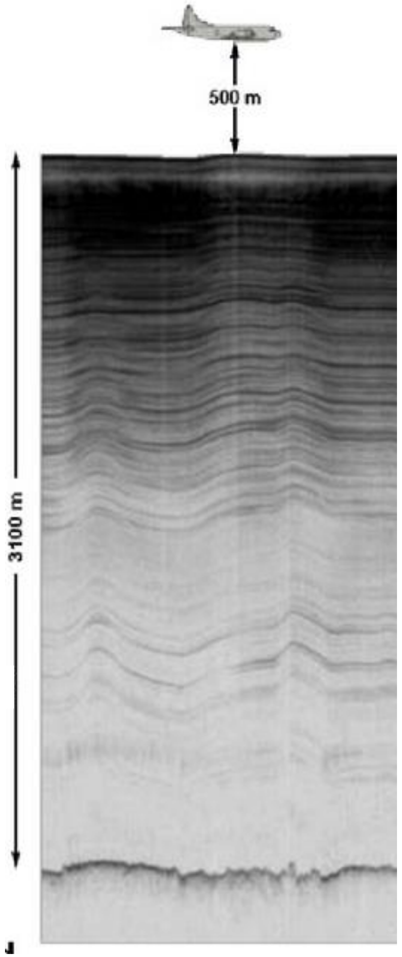
Source : nasa.gov

Case study data

MCoRDS/I – Multichannel Coherent Radar Depth Sounder/Imager*

System parameters

	2012	2009
Season	2012	2009
Operating frequency	180-210 MHz	140-160 MHz
Pulse Duration	1,3,10 μs	1,3,10 μs
Sampling freq	111.11MHz	120 MHz
Max Tx channels	8	6
Max Rx channels	16	6
Peak Tx Power	~1200W	~800W
A/D resolution	12 bits	12 bits
Min detectable signal	-161 dBm	-161 dBm
Noise Figure	5 dB	5 dB
Platform	NASA P3	Twin Otter

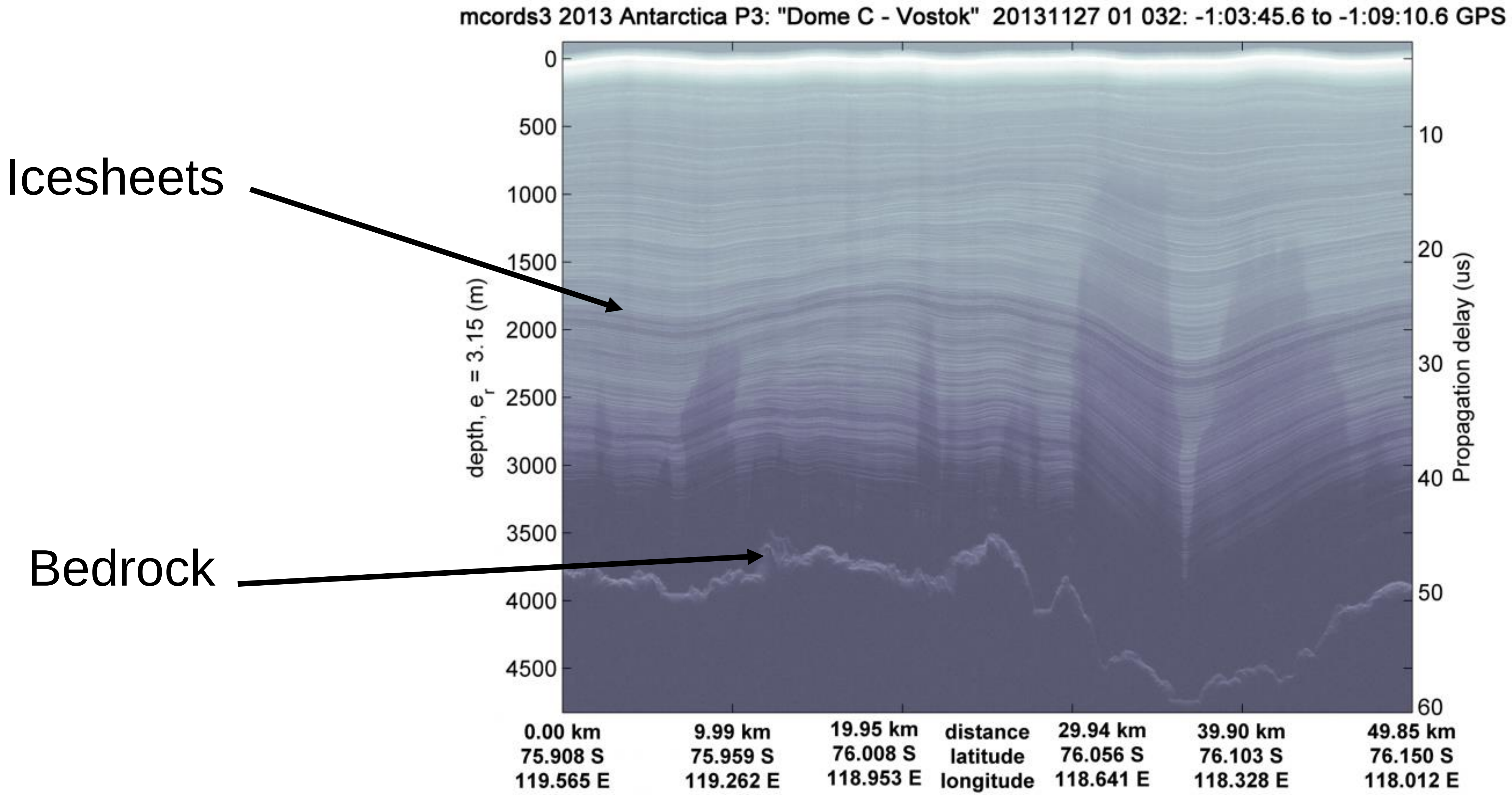


*CReSIS. 2018. MCoRDS Data, Lawrence, Kansas, USA. Digital Media. http://data.cresis.ku.edu/

*Gogineni, S., J.-B. Yan, et al., "Bed topography of fast-flowing glaciers and fine-resolution mapping of internal layers", 26th IUGG General Assembly 2015, Prague, 06/22-07/2, 2015.

Case study data

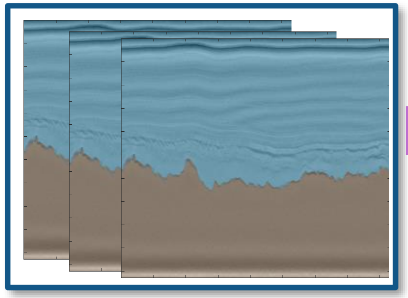
Develop automated algorithm for labeling the icesheets and bedrock pixels



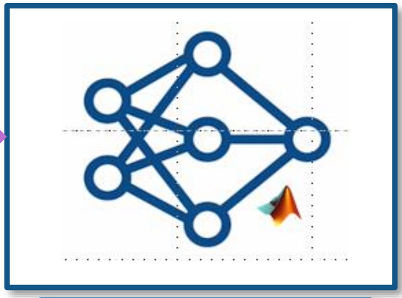
Developing Artificial Intelligence algorithm for automated labeling

Traditional approach – **Did not work** ☹

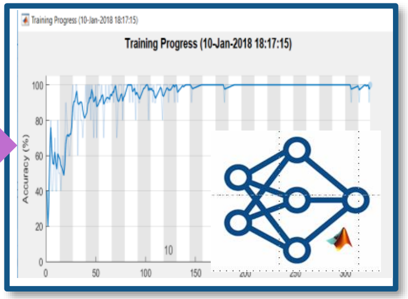
Training :



Label Seismic Data

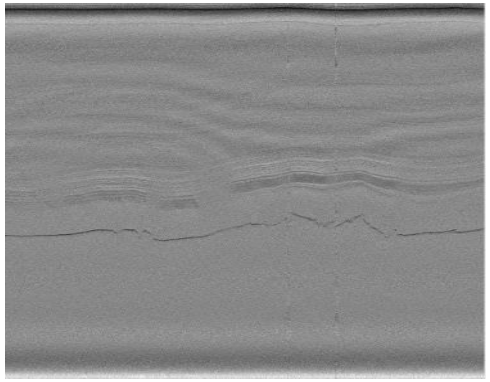


Train Deep Networks using CNNs

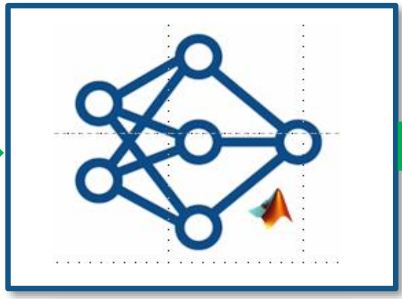


Train Network

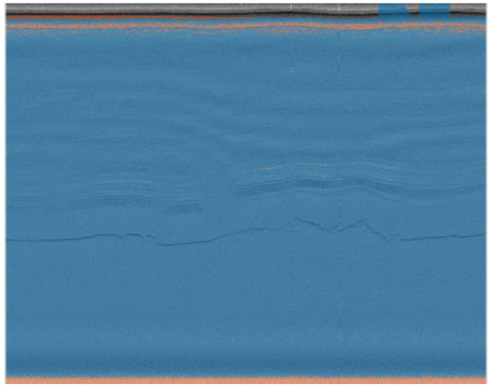
Deployed model :



New Data



Trained Model

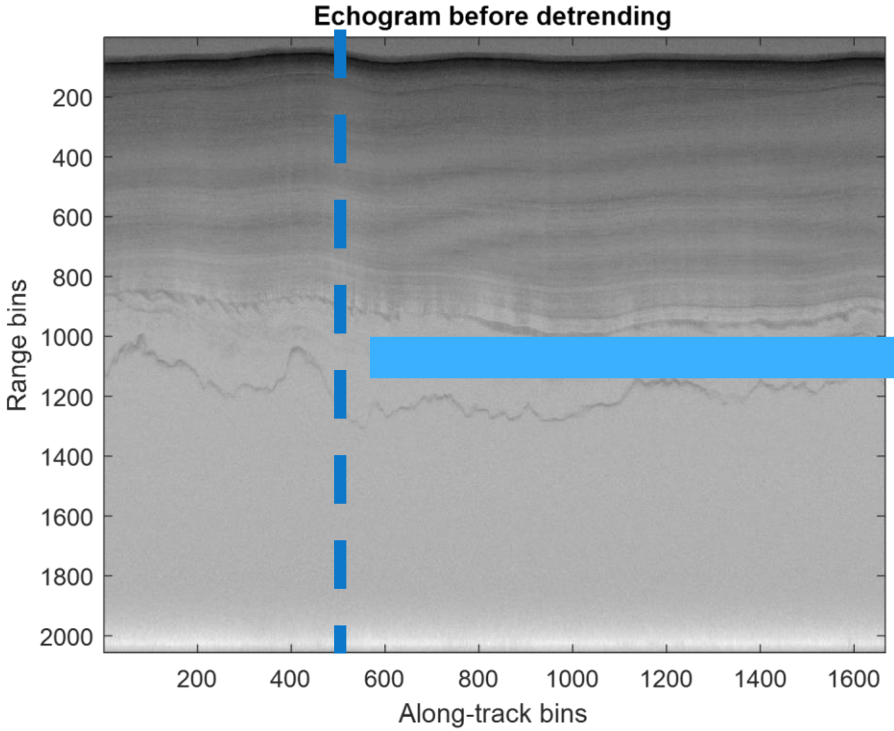


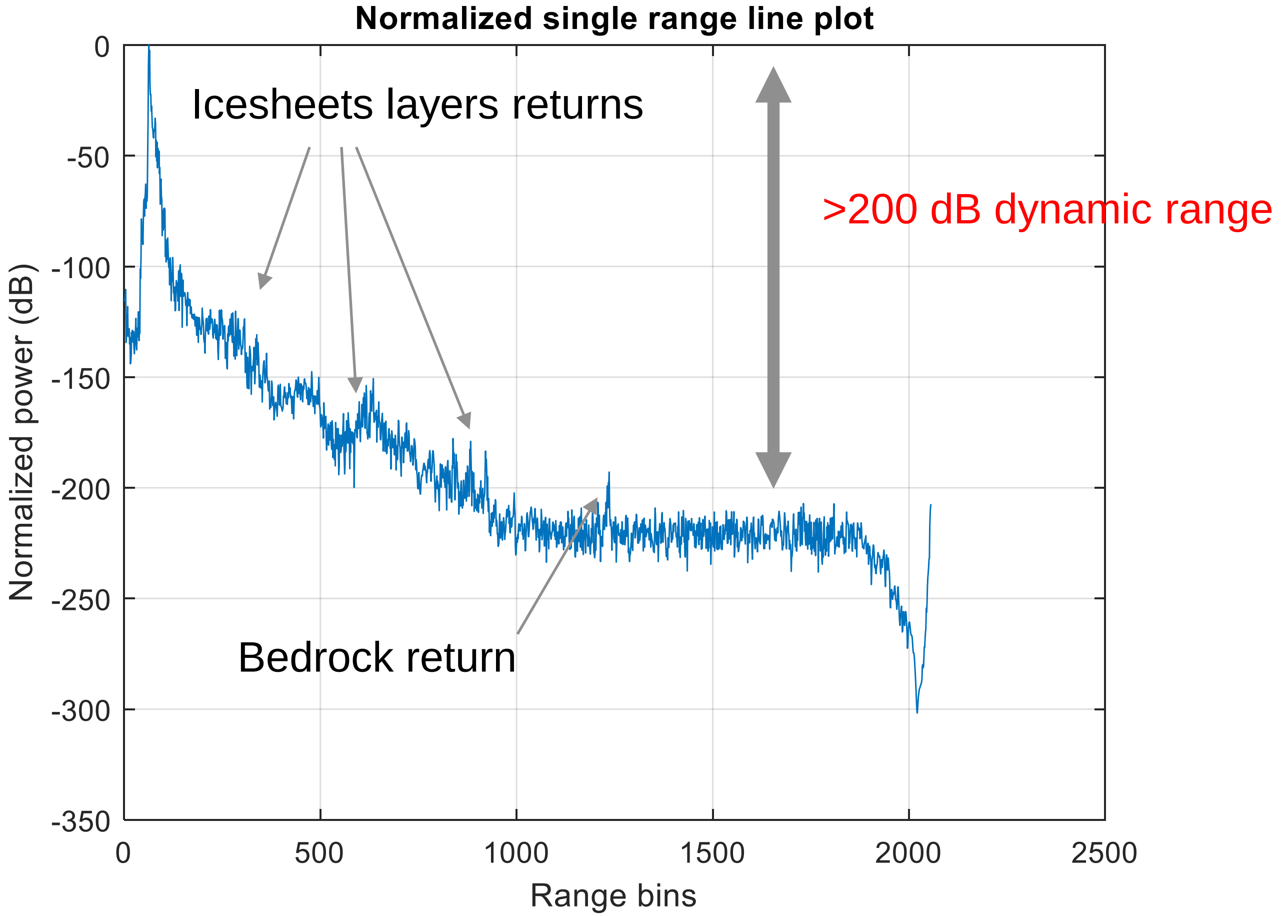
Semantic Segmented Data

Global accuracy of trained model <10%

Why did our model fail?

Let's understand the training data





High dynamic range results in :

- Poor contrast in seismic image
- Bedrock signal power very low
- AI model cannot distinguish icesheet layers and bedrock

How to detrend this data ?

Some techniques available in literature :

1. Curve fitting
   - Fit low order polynomial
   - Fit an exponential function

2. Predictive deconvolution
   - Inverse filtering

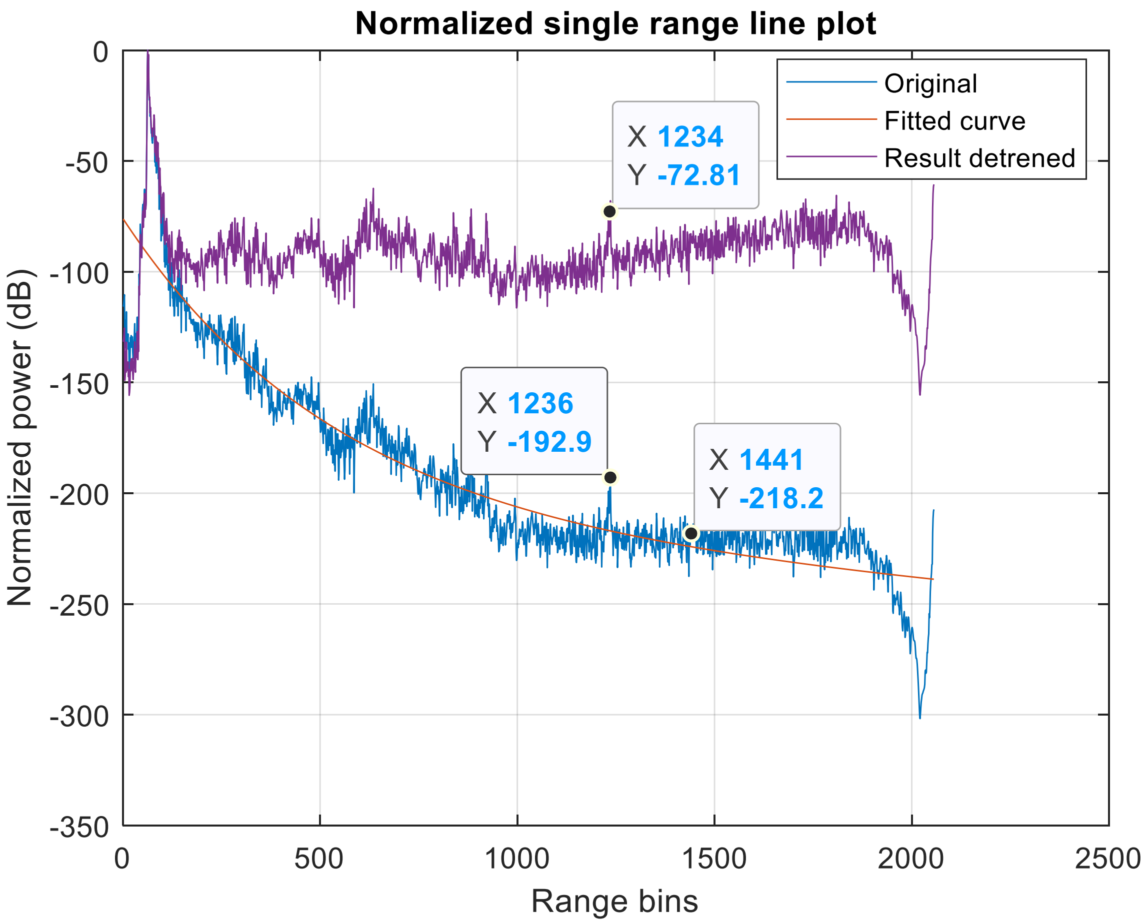
Result :

Loss in SNR of the bedrock return

Original signal bed SNR = ~27 dB
Detrended signal bed SNR = ~20 dB

Example :
Exponential curve fit

```
General model Exp2:
val(x) = a*exp(b*x) + c*exp(d*x)
Coefficients (with 95% confidence bounds):
  a =        -336  (-352.2, -319.9)
  b =   3.661e-05  (1.381e-05, 5.942e-05)
  c =       139.8  (125.1, 154.4)
  d =   -0.001847  (-0.002127, -0.001568)
```

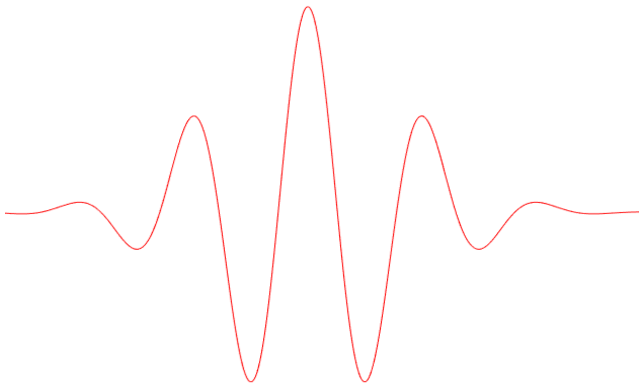


Which technique to use ?

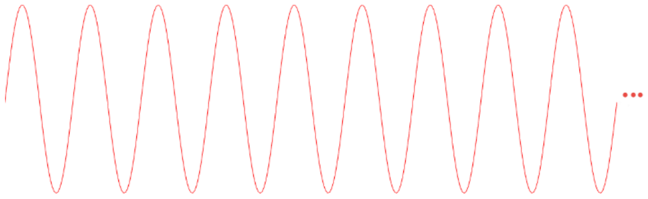
Ans: Use wavelets analysis

- A wavelet is a rapidly decaying wave like oscillation with zero mean
- Wavelets are best suited to localize frequency content in real world signals
- Availability of a wide variety of wavelets is a key strength of wavelet analysis

Wavelet

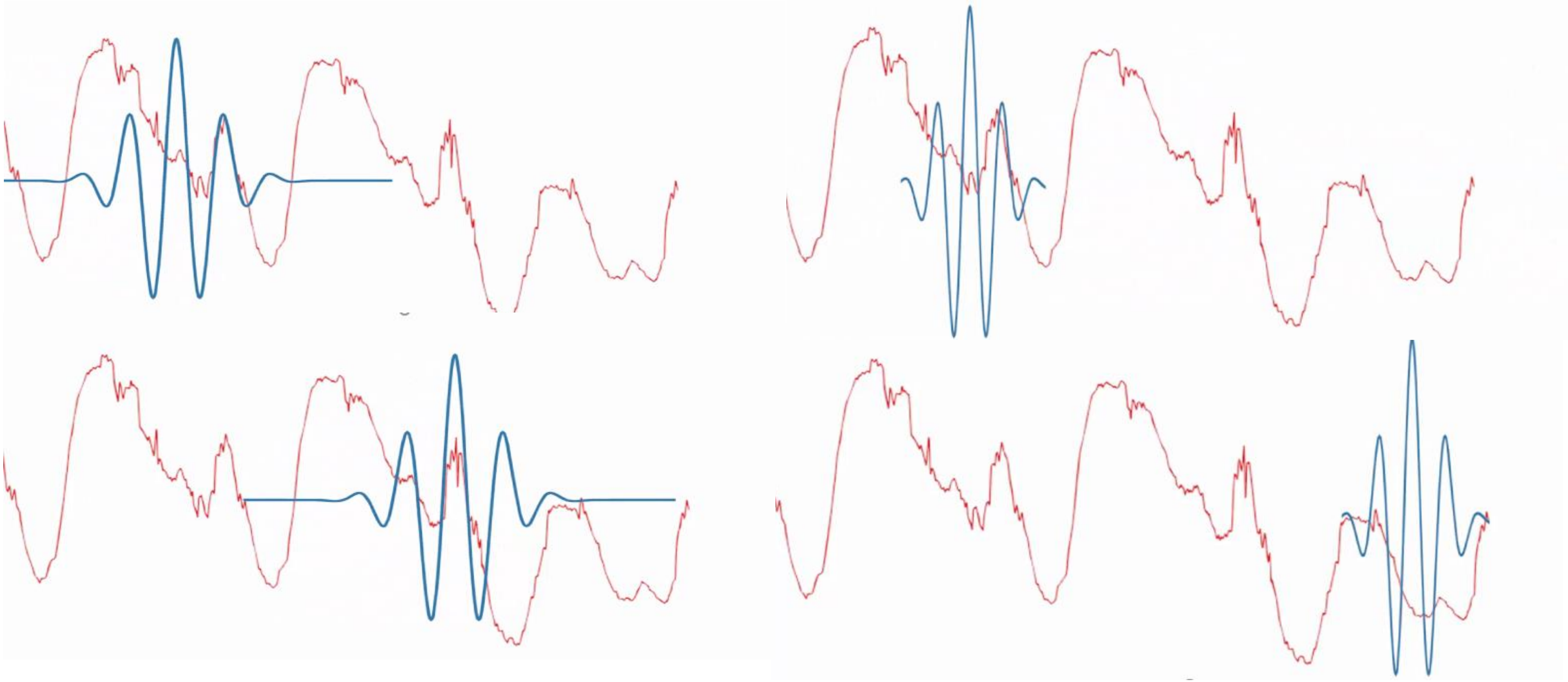


Sine wave



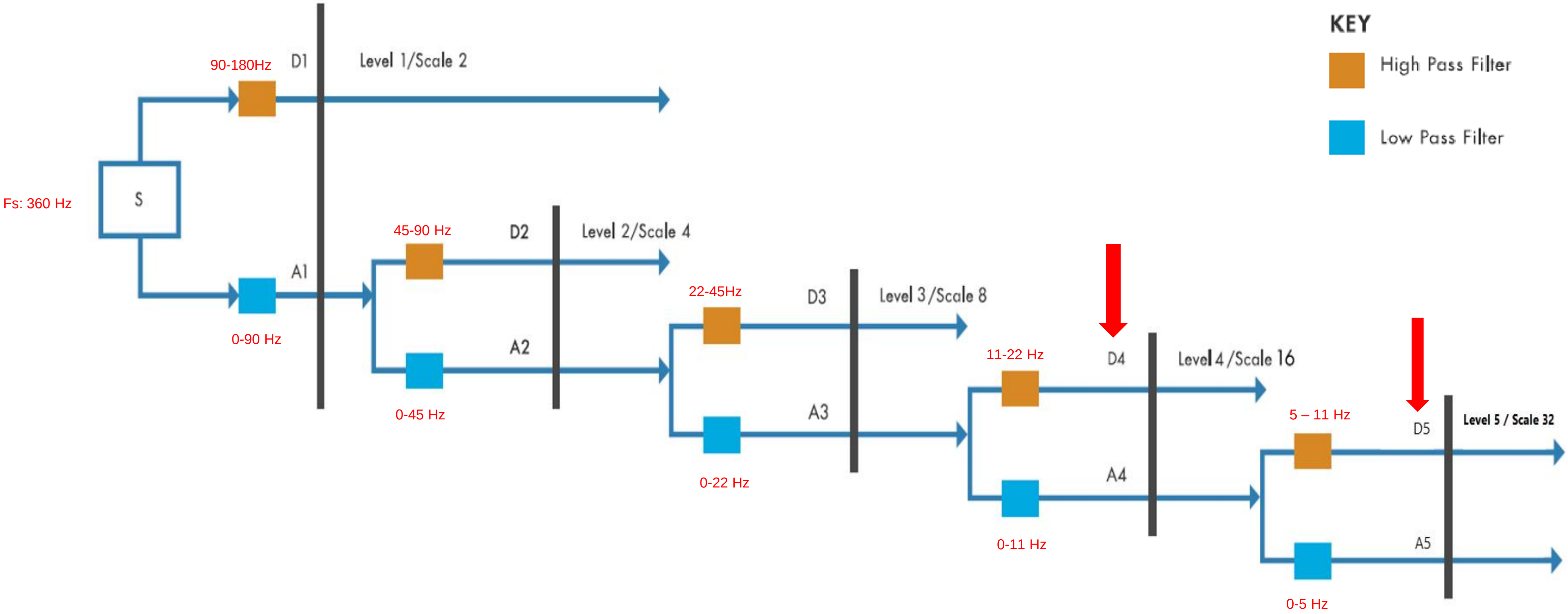
More on wavelets:

Translation and Scaling :



Introduction to Wavelet Multiresolution Analysis

Using DWT (Discrete Wavelet Transform) analyze signals into progressively finer octave bands

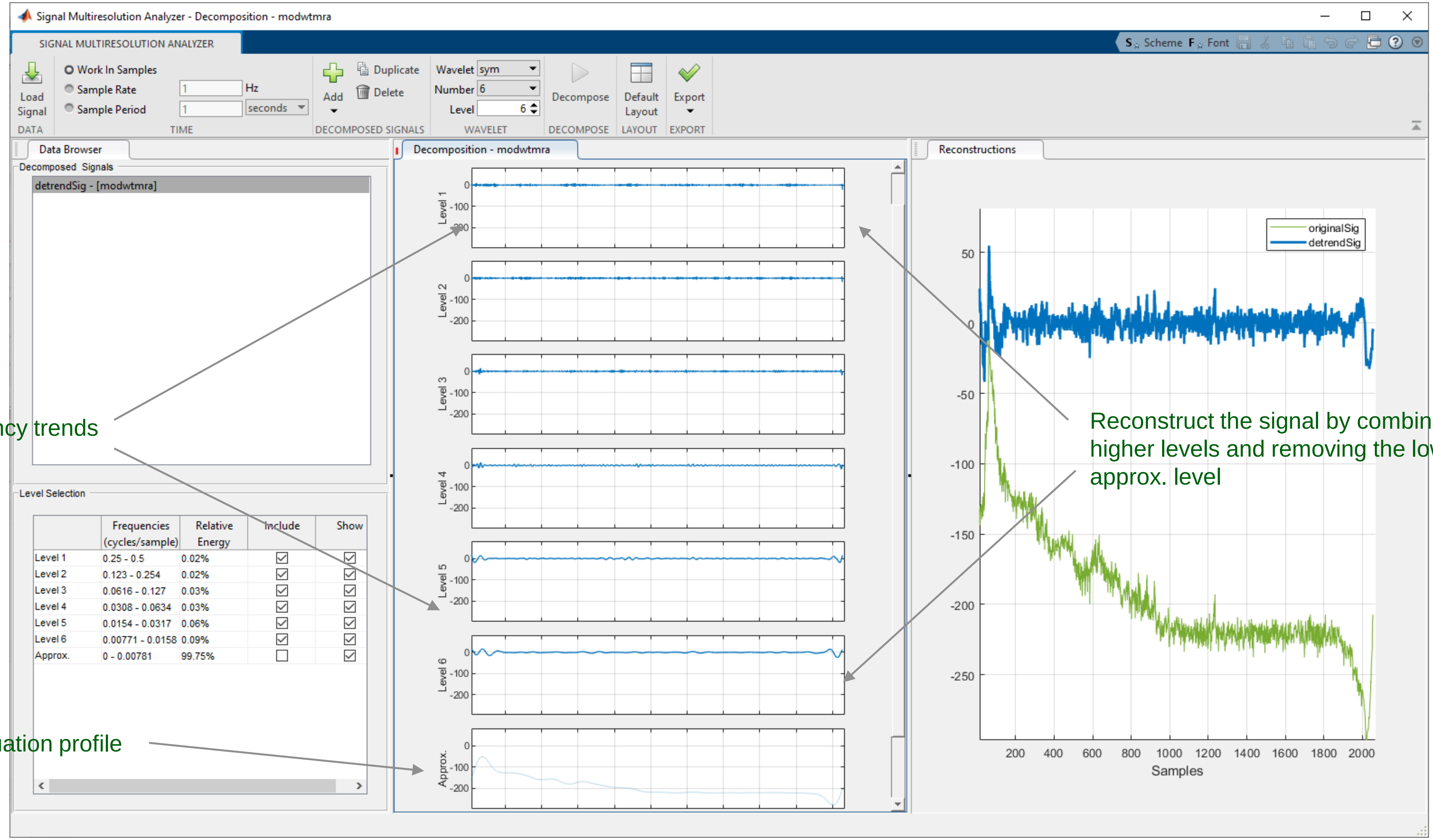


Signal Preprocessing using Wavelet Multiresolution Analysis

Decompose signal into multiple resolutions using wavelets

Higher levels capture high frequency trends

Lower levels capture signal attenuation profile



	Frequencies (cycles/sample)	Relative Energy	Include	Show
Level 1	0.25 - 0.5	0.02%	☑	☑
Level 2	0.123 - 0.254	0.02%	☑	☑
Level 3	0.0616 - 0.127	0.03%	☑	☑
Level 4	0.0308 - 0.0634	0.03%	☑	☑
Level 5	0.0154 - 0.0317	0.06%	☑	☑
Level 6	0.00771 - 0.0158	0.09%	☑	☑
Approx.	0 - 0.00781	99.75%	☐	☑

Reconstruct the signal by combining higher levels and removing the lowest approx. level

Signal Preprocessing using Wavelet Multiresolution Analysis

Results of multiresolution analysis :

1. SNR of bedrock return is preserved as original signal ~**27 dB**

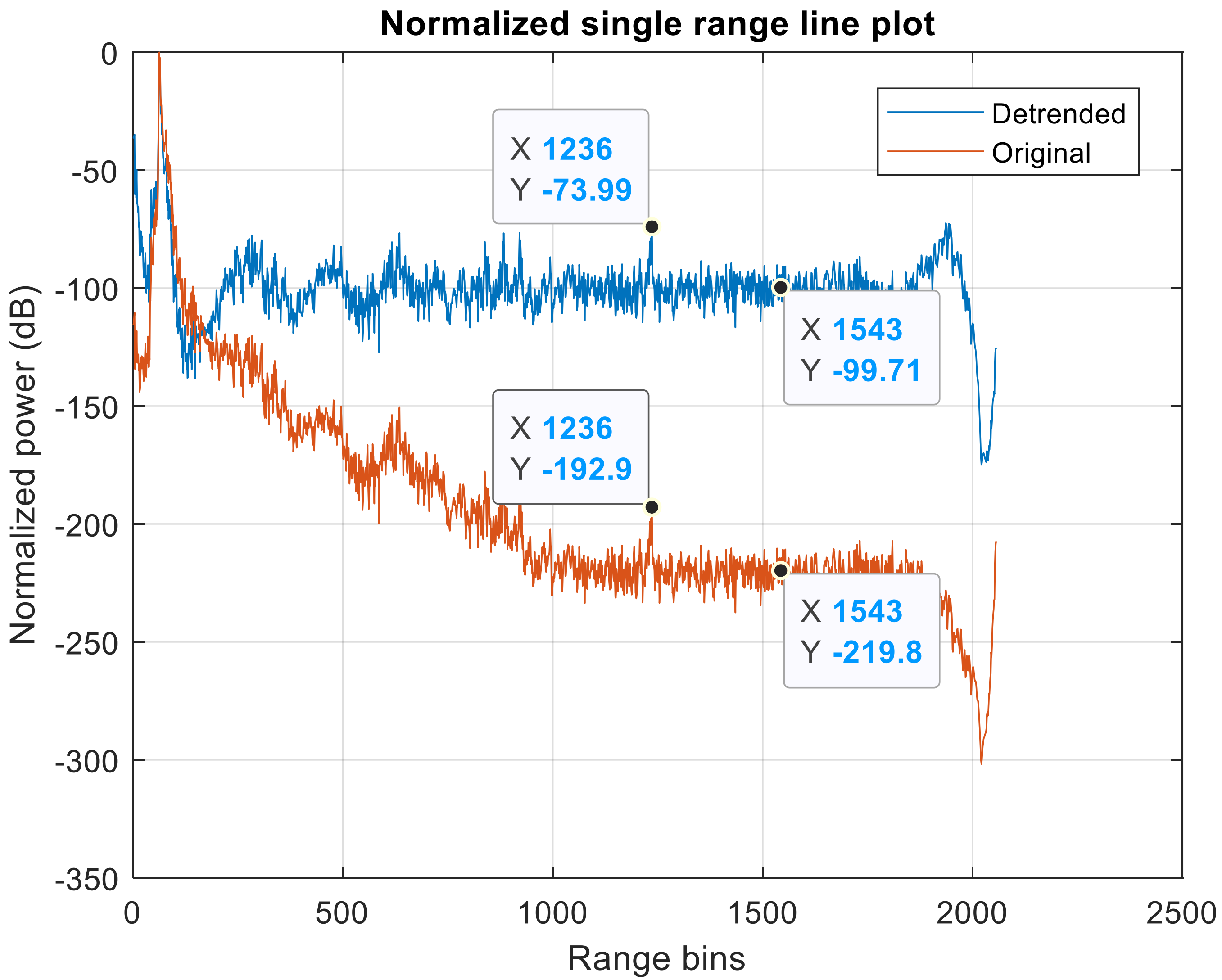
2. Used sym6 wavelet to preform the decomposition

3. Same wavelet decomposition method can be applied to all traces

4. Implement with Signal Multiresolution Analysis app https://www.mathworks.com/help/wavelet/ref/signalmultiresolutionanalyzer-app.html

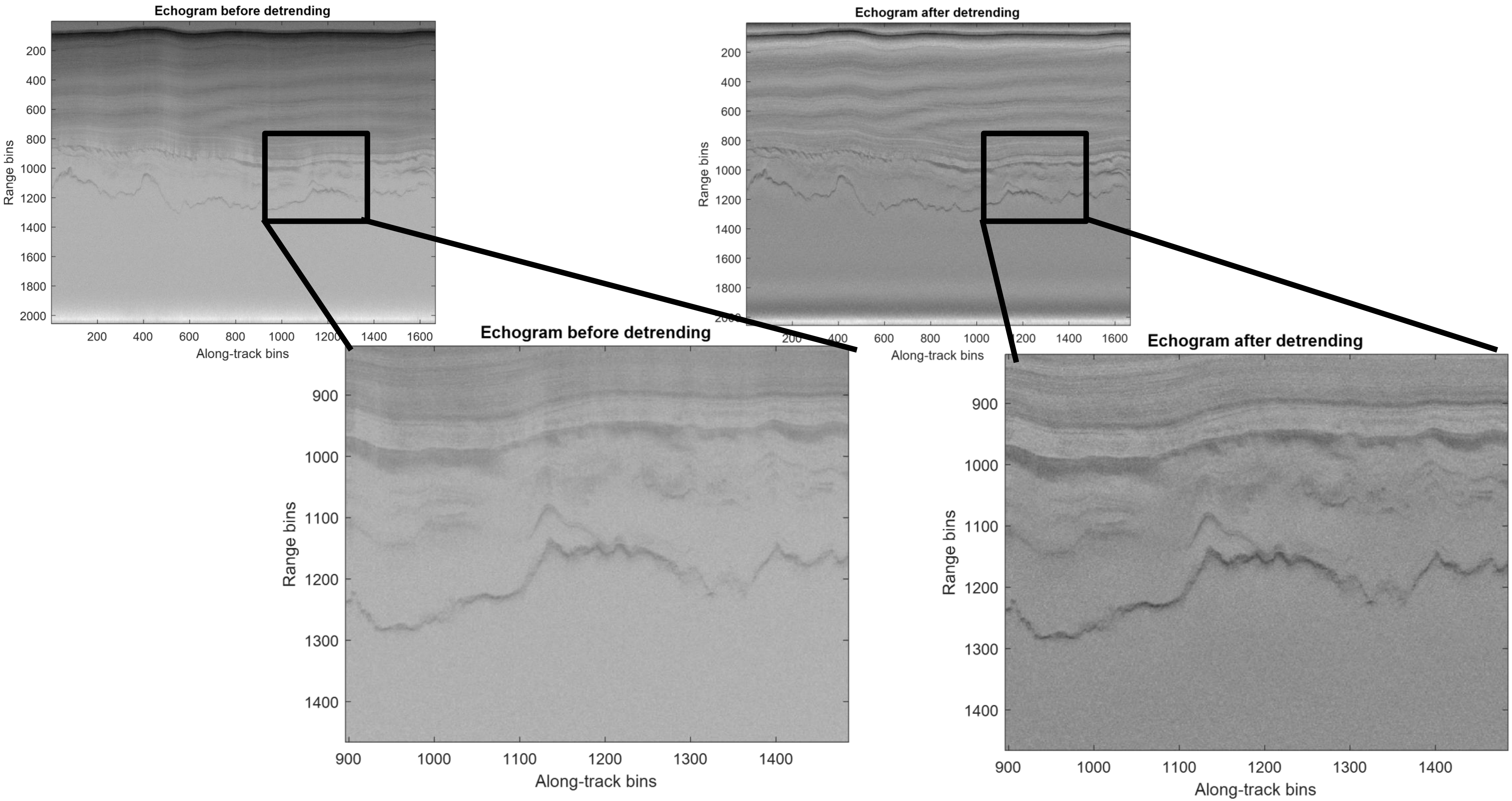
5. Automate the process by generating code directly from the app

6. Contrast of the seismic image improved



Signal Preprocessing using Wavelet Multiresolution Analysis

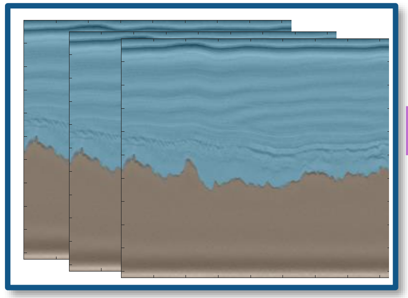
Results of multiresolution analysis :



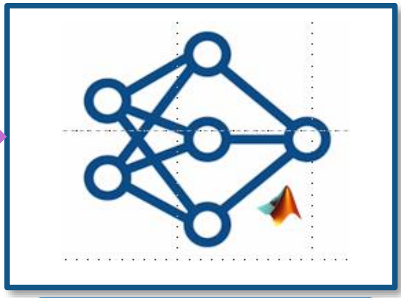
Developing Artificial Intelligence algorithm for automated labeling

Traditional approach – **Did not Work ☹**

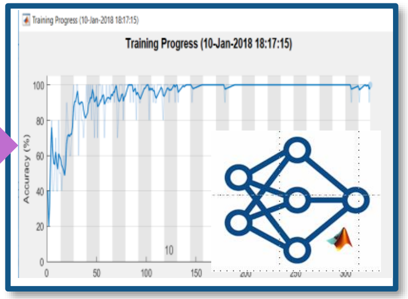
Training :



Label Seismic Data

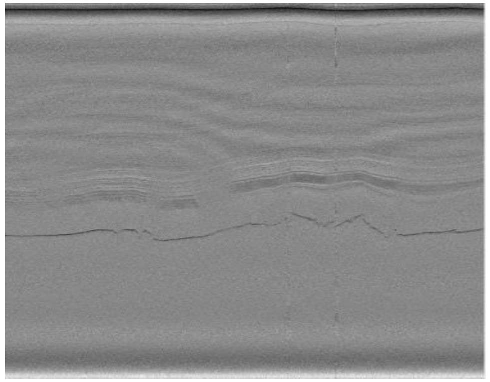


Train Deep Networks using CNNs

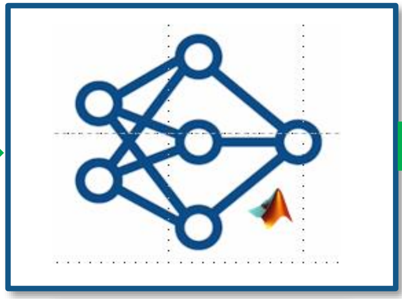


Train Network

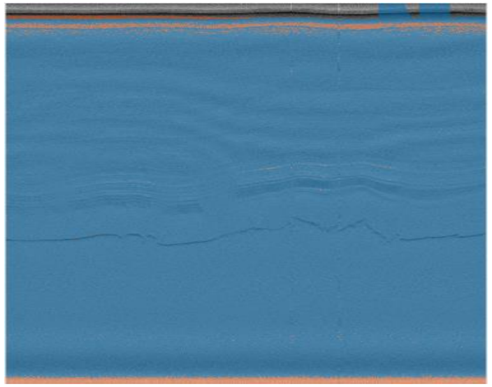
Deployed model :



New Data



Trained Model



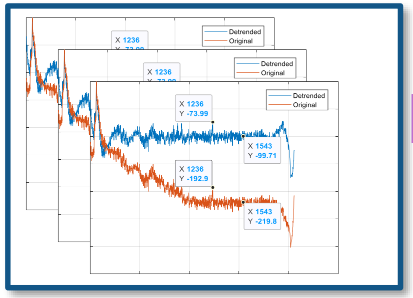
Semantic Segmented Data

Global accuracy of trained model <10%

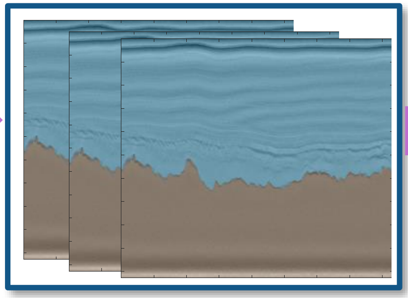
Developing Artificial Intelligence algorithm for automated labeling

New Wavelets based approach: AI model works ☺

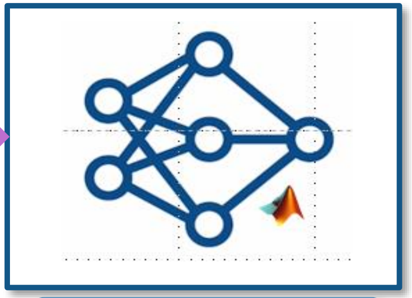
Training :



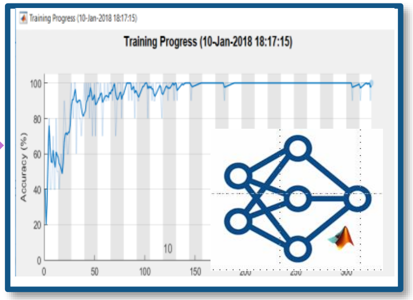
Signal Preprocessing with wavelets



Label Seismic Data

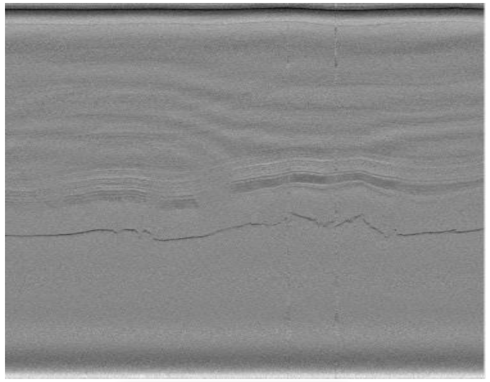


Train Deep Networks using CNNs

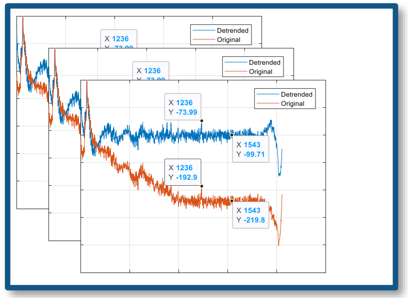


Train Network

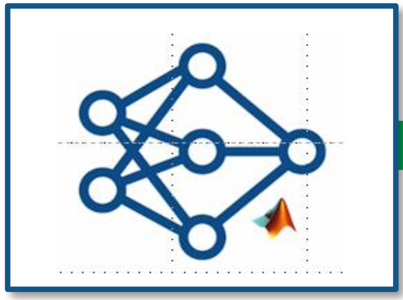
Deployed model :



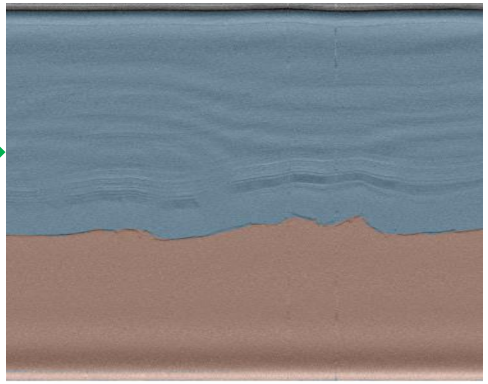
New Data



Signal Preprocessing with wavelets



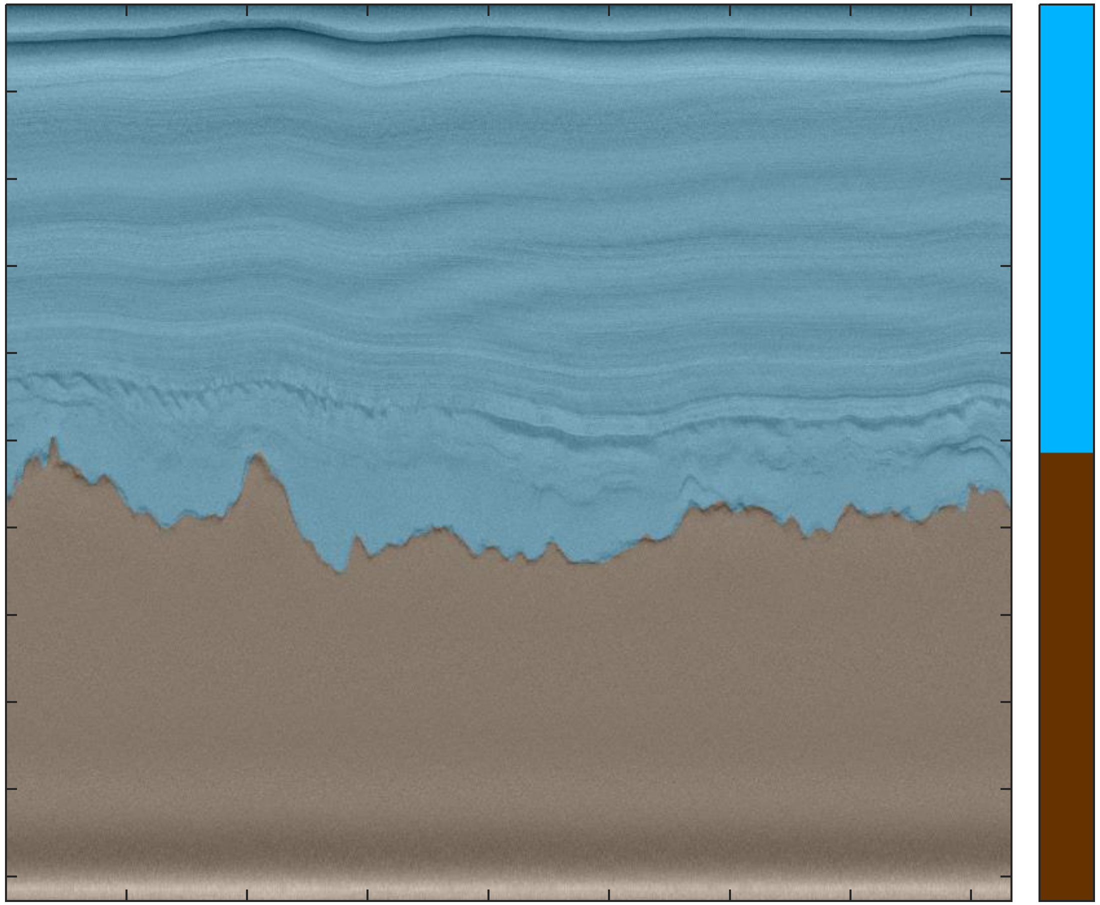
Trained Model



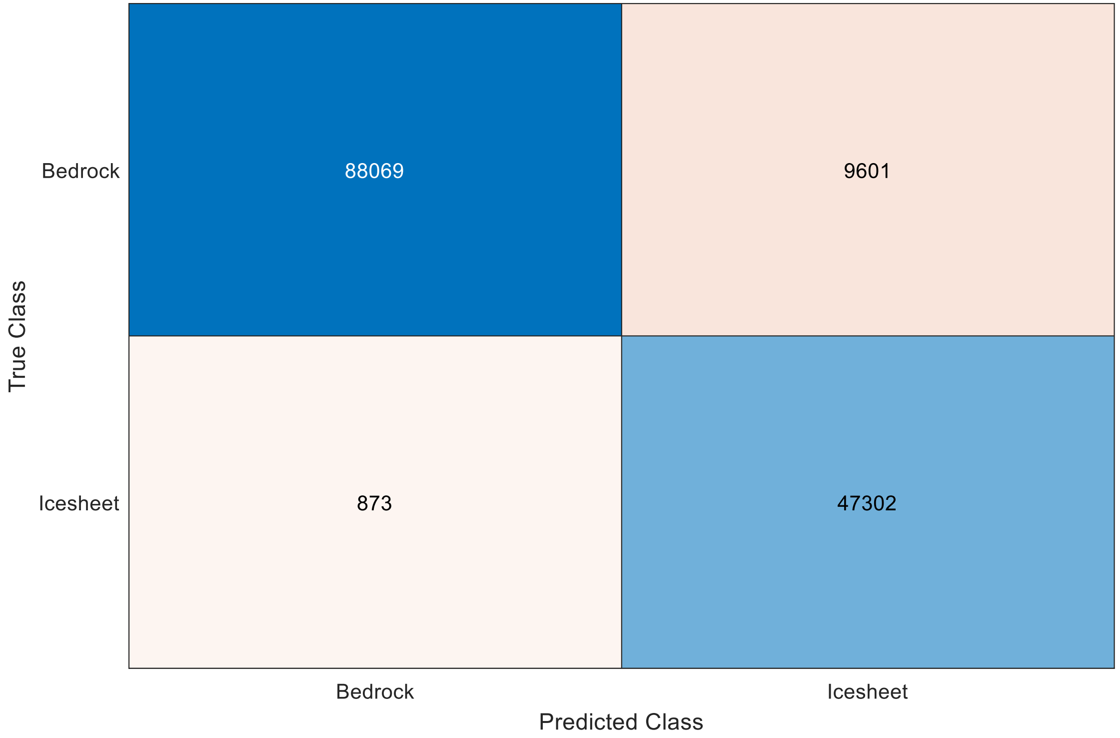
Semantic Segmented Data

Global accuracy of trained model ~ 97%

Overall result :



Semantic Segmented Data



Confusion matrix plot for all pixels

```
metrics = evaluateSemanticSegmentation(pxdsResults,pxdsTruth)
```

```
Evaluating semantic segmentation results
----------------------------------[==================================================] 100%
Elapsed time: 00:00:02
Estimated time remaining: 00:00:00
* Finalizing... Done.
* Data set metrics:
```

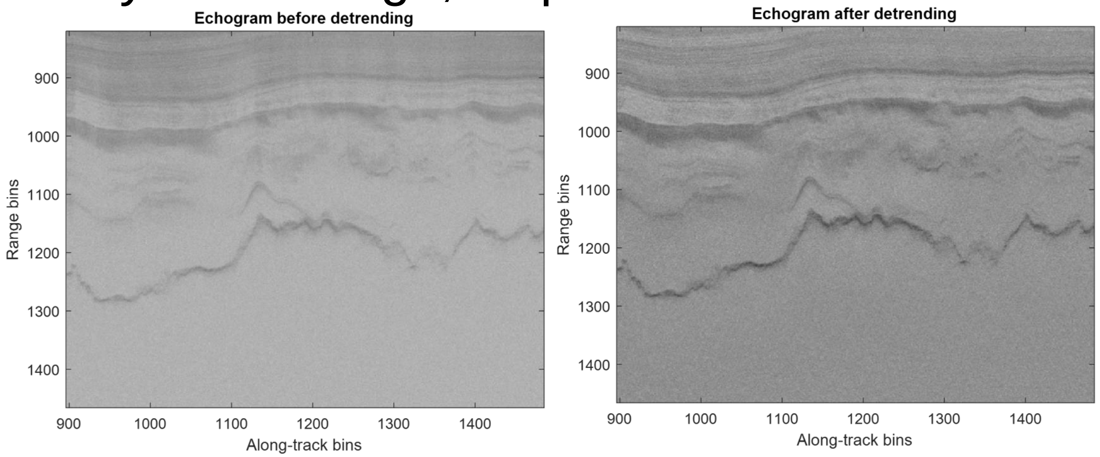
GlobalAccuracy	MeanAccuracy	MeanIoU	WeightedIoU	MeanBFScore
0.90624	0.95085	0.61588	0.87529	0.40652

Summary of case study:

- Signal preprocessing helped leverage the latest techniques in AI for seismic interpretation

- Seismic labeling automation helps increase productivity of seismic interpreter ~ **>10x**

- Overall SNR Improvement in signals :
  - Multiresolution analysis decreases the dynamic range, helps uncover features in low SNR scenarios



Improved features of icesheet layers and bed rock

Poster presented at AAPG ICE2019

Seismic Analysis with Wavelets and Deep Learning

Akhilesh Mishra, Kirthi Devleker, Samvith Rao

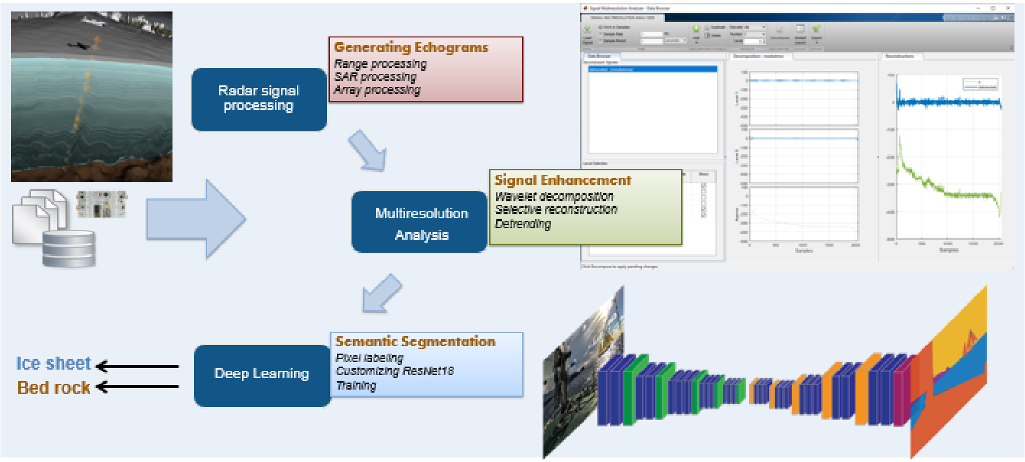
MathWorks

Abstract

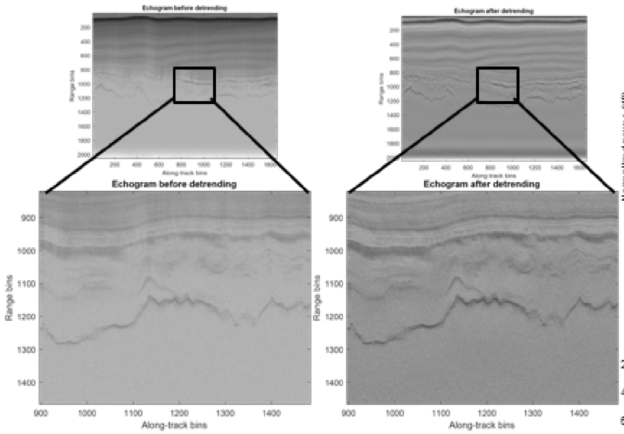
Seismic Reflection analysis is the most common method to obtain subsurface information for reservoir characterization. However, seismic reflection is often distorted by complex salt bodies and other geological structures and its vertical resolution is often of the order of dozens of meters. In addition, analyzing large amounts of seismic data is a computationally challenging and time-consuming task. To circumvent these challenges, in this work, we present an approach using wavelets and deep learning to accelerate seismic analysis tasks.

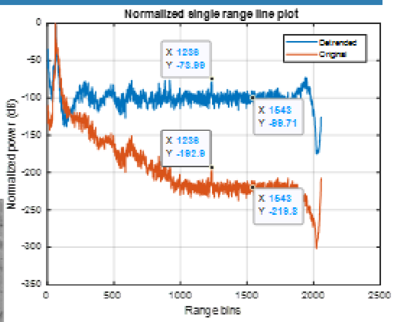
We explore the use of wavelet transforms in conjunction with deep learning for seismic data analysis. The field studies were done on seismic data from Antarctica ice sheets, and we could clearly identify the interfaces between ice sheet and bed rock. Our recent results obtained from this approach are promising to distinguish among different facies, thereby increasing the productivity of the interpreter by ~10x.

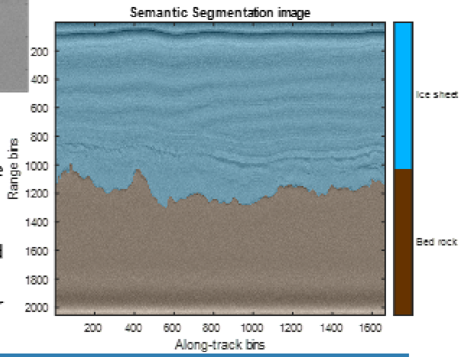
Methods



Results and Conclusion







Results

- Detrending improved the dynamic range while preserving the sharp features.
- SNR of bed rock enhanced.
- Semantic Segmentation automatically classifies the ice sheet and bed rock interface.
- Productivity of seismic interpretation improved ~10x per echogram.

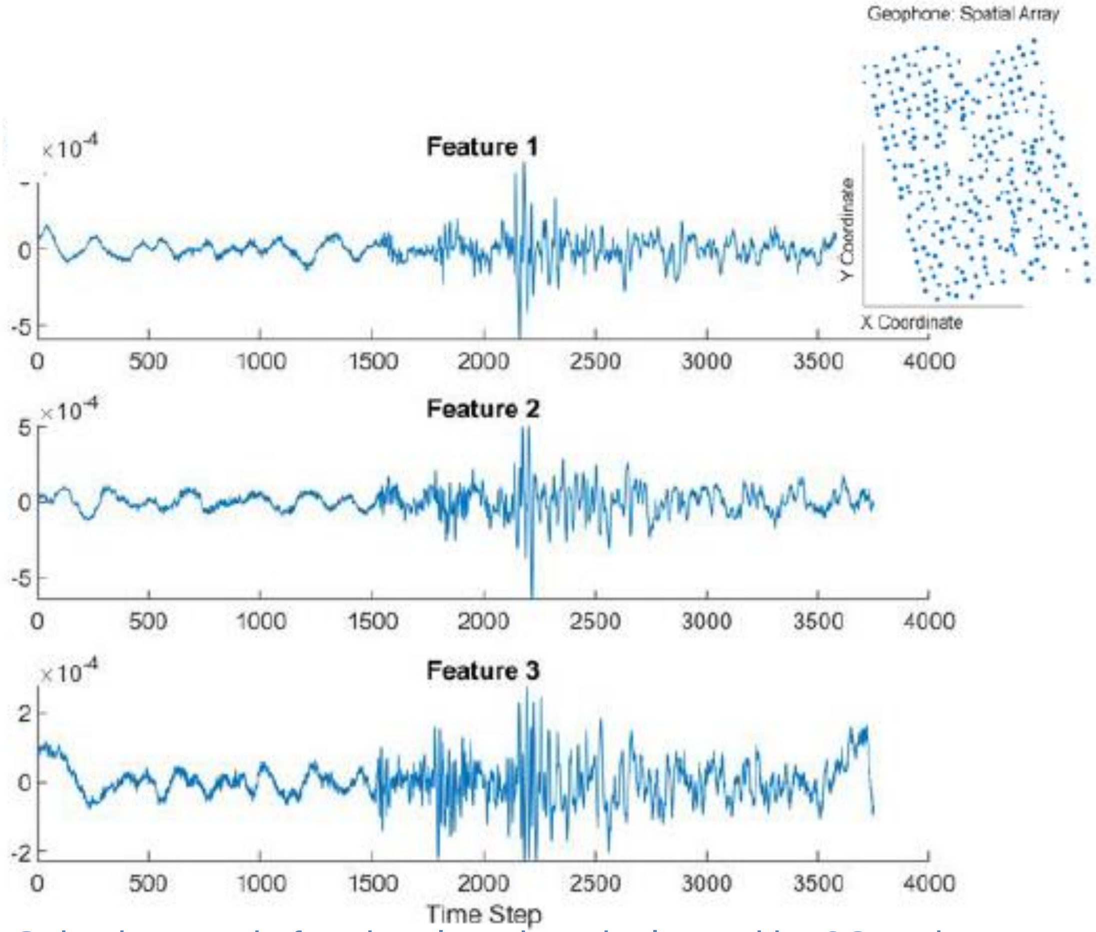
References

- CReSIS. 2018. MCoRDS Data, Lawrence, Kansas, USA. Digital Media. http://data.cresis.ku.edu/
- Gogineni, S., J.-B. Yan, et al., "Bed topography of fast-flowing glaciers and fine-resolution mapping of internal layers", 26th IUGG General Assembly 2015, Prague, Czech Republic, 06/22-07/2, 2015.
- Percival, D. B., and A. T. Walden. Wavelet Methods for Time Series Analysis. Cambridge, UK: Cambridge University Press, 2000.

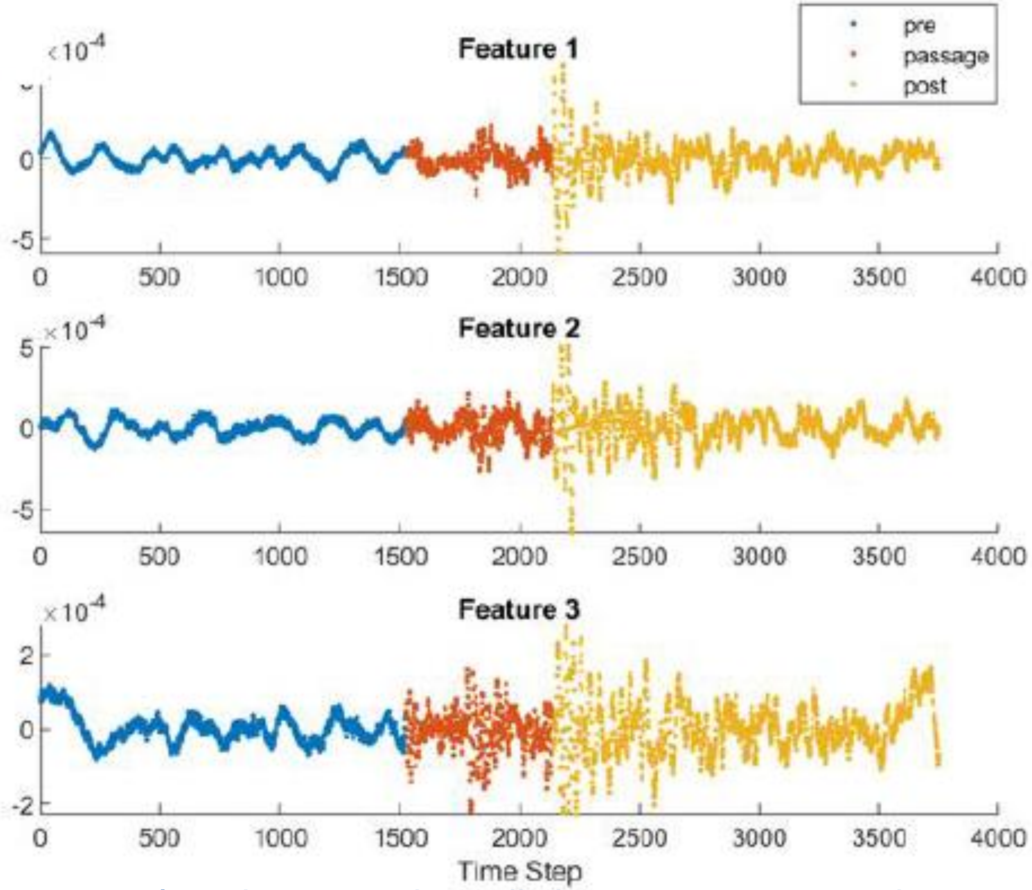
Case Study II :
Automated P- and S-wave arrival times detection in earthquake seismograms

Picking P- and S-waves arrival times with AI

Automation of labeling of P- and S-wave events



Seismic record of regional earthquake logged by 3C node



Deep learning network prediction on unseen record

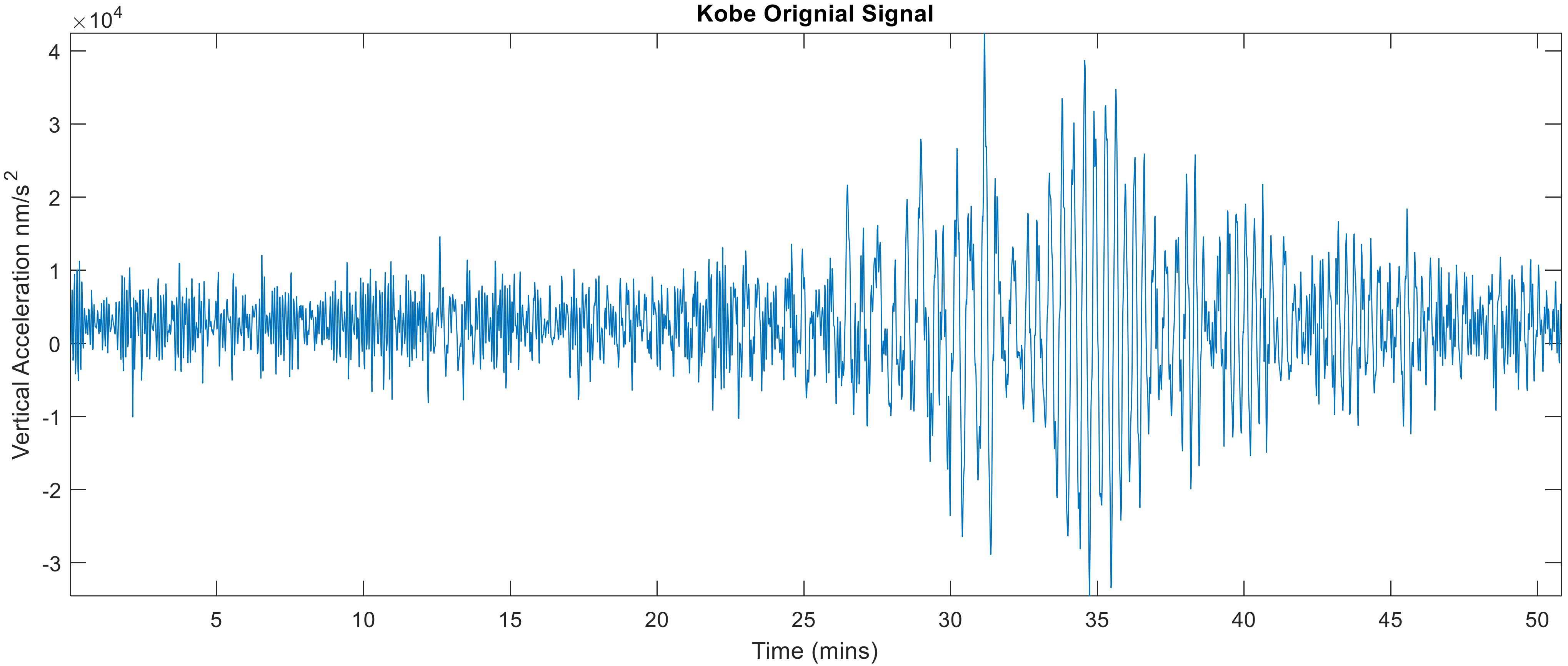
Source : **Detecting P- and S-wave Arrivals with a Recurrent Neural Network**

David Kirschner, Royal Dutch Shell; Nick Howes, Conor Daly, and Joyeeta Mukherjee, Mathworks; Junlun Li, University of Science and Technology of China (formerly w/ RDSA)

Case study data :

- Earthquake event occurred in Kobe, Japan - January 17, 1995 (January 16 at 20:46 GMT)

- Goal: Develop AI model to automatically label the P- and S-waves

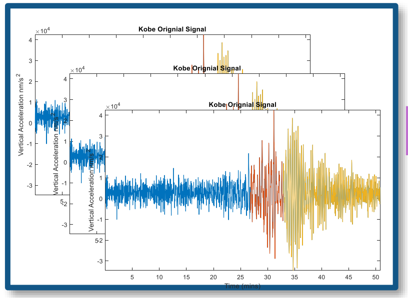


Data source : *NOAA National Geophysical Data Center (2012): Natural Hazard Images Database (Event: January 1995 Hanshin-Awaji (Kobe), Japan Images). NOAA National Centers for Environmental Information. doi:10.7289/V5154F01*

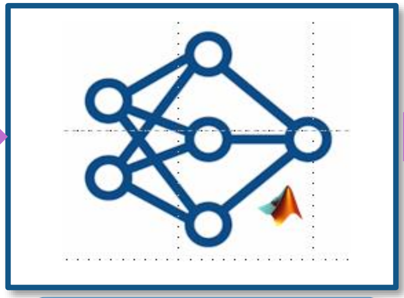
Developing AI algorithm for automated labeling

Traditional approach – **Very challenging**

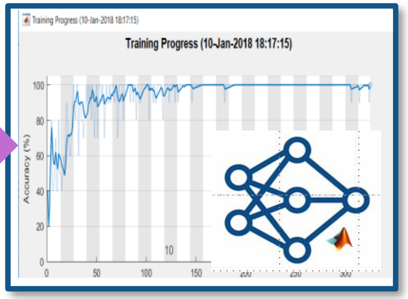
Training :



Manually labelled signal – v difficult

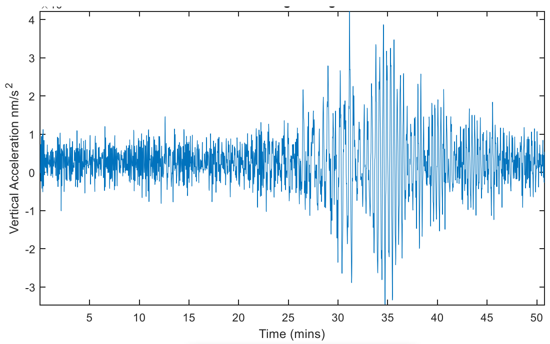


Train Deep Networks using RNNs

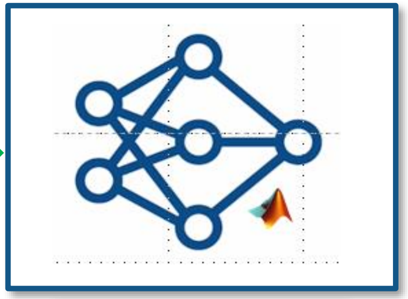


Train Network

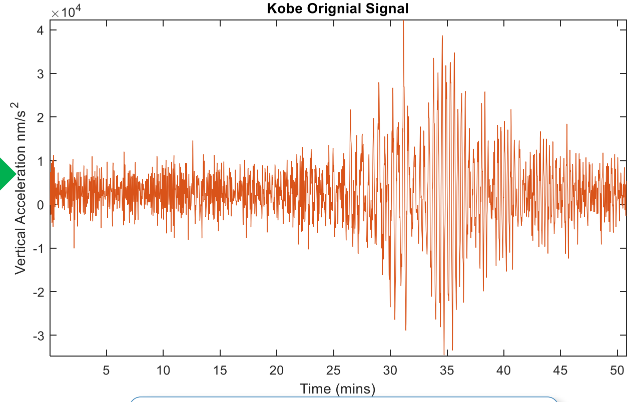
Deployed model :



New Data



Trained Model

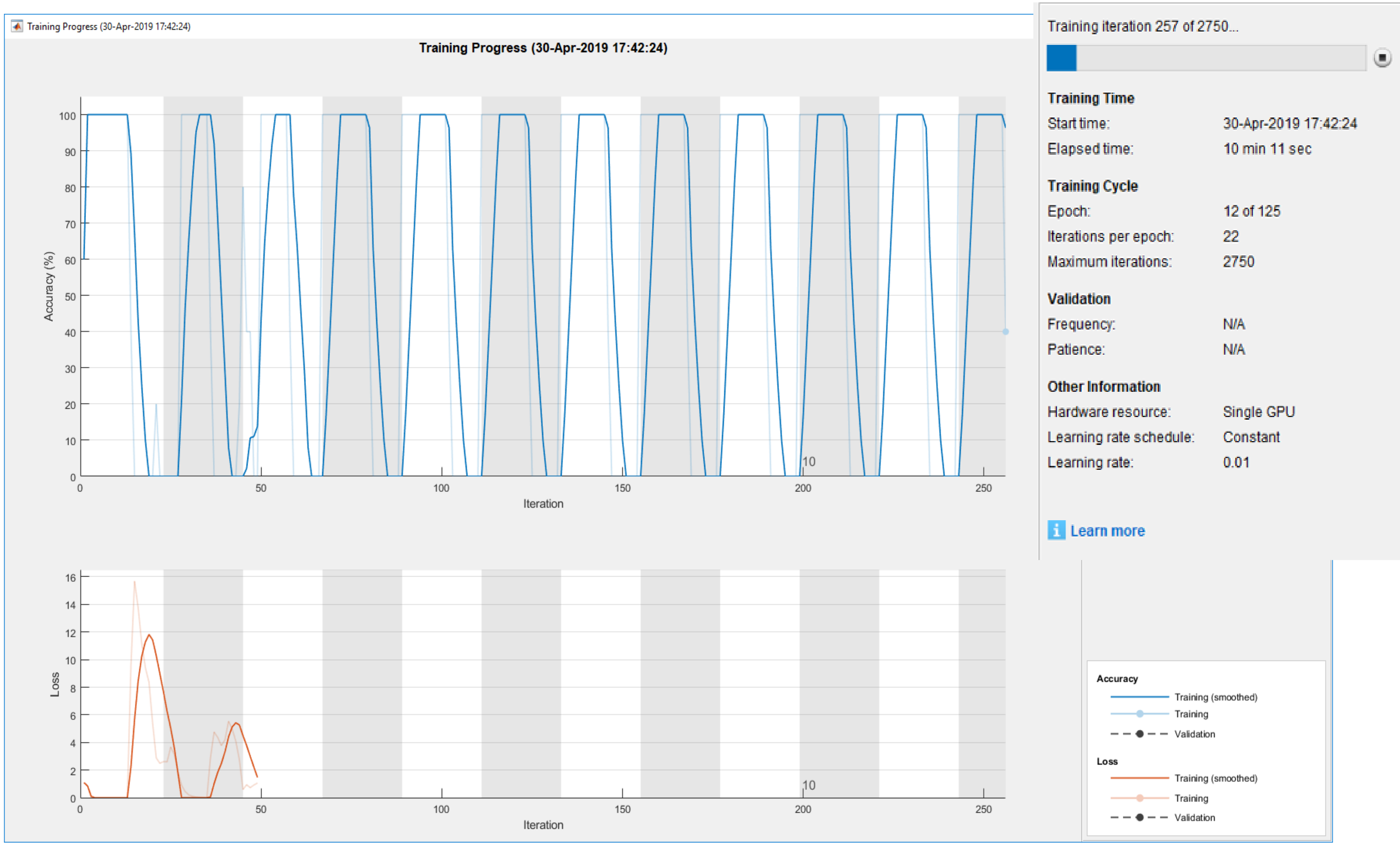


Labeled signal

Global accuracy of trained model low

Challenges with traditional AI approach

- Labeling the P- and S-waves arrival durations manually is challenging
  - Difficult to interpret time domain signal
- Seismic signals are highly **non-stationary** and features change quickly with time
- Recurrent Neural Networks for deep learning, e.g. LSTM (Long Short Term Memory) do not train on raw data

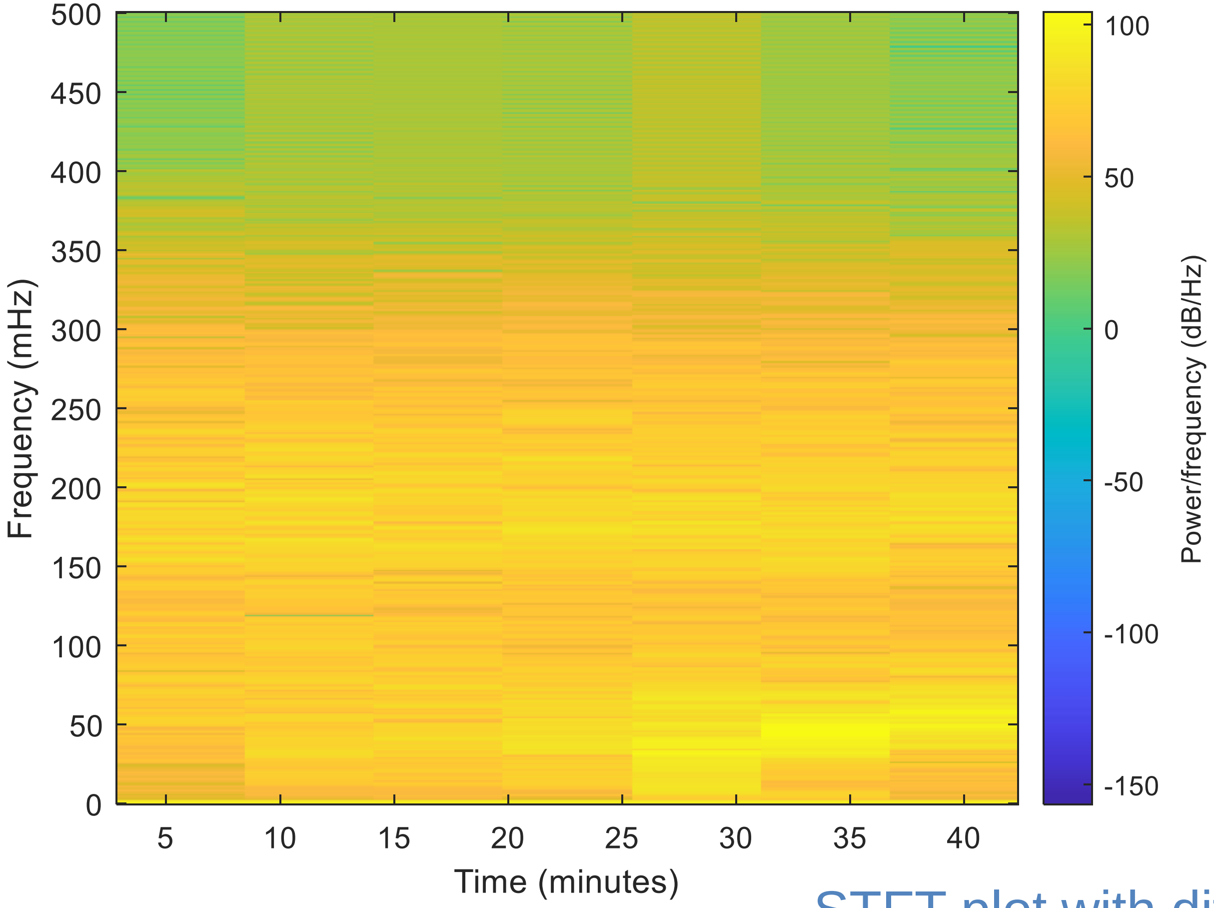


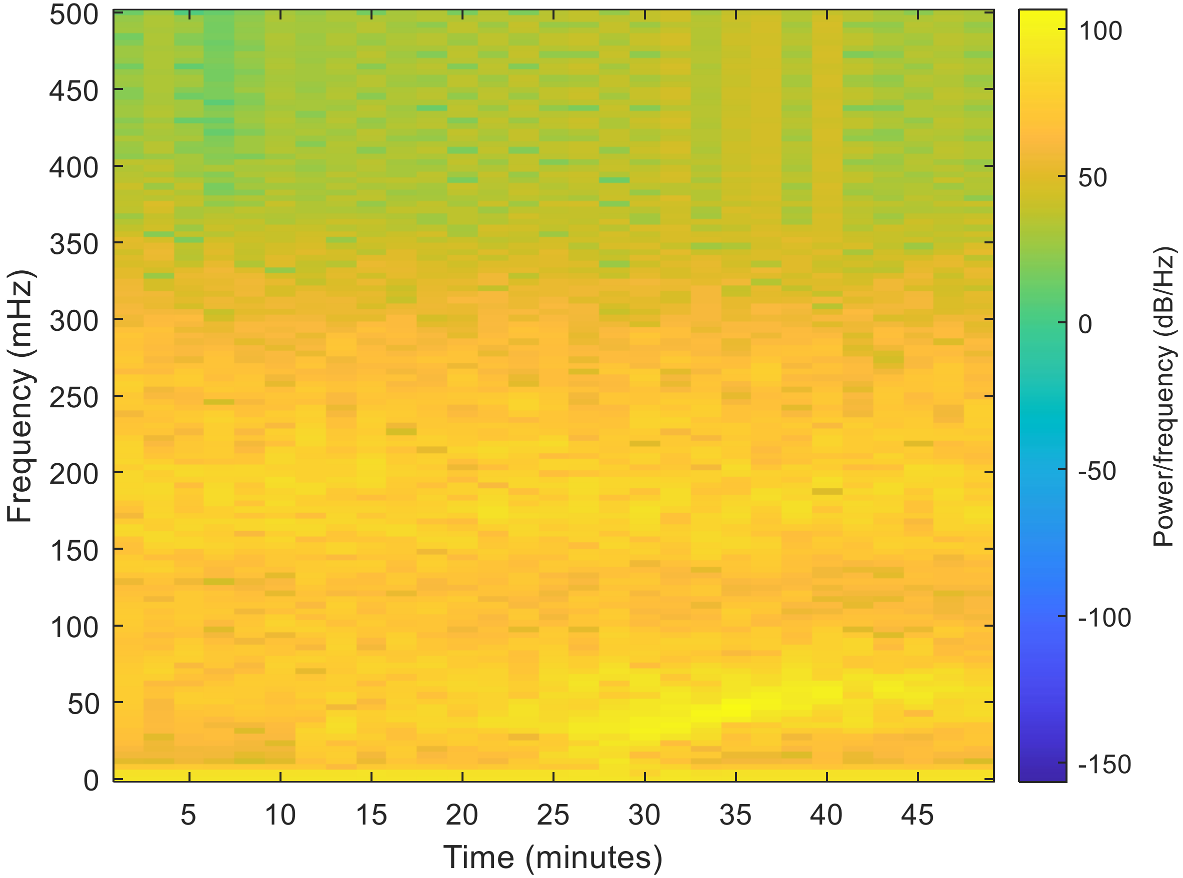
Sample training accuracy plot on non-stationary signals

Maybe we can localize the events in time and frequency space?

Let's analyze these signals : Time-frequency method to separate out the localized events

Results of Short Time Fourier Transform (STFT)



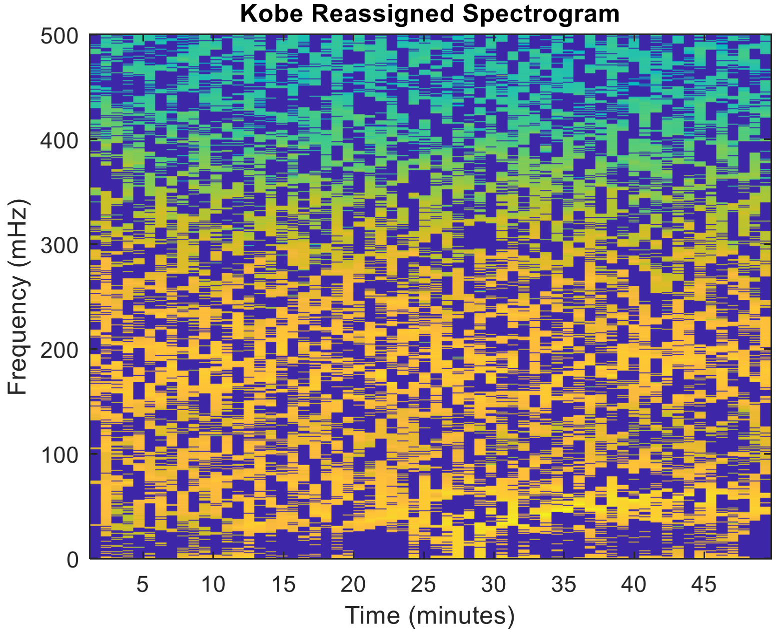


STFT plot with different time windows

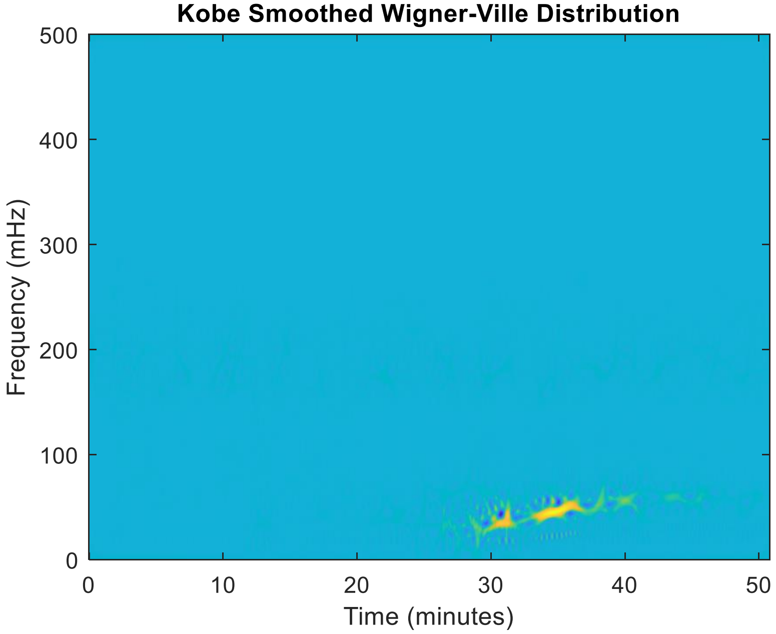
Poor resolution in time and frequency domains ☹

Other time-frequency techniques

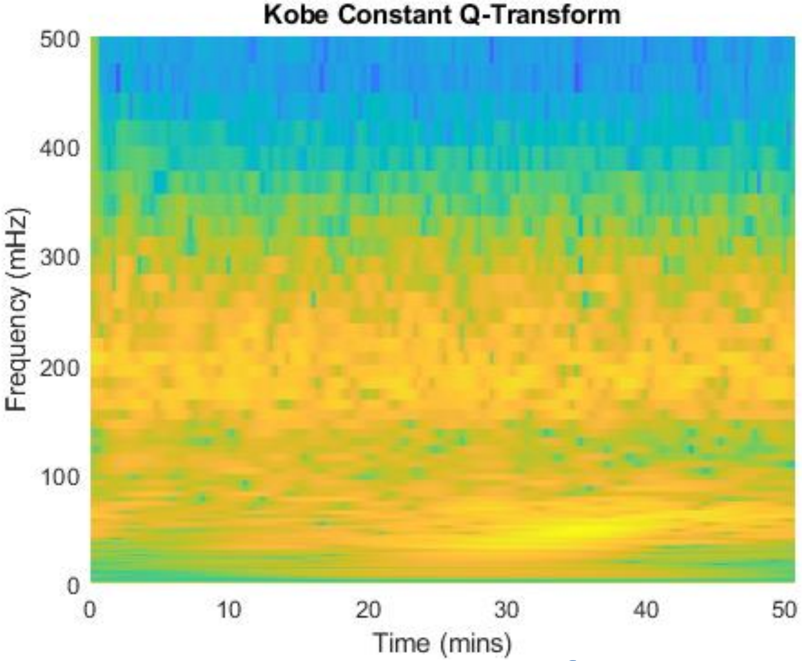
- Modified Fourier based methods also use sine/cosine waves
- Sine/cosine waves does not do a good job with seismic signals



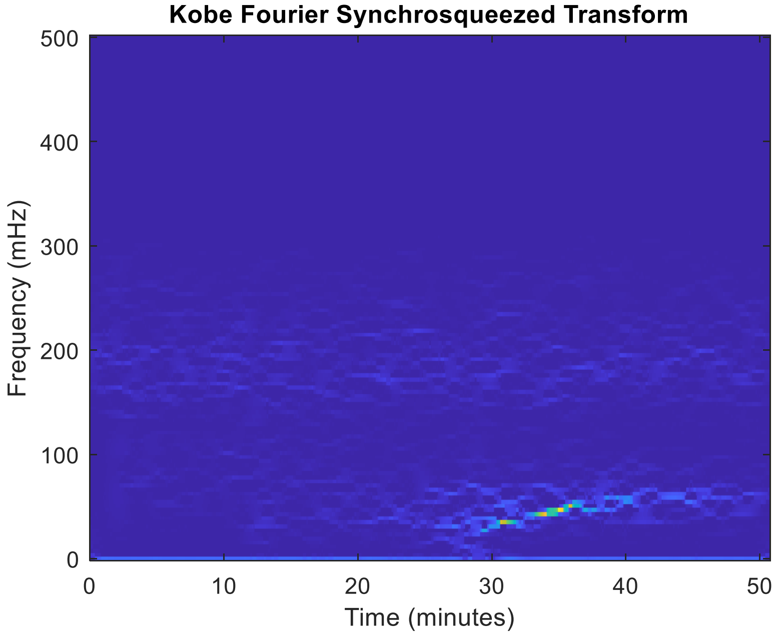
Reassigned Spectrogram



Pseudo Wigner-Ville Distribution



Constant-Q Transform

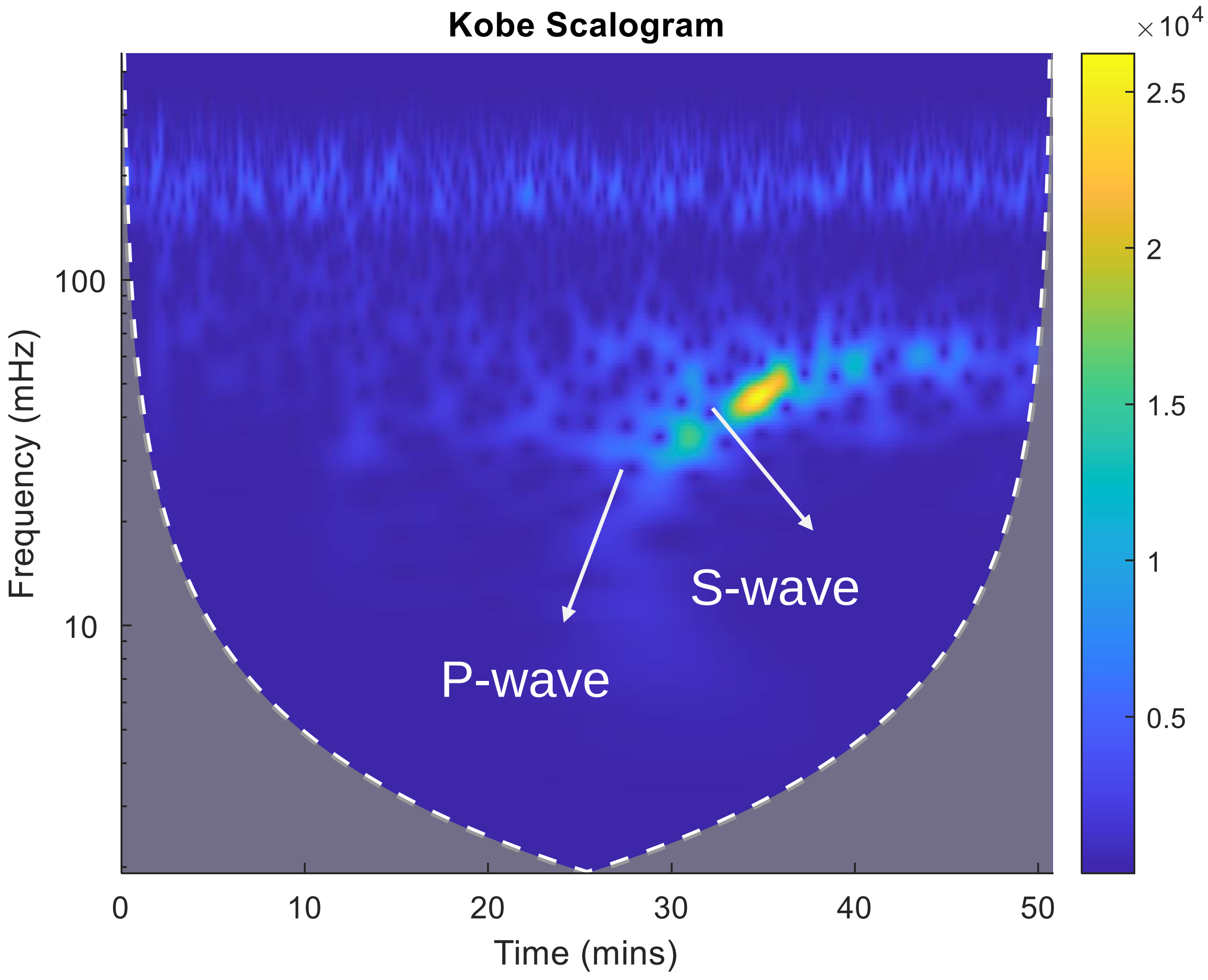


Fourier Synchrosqueezed Transform

Wavelets again

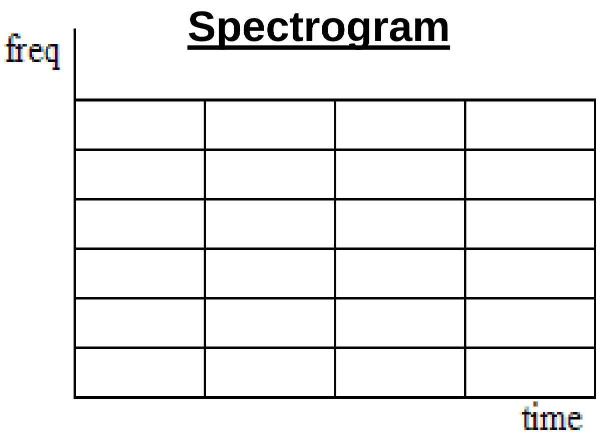
Continuous wavelet transform

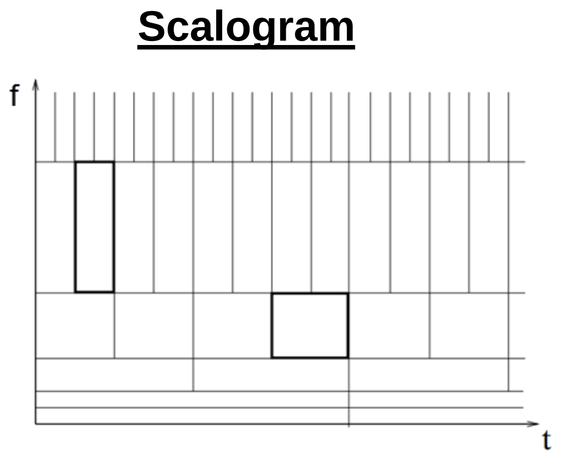
>> cwt(kobe, fs)

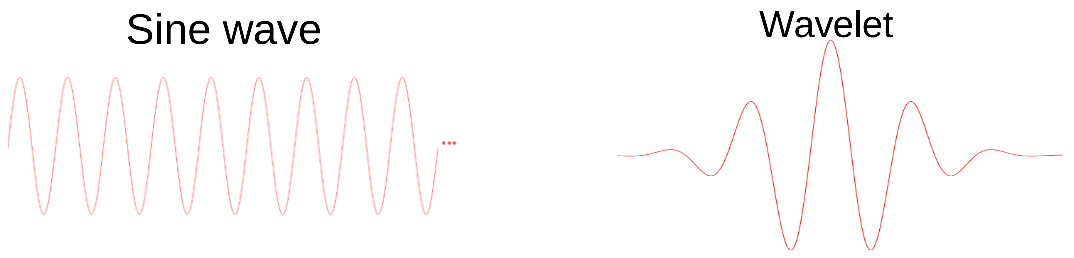


Advantages :

- Variable sized windows (scaled wavelets) help capture features occurring at different scales
- These scaled wavelets are shifted (translated) along the entire length and compared with the signal
- High frequency events are better resolved in time and low frequency events are better resolved in frequency

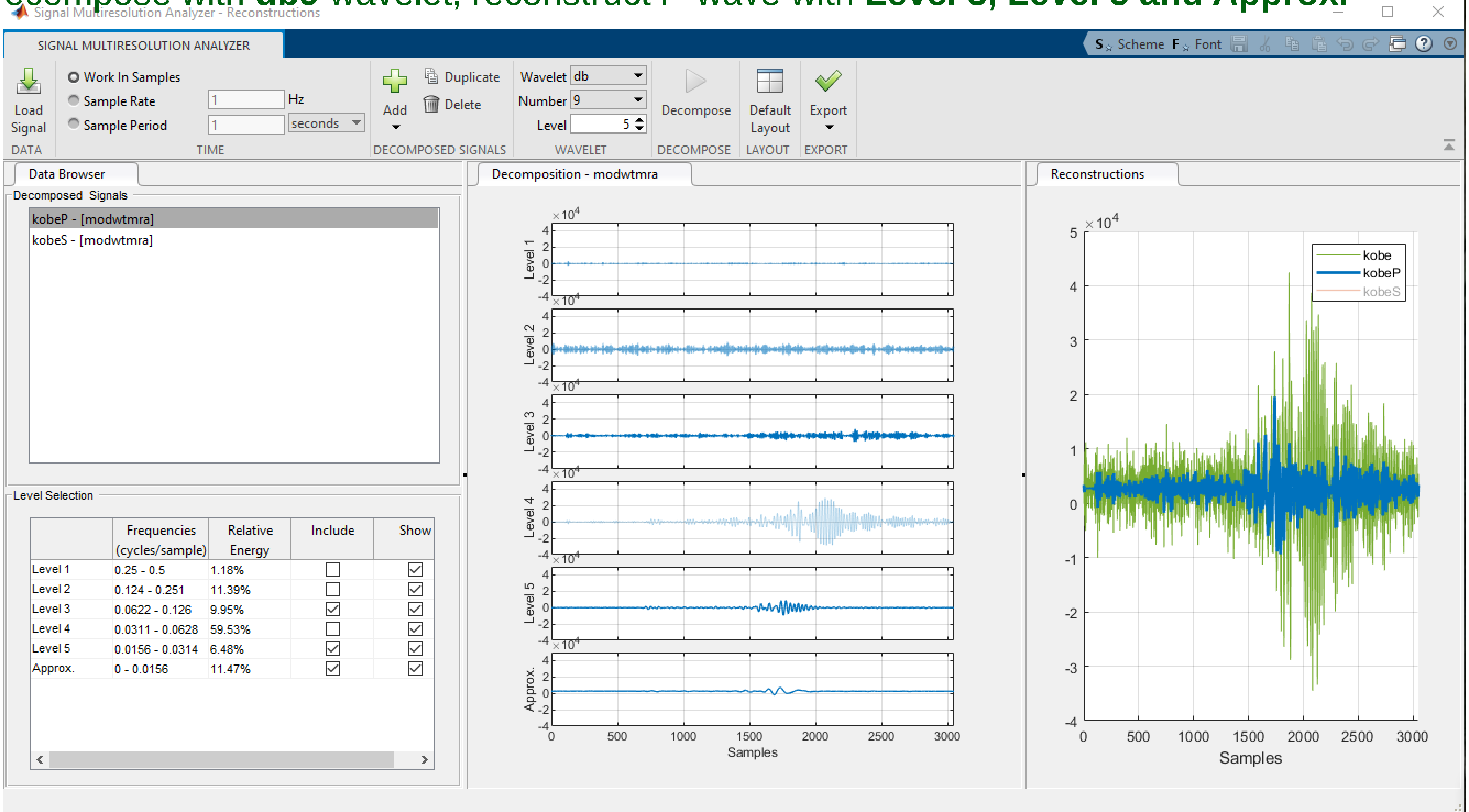






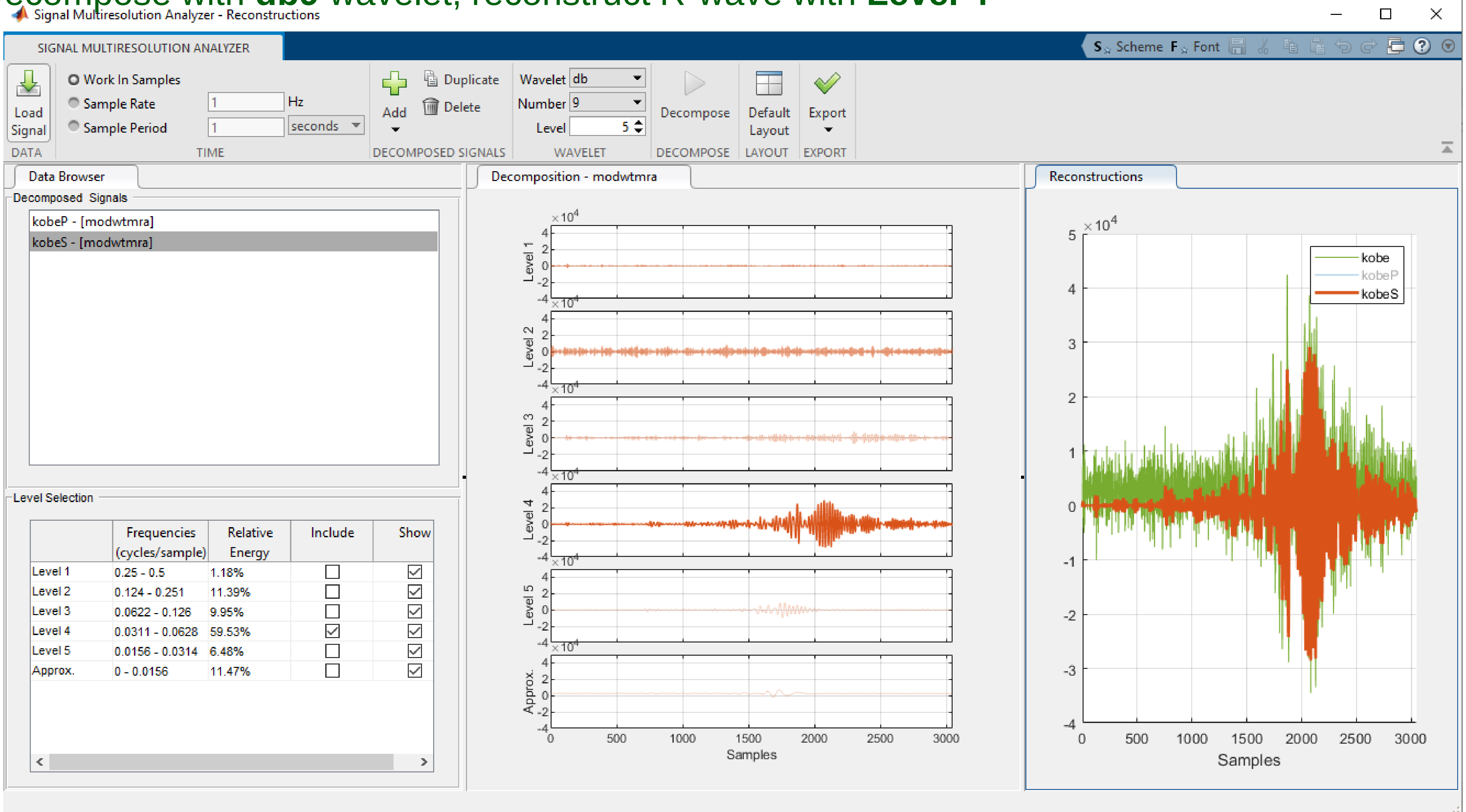
Use wavelet multiresolution analysis to spilt the components

Decompose with **db9** wavelet, reconstruct P-wave with **Level 3, Level 5 and Approx.**

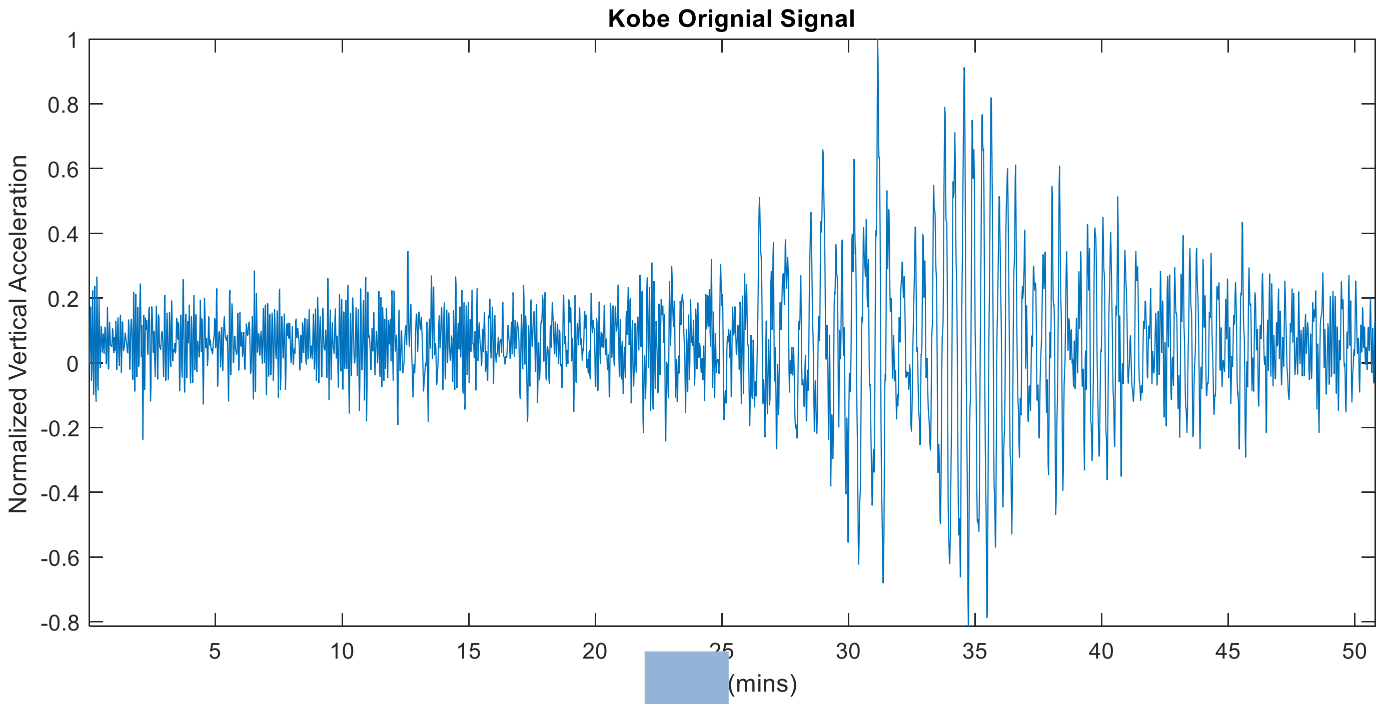


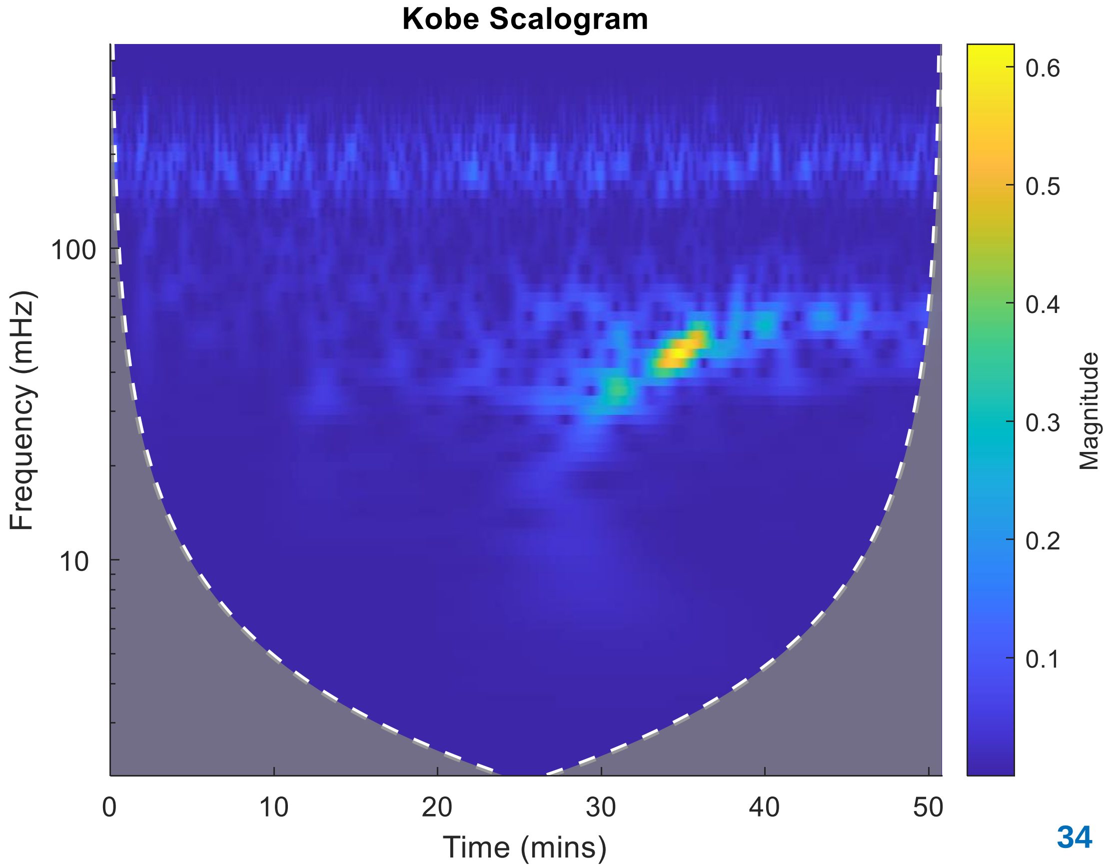
Use wavelet multiresolution analysis to spilt the components

Decompose with **db9** wavelet, reconstruct R-wave with **Level 4**

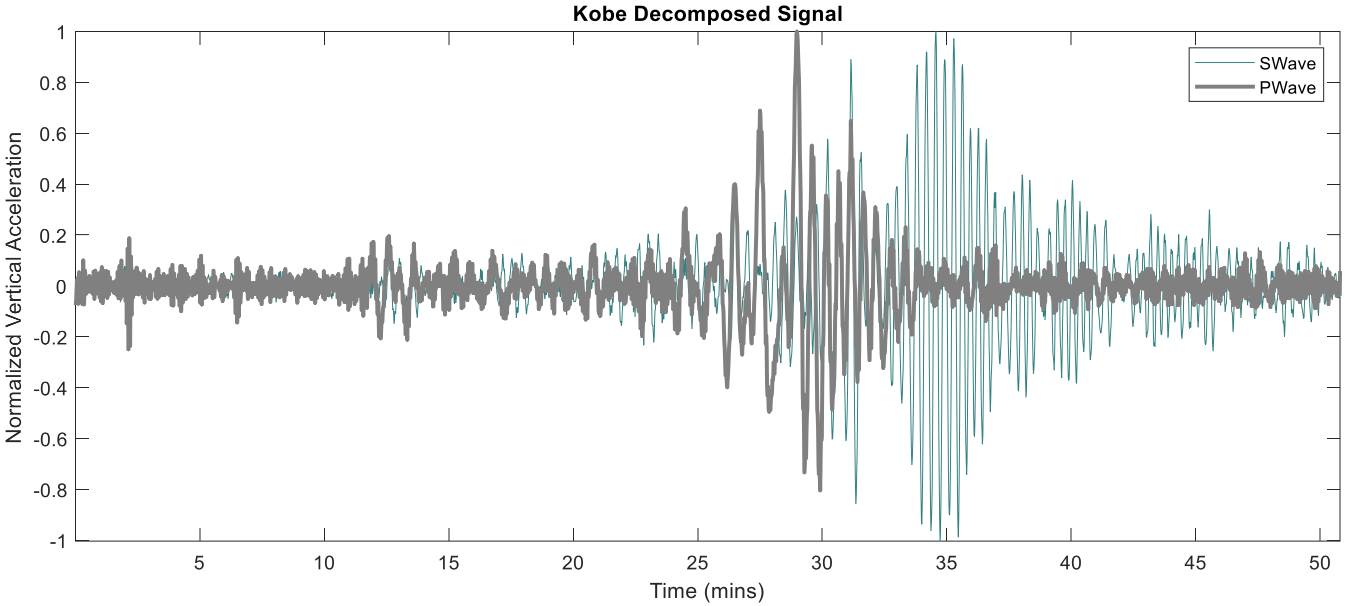


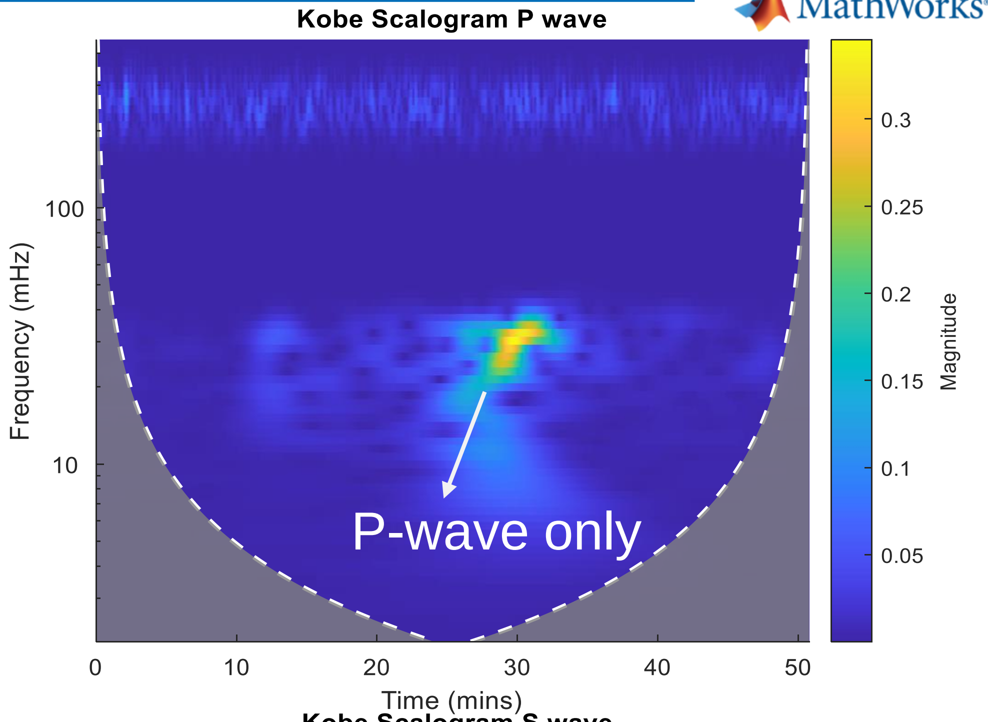
Original cwt

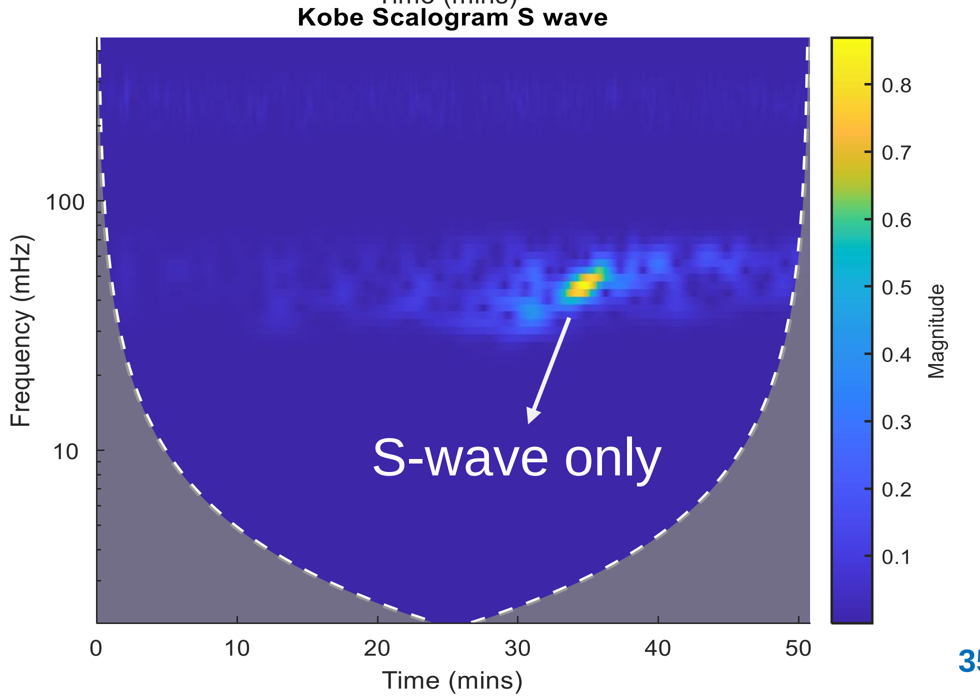




Cwt of reconstructed signals





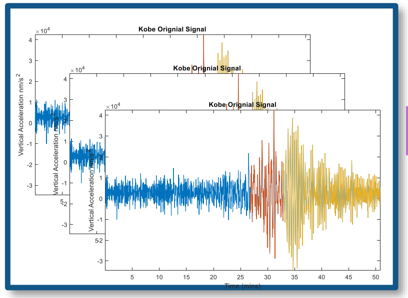


- P- and S-waves are separated
- Signal lengths are same, energies are preserved
- Removed the noise in data (Level 2 and Level 1)

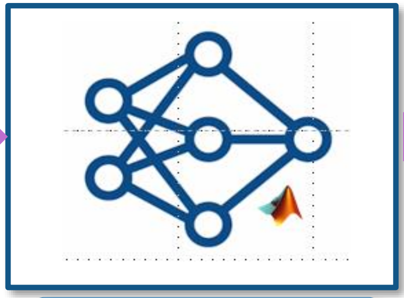
Developing AI algorithm for automated labeling

Traditional approach – **Very challenging**

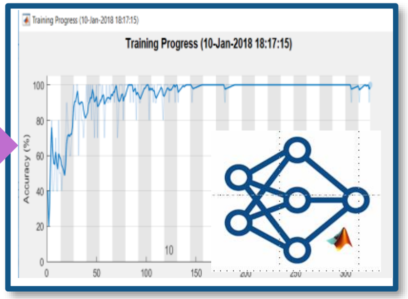
Training :



Manually labelled signal – v difficult

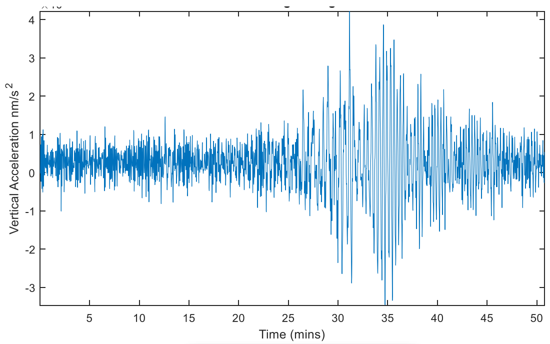


Train Deep Networks using RNNs

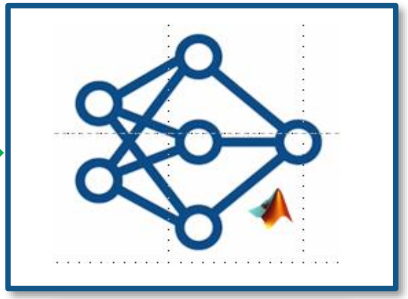


Train Network

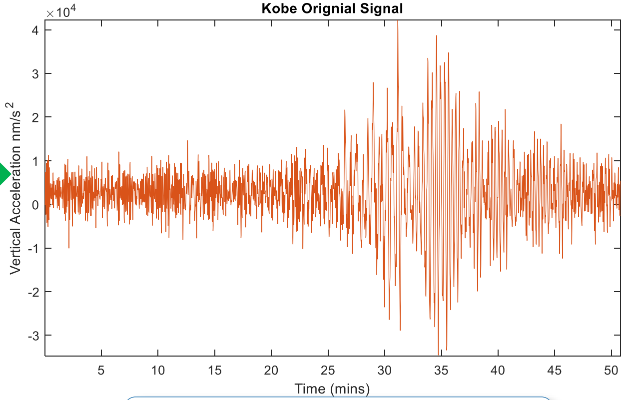
Deployed model :



New Data



Trained Model



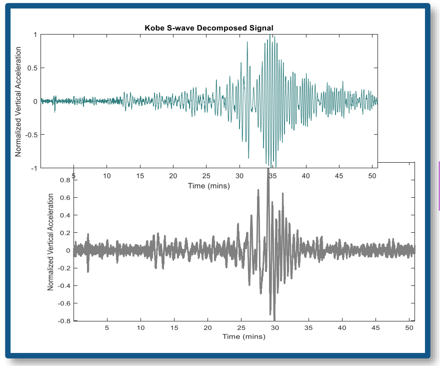
Labeled signal

Global accuracy of trained model low

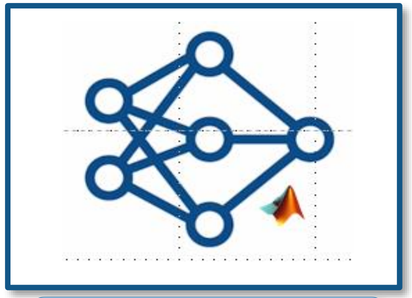
Developing AI algorithm for automated labeling

New Wavelets based approach: AI model works ☺

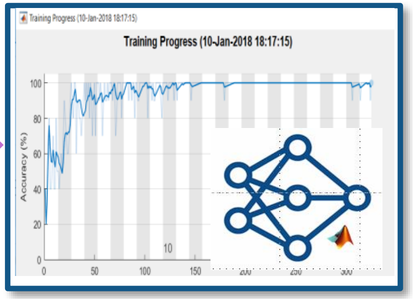
Training :



Signal Preprocessing with wavelets

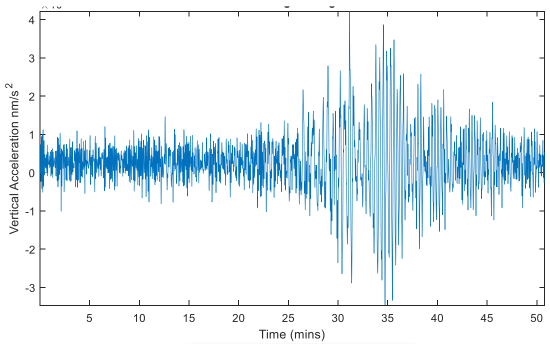


Train Deep Networks using CNNs

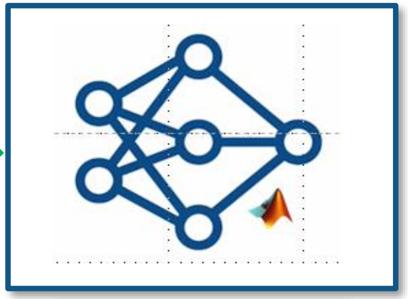


Train Network

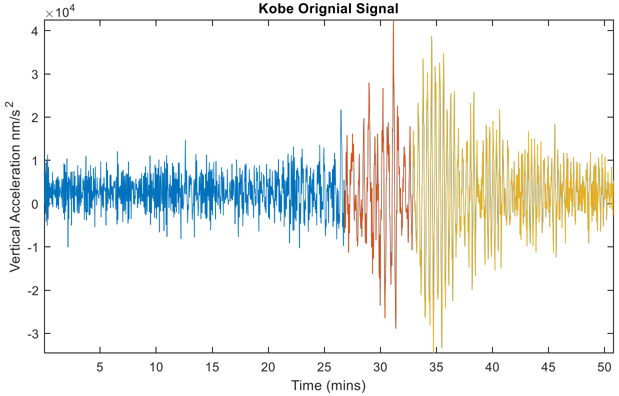
Deployed model :



New Data



Trained Model



Labeled signal

Global accuracy of trained model v high

Conclusion

- Use wavelets for analyzing real-world seismic signals
- Wavelet techniques such as multiresolution analysis can be very powerful for signal analysis and decomposition
- MATLAB provides single platform for signal analysis/preprocessing and developing and deploying AI models
  - Need not be signal processing expert.
  - Easy to use GUI-based apps to help you get started

What else in Wavelets ?

Discrete Multiresolution Analysis

Signal Analysis

wavedec	1-D wavelet decomposition
waverec	1-D wavelet reconstruction
dwtfilterbank	Discrete wavelet transform filter bank
dualtree	Kingsbury Q-shift 1-D dual-tree complex wavelet transform
idualtree	Kingsbury Q-shift 1-D inverse dual-tree complex wavelet transform
haart	Haar 1-D wavelet transform
ihaart	Inverse 1-D Haar wavelet transform
mlpt	Multiscale local 1-D polynomial transform
imlpt	Inverse multiscale local 1-D polynomial transform
dddtree	Dual-tree and double-density 1-D wavelet transform
idddtree	Inverse dual-tree and double-density 1-D wavelet transform
mlptrecon	Reconstruct signal using inverse multiscale local 1-D polynomial trai
wrcoef	Reconstruct single branch from 1-D wavelet coefficients
dwpt	Multisignal 1-D wavelet packet transform
idwpt	Multisignal 1-D inverse wavelet packet transform
wpdec	
wprec	
wpcoef	
wprcoef	
besttree	
wpspectrum	

Image Analysis

wavedec2	2-D wavelet decomposition
waverec2	2-D wavelet reconstruction
appcoef2	2-D approximation coefficients
detcoef2	2-D detail coefficients
haart2	2-D Haar wavelet transform
ihaart2	Inverse 2-D Haar wavelet transform
dualtree2	Kingsbury Q-shift 2-D dual-tree complex wavelet transform
idualtree2	Kingsbury Q-shift 2-D inverse dual-tree complex wavelet transform
qbiorthfilt	First-level dual-tree biorthogonal filters
qorthwavf	Kingsbury Q-shift filters
dddtree2	Dual-tree and double-density 2-D wavelet transform
idddtree2	Inverse dual-tree and double-density 2-D wavelet transform
dtfilters	Analysis and synthesis filters for oversampled wavelet filter banks
dddtreecfs	Extract dual-tree/double-density wavelet coefficients or projections
wrcoef2	Reconstruct single branch from 2-D wavelet coefficients
wpdec2	Wavelet packet decomposition 2-D
wprec2	Wavelet packet reconstruction 2-D
wpcoef	
wprcoef	
besttree	
depo2ind	
ind2depo	

Machine Learning and Deep Learning

waveletScattering	Wavelet time scattering
waveletScattering2	Wavelet image scattering
cwtfilterbank	Continuous wavelet transform filter bank

Filter Banks

Orthogonal and Biorthogonal Filter Banks

dwtfilterbank	Discrete wavelet transform filter bank
biorwavf	Biorthogonal spline wavelet filter
biorfilt	Biorthogonal wavelet filter set
coifwavf	Coiflet wavelet filter
dtfilters	Analysis and synthesis filters for oversampled wavelet filter ba
dbaux	Daubechies wavelet filter computation
dbwavf	Daubechies wavelet filter
fejerkorovkin	Fejér-Korovkin wavelet filters
orthfilt	Orthogonal wavelet filter set
rbiowavf	Reverse biorthogonal spline wavelet filters
qmf	Scaling and Wavelet Filter

Denoising

wdenoise	Wavelet signal denoising
wdenoise2	Wavelet image denoising
cmddenoise	Interval-dependent denoising
mlptdenoise	Denoise signal using multiscale local 1-D polynomial transform
wpdencmp	Denoising or compression using wavelet packets
measerr	Quality metrics of signal or image approximation
wdencmp	Denoising or compression
wnoisest	Estimate noise of 1-D wavelet coefficients
wvarchg	Find variance change points
wnoise	Noisy wavelet test data
ddencmp	Default values for denoising or compression
thselect	Threshold selection for denoising
wpthcoef	Wavelet packet coefficients thresholding
wthcoef	1-D wavelet coefficient thresholding
wthcoef2	Wavelet coefficient thresholding 2-D
wthresh	Soft or hard thresholding

Compression

wcompress	True compression of images using w
wdencmp	Denoising or compression
wpdencmp	

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