Characterization and Classification of Sonar Targets Using Ellipsoid Features

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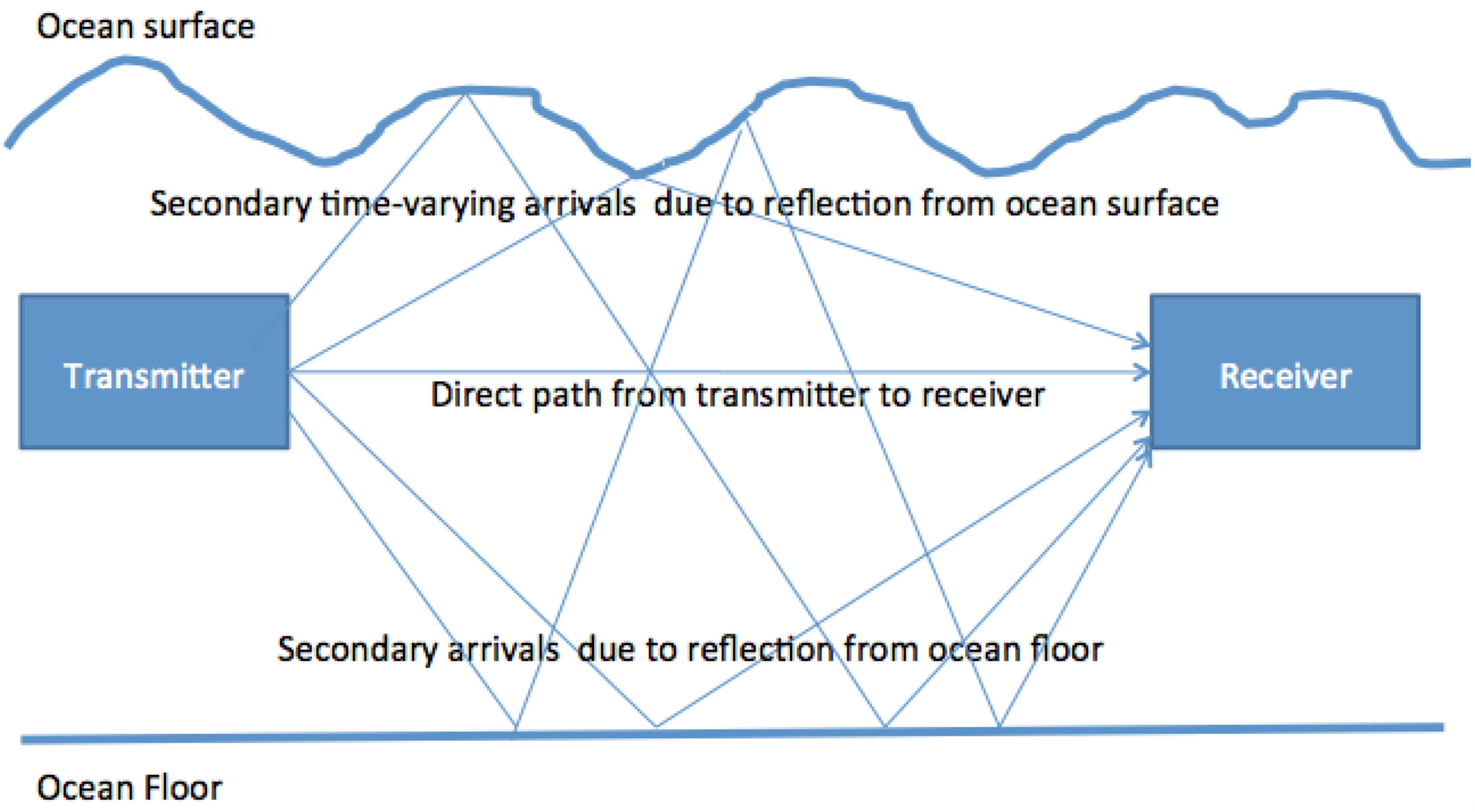
Problem Statement

- Characterization of underwater targets using active sonar is confounded by several factors:
  - **Many different and complex types of true and false targets in ocean environments**
  - Stochastic uncertainties in interference models due to shifting boundary conditions at the moving sea surface
  - Weak ground truths for naturally occurring objects that pose false alarm risks
  - Environmental clutter (e.g. a high activity environment such as a fishing port or busy harbor).

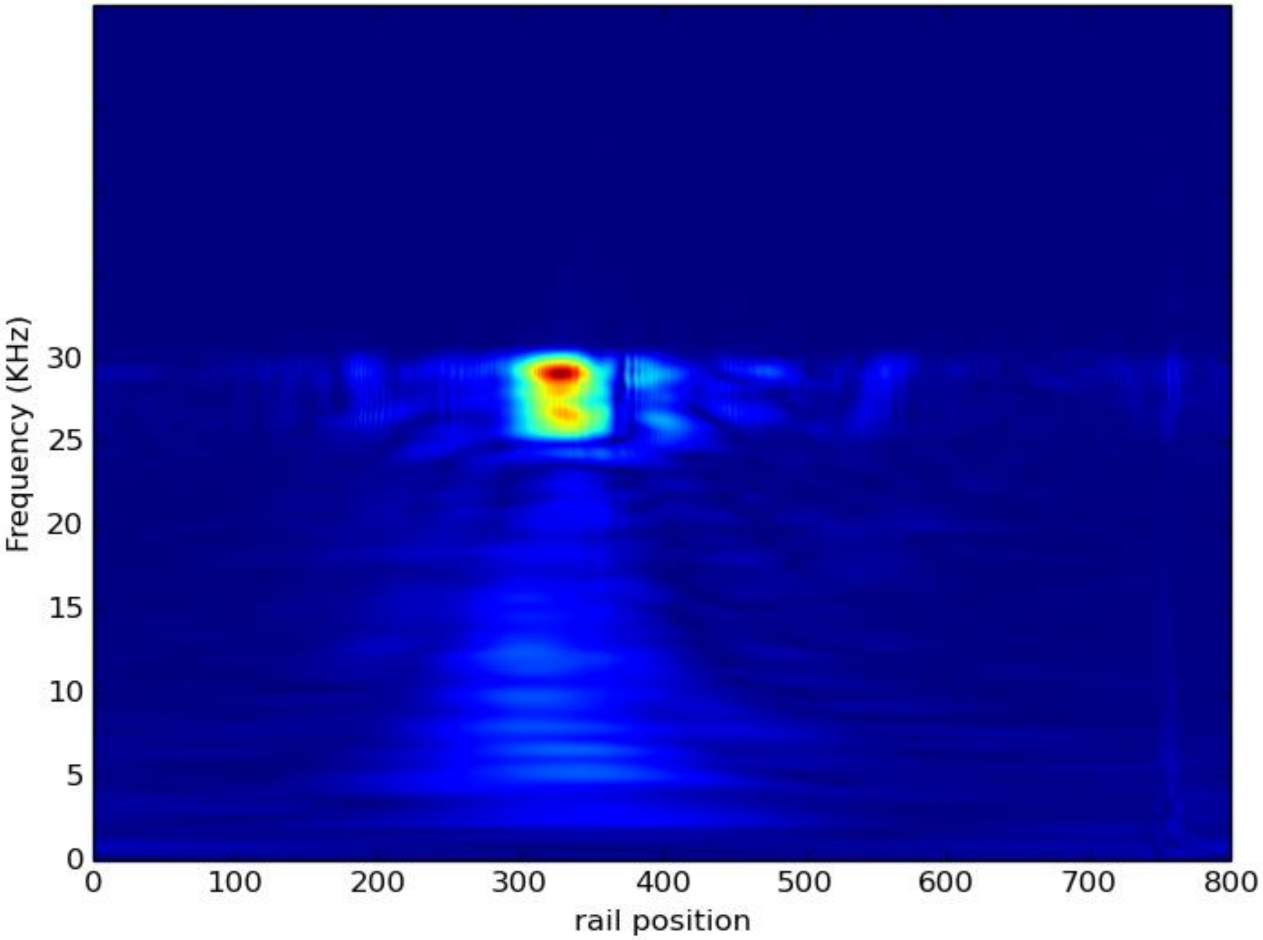
Problem Statement – Real Environments

Sonar detection in practical ocean environments difficult to model



Problem Statement – Acoustic Color Features

Acoustic Color Features of a steel UXO

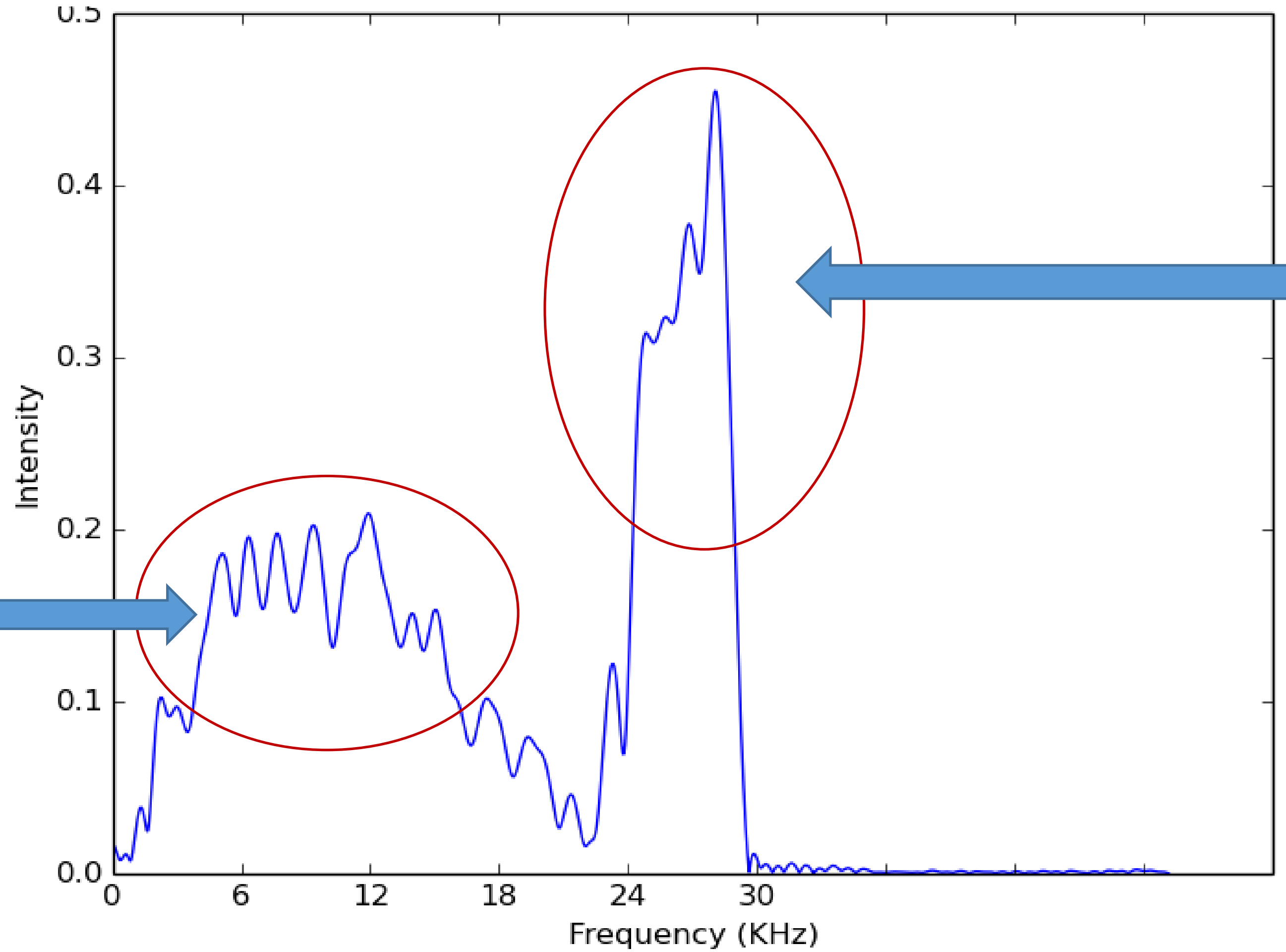


Data courtesy of the University of Washington's Applied Physics Laboratory

Problem Statement – Acoustic Color Sample

Acoustic Color Features at One Sensor Position for a Steel UXO at 0° Orientation

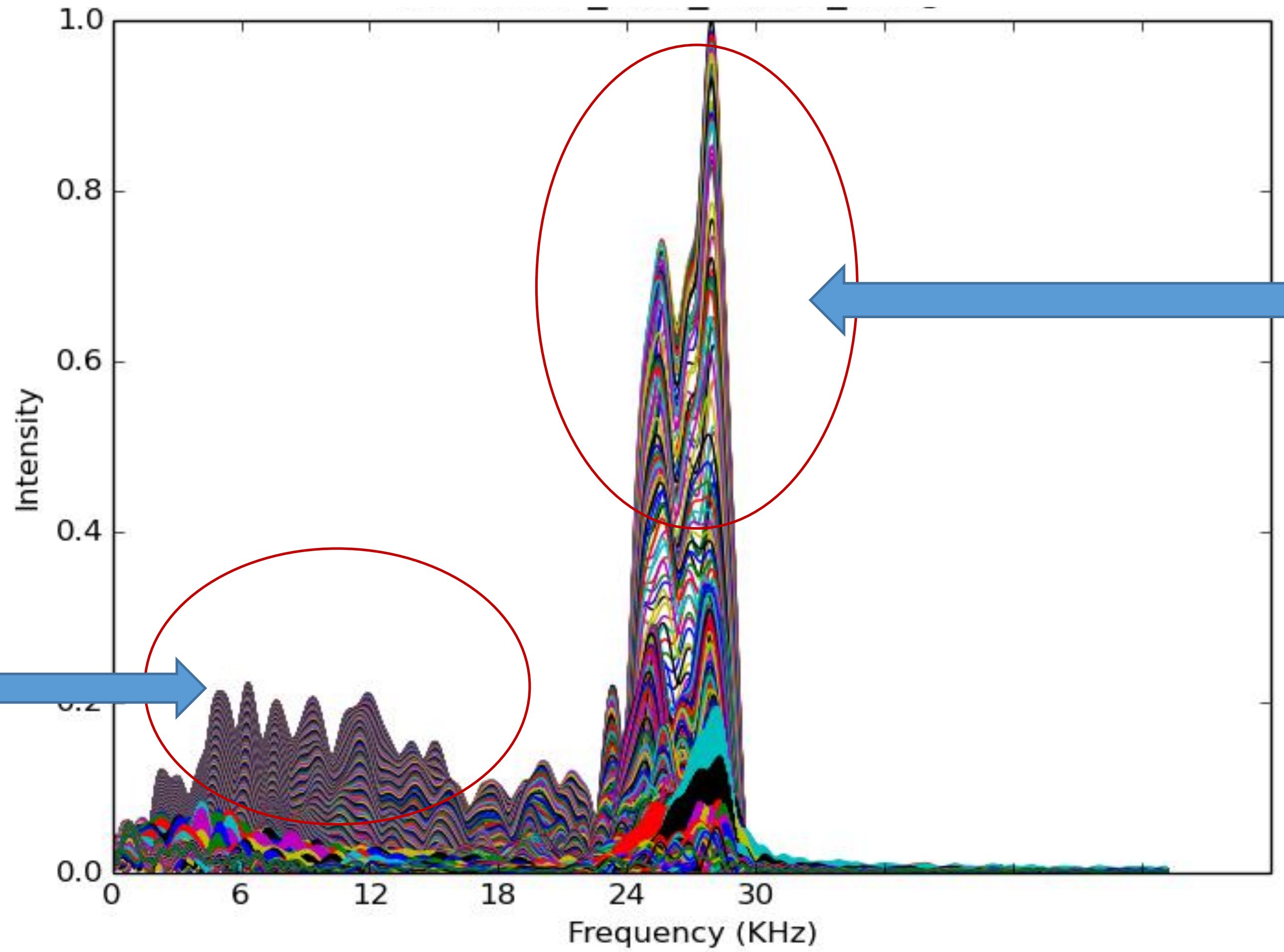
Secondary wave features convolved with multipath channel effects



Direct-path features showing primary wave response from target

Problem Statement – Acoustic Color Sample Composite

Acoustic Color Features at All Sensor Positions for a Steel UXO at 0° Orientation

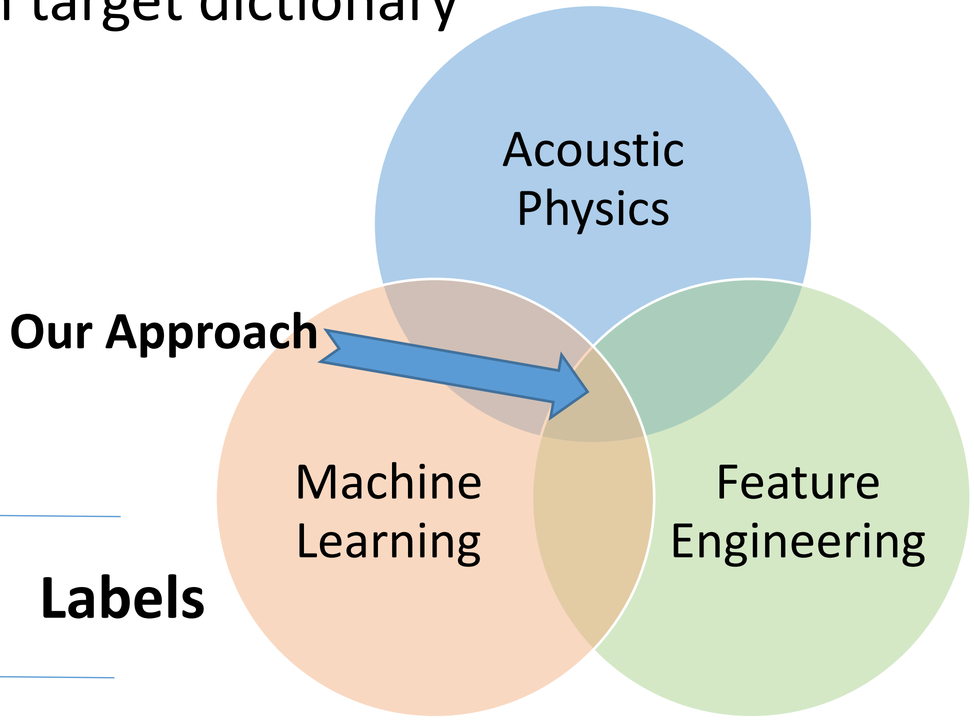


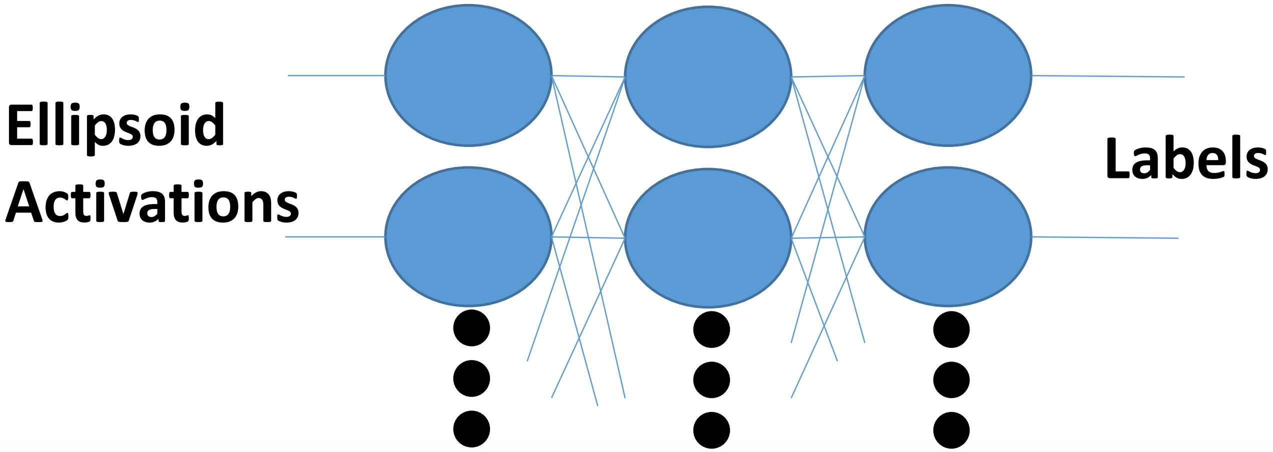
Smooth tractable deformations

Untractable severe deformations

Background Theory - Roadmap

- Combining acoustic physics with signal processing
  - Embed elastic wave microstructure in target dictionary
- Machine learning
  - Neural network





Background Theory – Acoustic Physics Models

Why elastic Waves?

- Resonance waves due to surface acoustic waves on the target [1]
- Highly dependent on material composition. [1]
- Sonar response can be modeled as a series of periodic Gaussians with exponential decay of peak magnitude. [2]

[1] SG Kargl, KL Williams,TM Marston, JL Kennedy, JL Lopes, "Acoustic response of unexploded ordnance (UXO) and cylindrical targets," Proc. OCEANS 2010 MTS/IEEE, Seattle WA 2010.

[2] Visscher, W. "Scattering of Rayleigh Surface Waves from Partly-Closed Surface-Breaking Cracks", Los Alamos, 1984

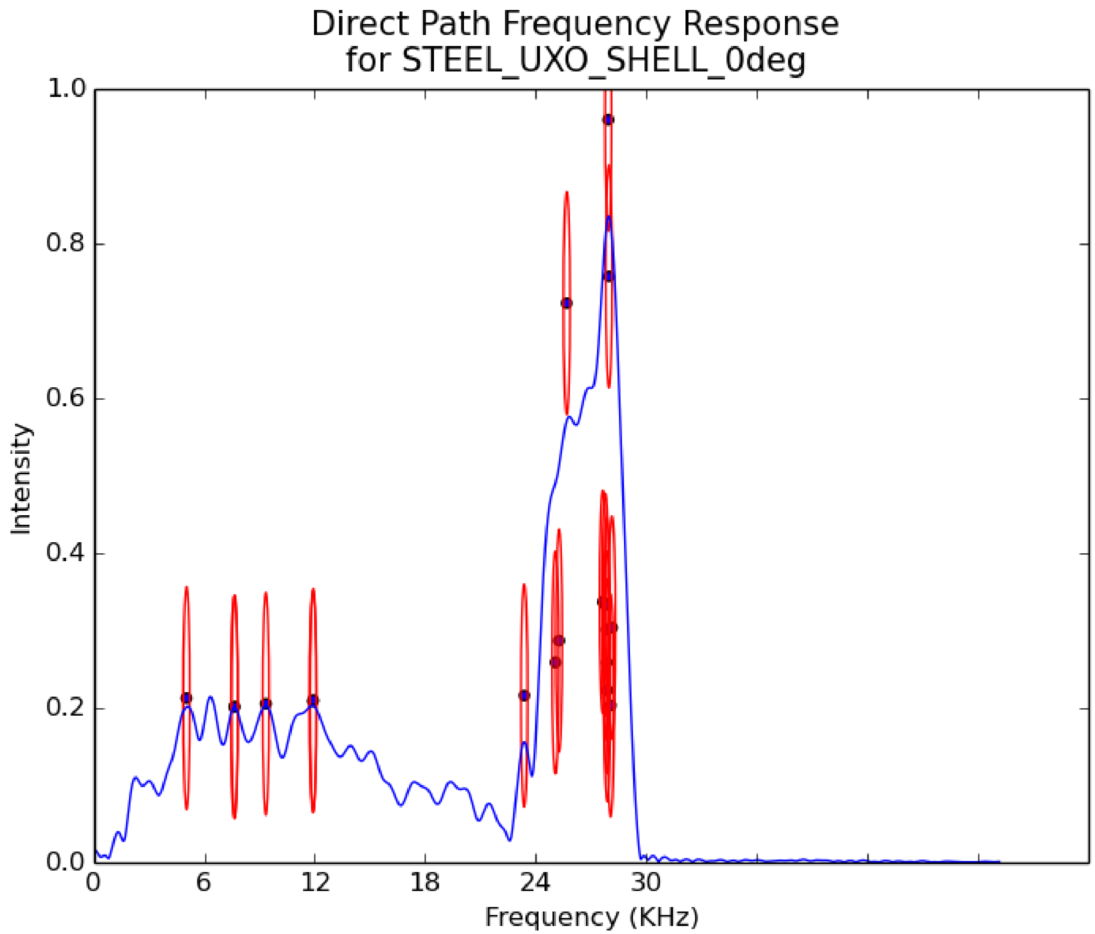
Background Theory – Machine Learning

Neural Network

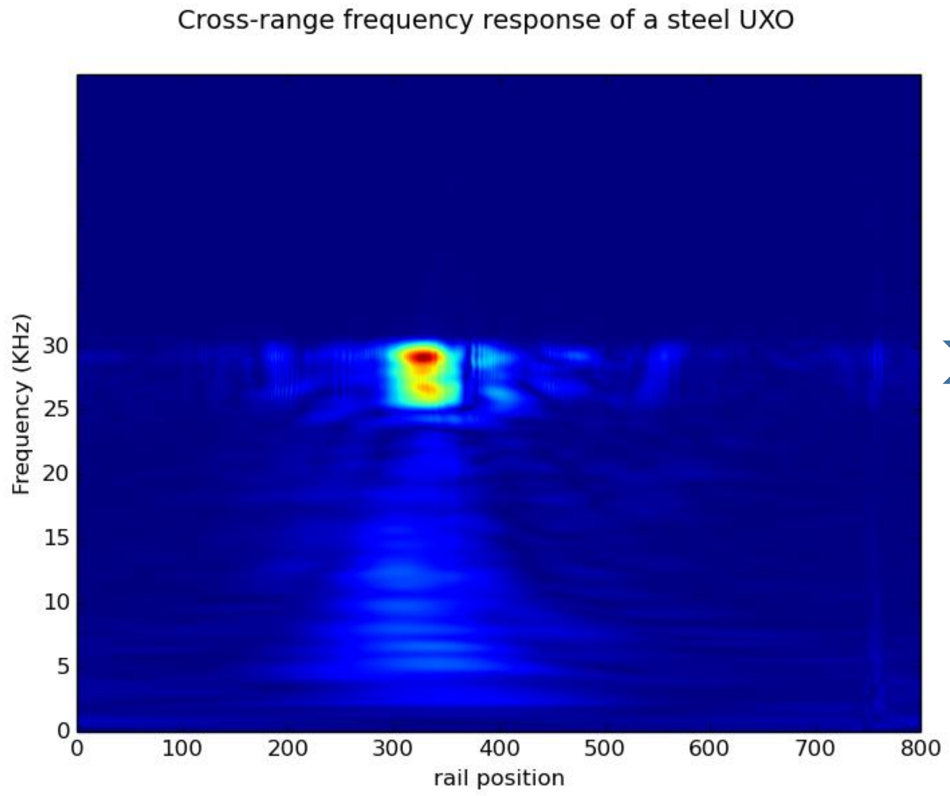
- Use a series of simple function to approximate more complex (and unknown) target function.
- Take a series of inputs to the first layer (input layer).
- The input layer is connected to some number of hidden layers.
- The hidden layers terminate with the output layer.
- Defined by
    - Weights at each layer
    - Updating process
    - Activation function (commonly tanh)

Technical Approach – Motivating Questions

- Can we build feature manifolds that take the full range of sensor positions into account?
- Will it improve discrimination at any one sensor position?

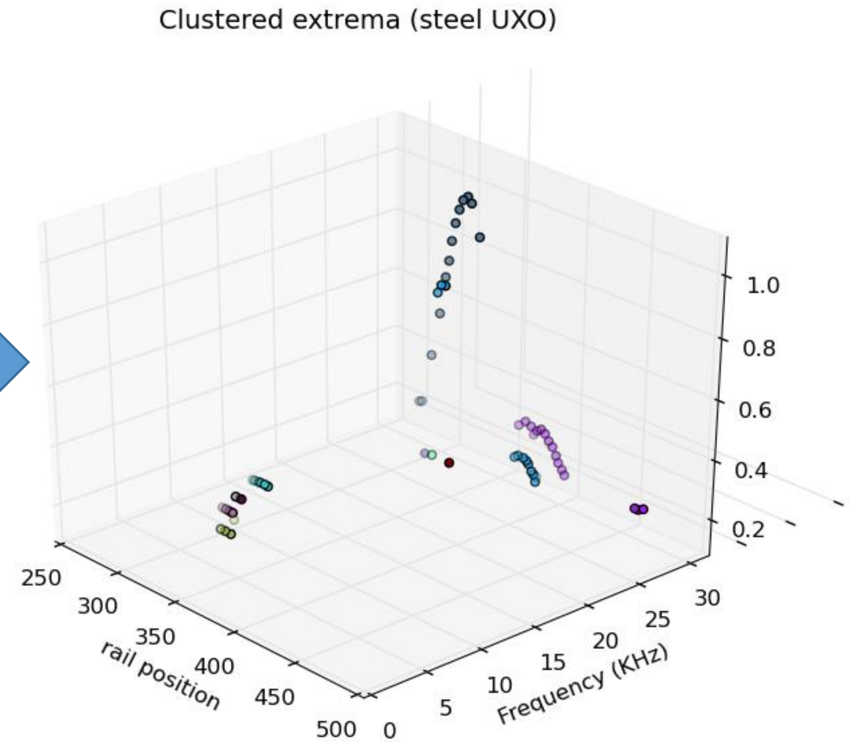


Technical Approach – Ellipsoidal Feature Manifolds



Extrema search

K-means clustering



Technical Approach – Manifold Construction

For each clustered group, ellipsoidal manifold is constructed using:
Mean of group -> manifold center
Standard deviation along each axis -> radius along that axis

Using the generalized ellipsoid equation: $$(\mathbf{x} - \mathbf{v})^{\mathrm{T}} A \, (\mathbf{x} - \mathbf{v}) = 1,$$

v is the center

A is a diagonal matrix, where $\lambda_i = \sigma_i$ for i in {x,y,z}

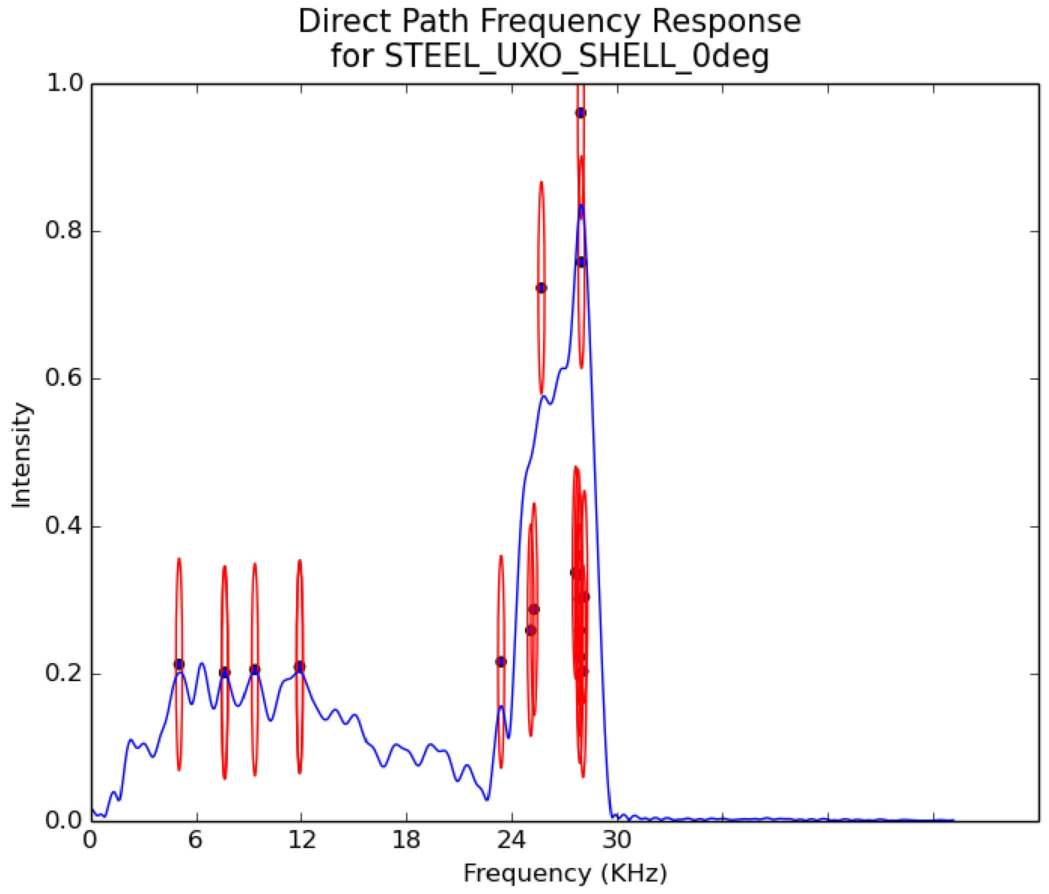
Technical Approach – Ellipsoidal Feature Manifolds

Technical aims:

- Build feature manifolds that take the full range of sensor positions into account
- Improve discrimination at any one sensor position using geometric feature engineering

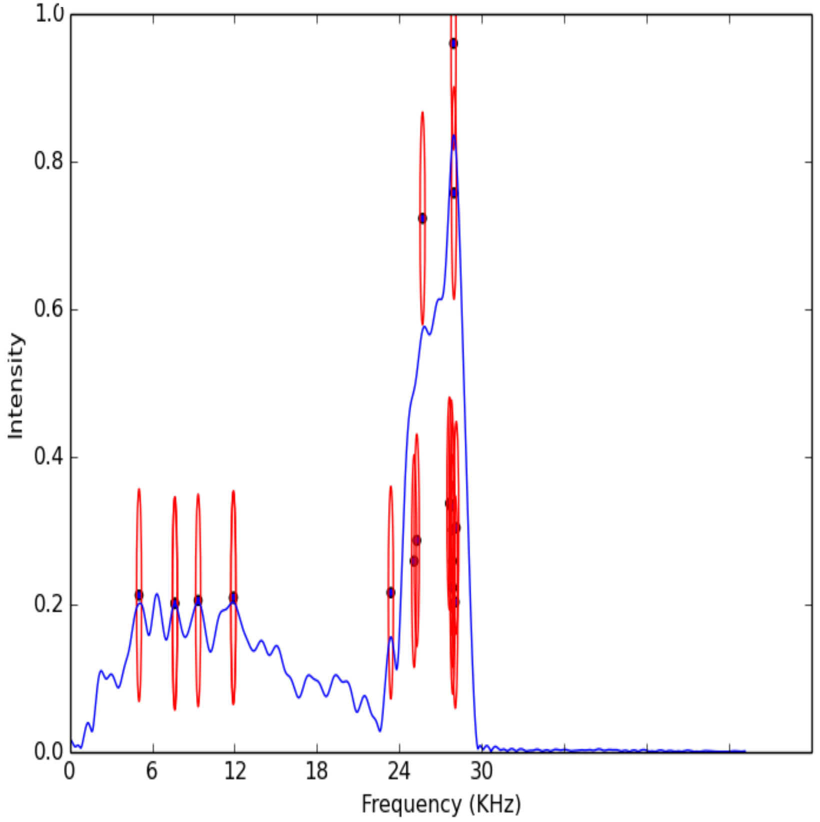
Key Steps

- Build ellipsoidal manifolds using peak topography information
- Use the cross-section of the manifold for discrimination



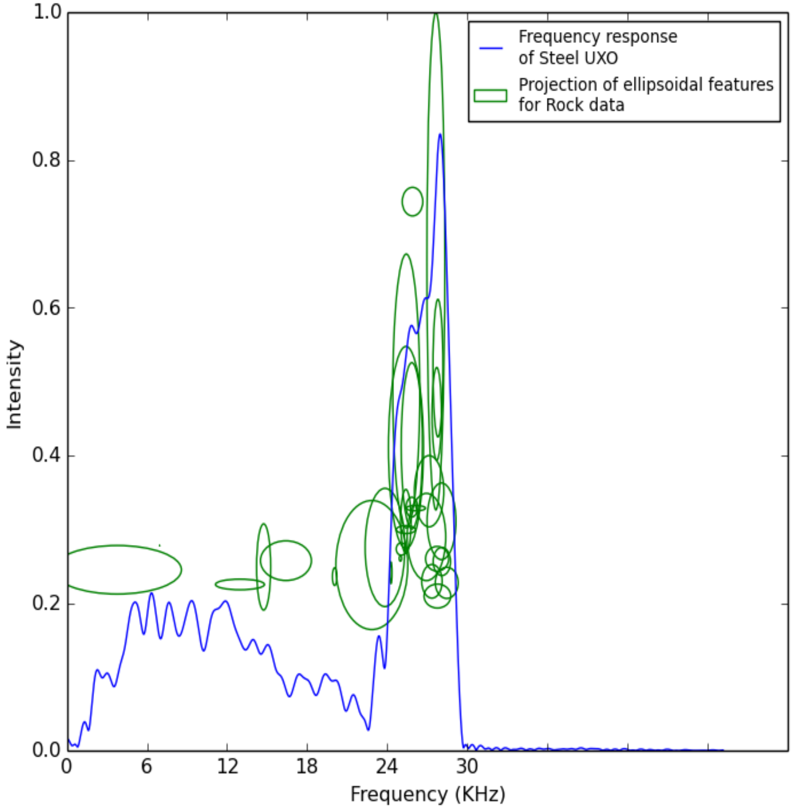
Technical Approach – Ellipsoidal Feature Manifolds

Comparing Steel UXO Ellipsoids to a Steel UXO Response



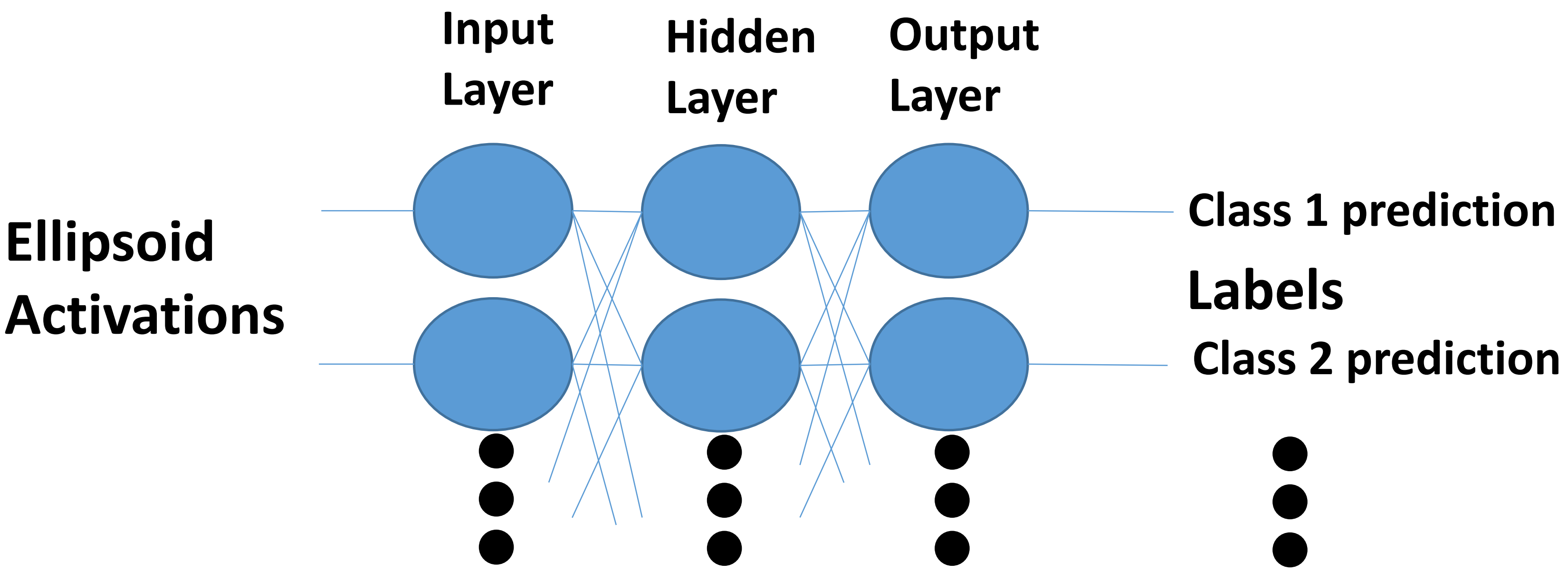
Ellipsoidal manifolds correlate very well to in-class samples and very poorly to inter-class samples

Comparing Rock Ellipsoids to a Steel UXO Response



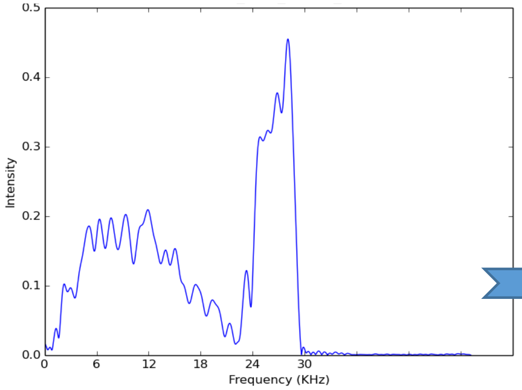
Technical Approach – Training & Classification

- Approach for classification:
  - Cull overlapping ellipsoids from consideration.
  - Use remaining ellipsoids as inputs to a neural network.
  - **Extrema within an ellipsoid activates the input node.**
  - Train the neural network.

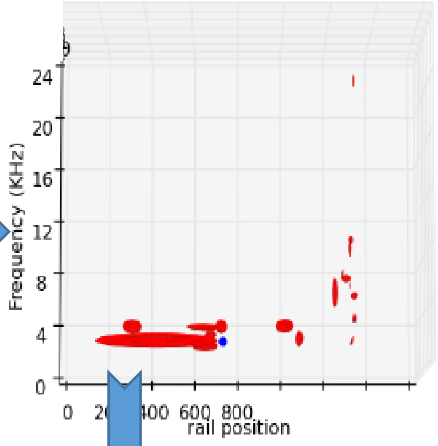


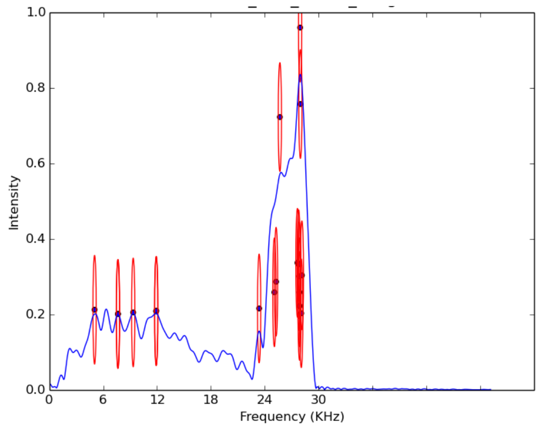
Technical Approach – Classification Process

Acoustic Color Features

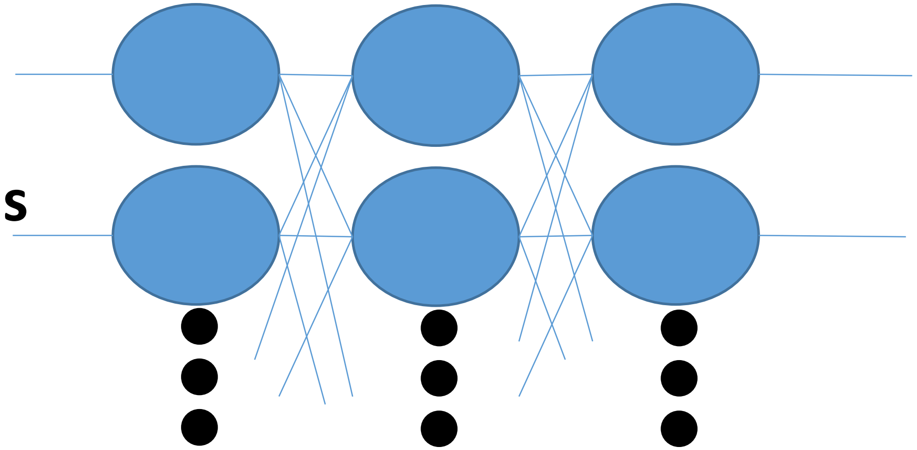


Extrema Matches to Ellipsoid Dictionary



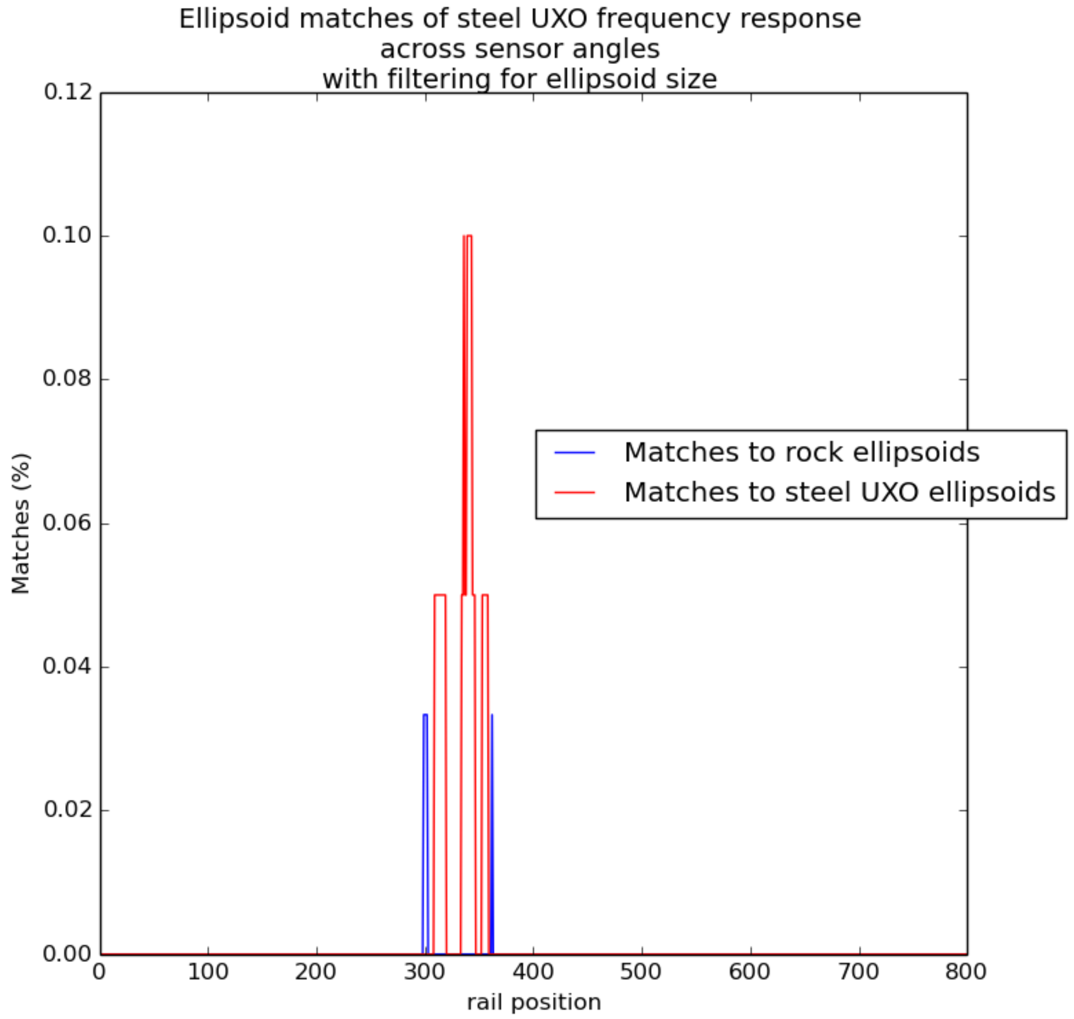


Ellipsoid Activations



Labels

Results – Matches Across Sensor Range



Results – Comparison

Correlations of steel UXO target data against different templates and techniques			
	Steel UXO	AL UXO	Rock
Cross Correlation	1	0.907	0.947
Ellipsoid match	0.1	0	0

While in-class matching performance is lower, inter-class matches are highly selected against

Conclusions

Advantages of proposed method:

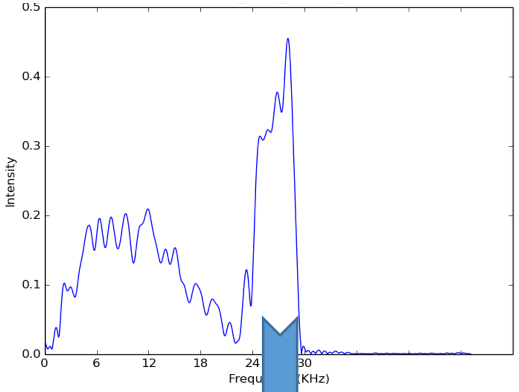
- Results in excellent classification for direct or near-direct sensor orientations.
- Excellent rejection of false positives

Ongoing challenges:

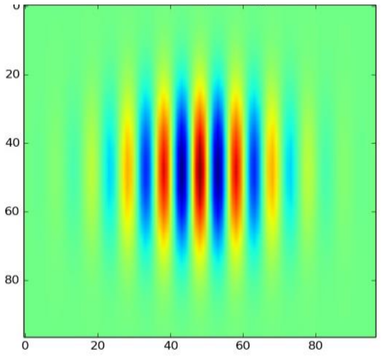
- Poor discrimination range over diversity sensor positions.
- Poor robustness to changing target orientation.

Continuing work: Combination of Feature Types

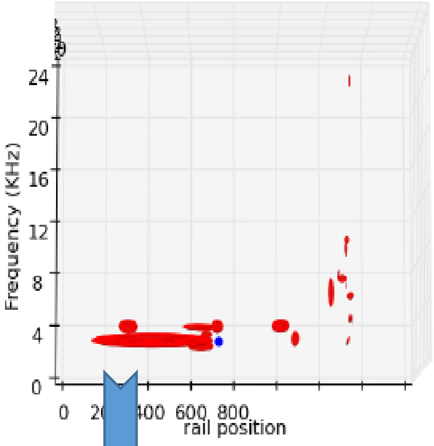
Acoustic Color Features



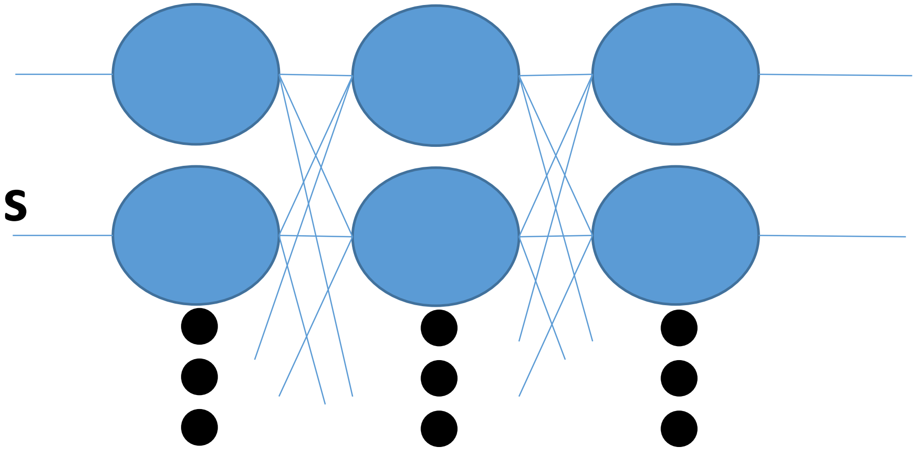
Gabor Feature Filter



Extrema Matches to Ellipsoid Dictionary

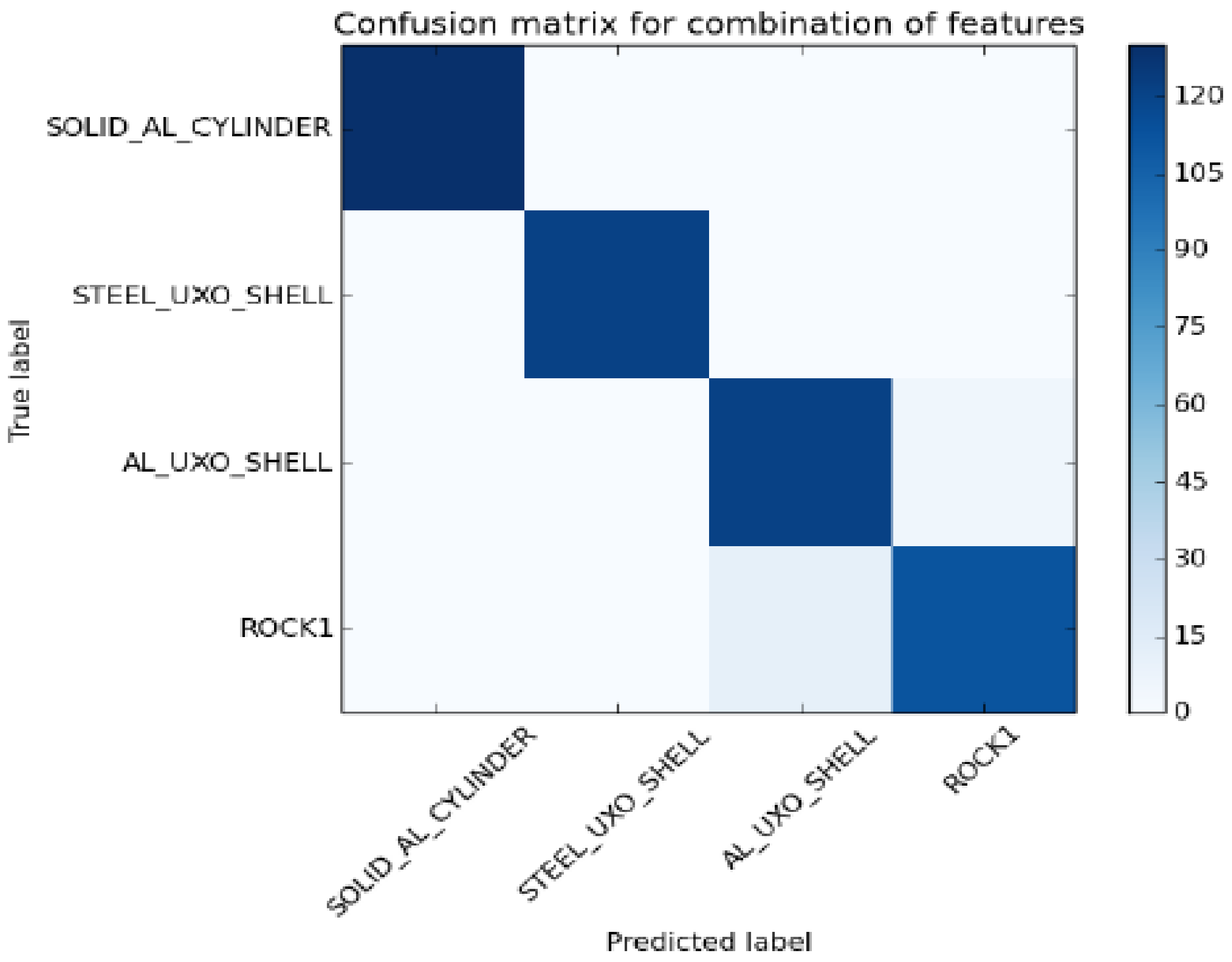


Ellipsoid Activations



Labels

Continuing work: Combination of Feature Types



Confusion matrix over full range, using the ellipsoids for four different Gabor feature filters: 5-fold cross validation accuracy of 95%

Acknowledgement

The authors would like to thank the University of Washington's Applied Physics Laboratory for providing public-domain active sonar field data, used for validation of techniques above.

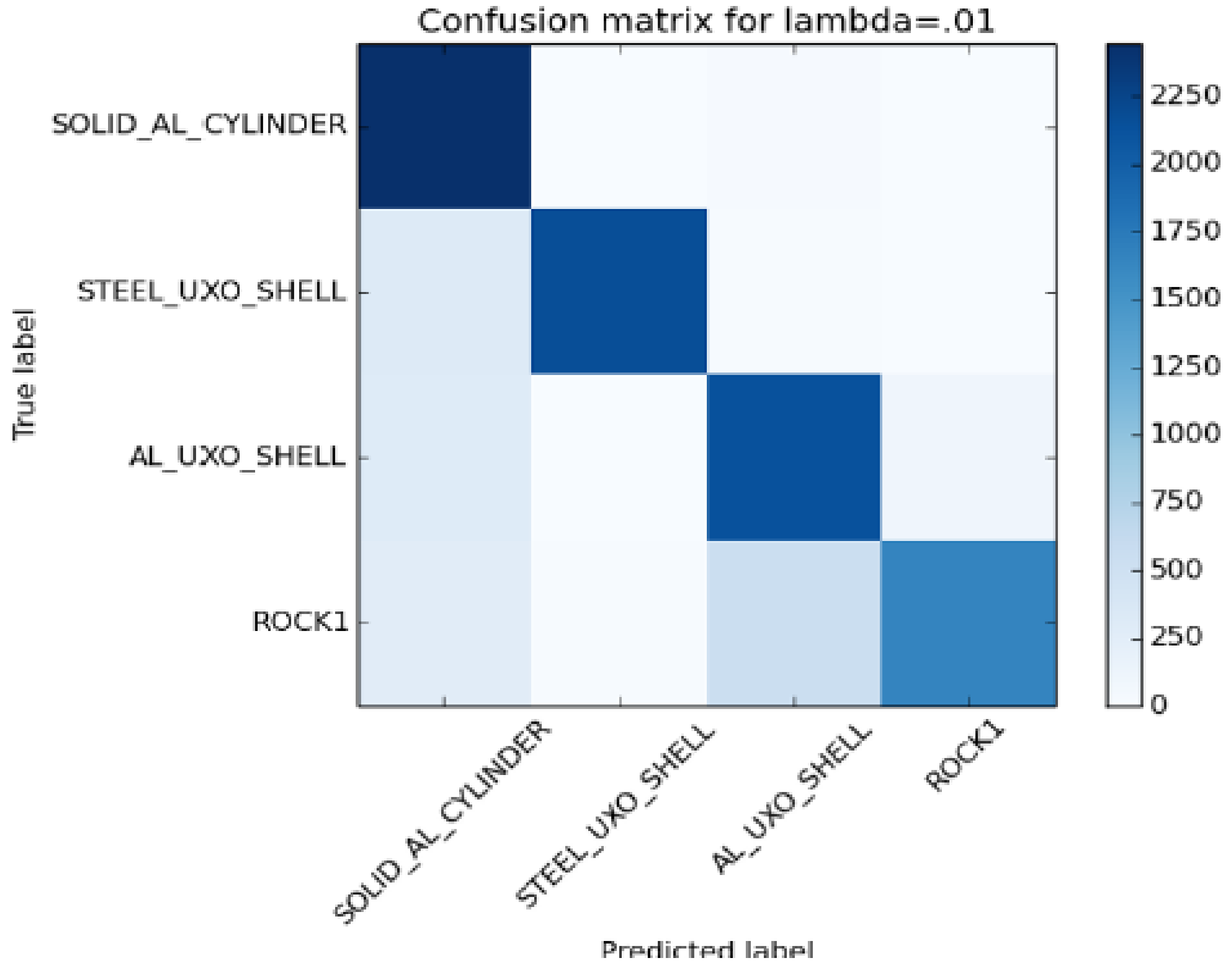
Questions

Appendix – Applications to Other Feature Sets

- Can we combine both approaches?
  - Keep high quality feature filters from Gabor investigation.
  - Use ellipsoidal clustering to select high quality feature manifolds.

- How does it perform?

Appendix – Improvement to Baseline

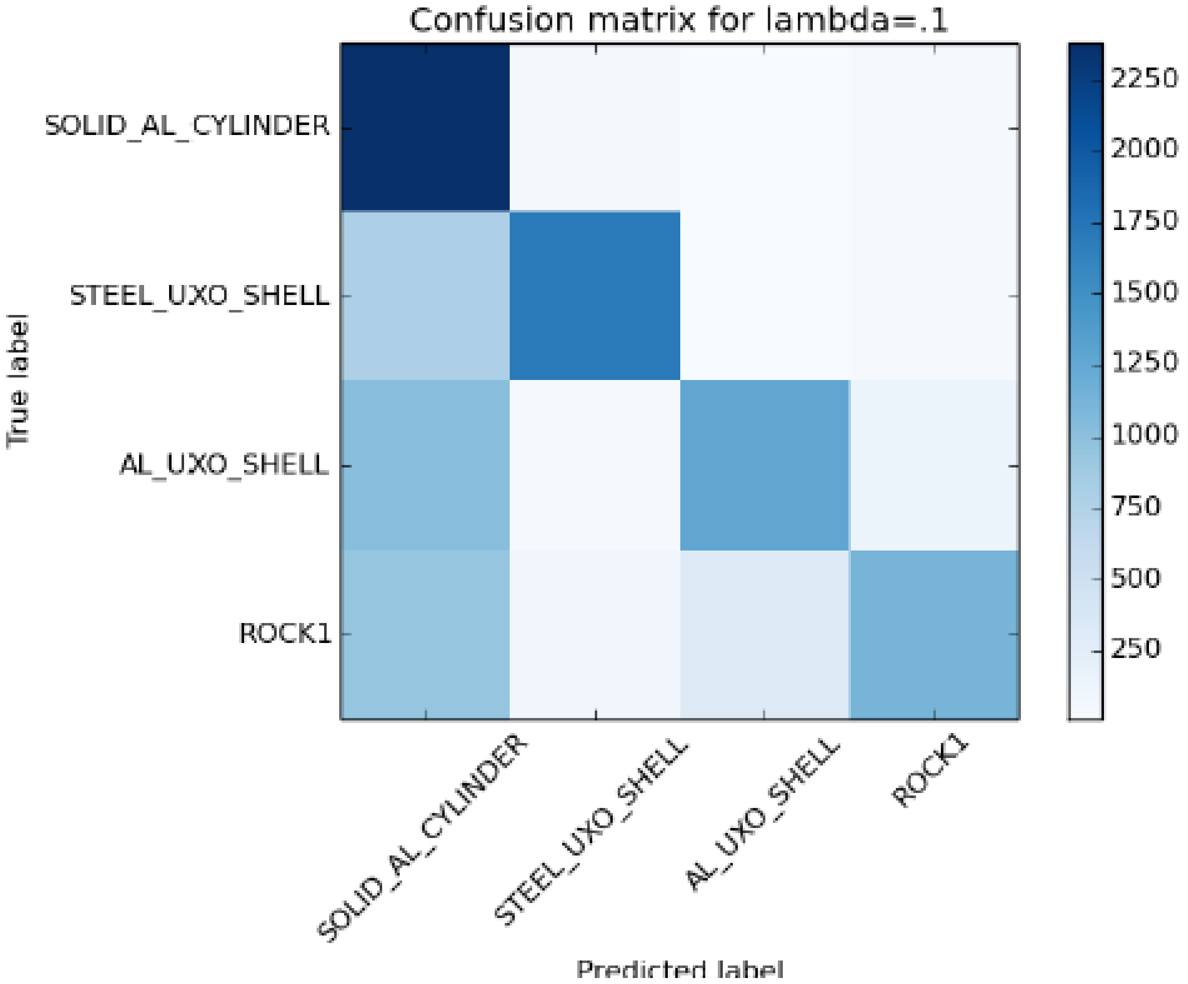


Confusion matrix over full range, using the ellipsoid clustering on a single kernel-transformed set: 5-fold cross validation accuracy of 84.3%

Appendix - Conclusions

- Our approach yielded high quality classification by:
  - Using our features engineered for isolation of high quality features.
  - Clustering the filtered features using our ellipsoidal method.
  - Combining the cluster activations with a neural network for classification.
- Ellipsoid method allows for high quality false positive and false negative rejection, while retaining good true positive performance
- Over all sensor positions, accuracy remains high when multiple Gabor-filtered features are combined.

Appendix – Baseline Accuracy



Confusion matrix over full range, using an SVM for classification of Gabor-modeled resonance features: 5-fold cross validation accuracy of 64.5%