Classification of Underwater Objects Using Synthetic Aperture Sonar Images and Waveforms[1]

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July 7, 2008

[1]Partially supported by ONR grant N00014–07-1-0166.

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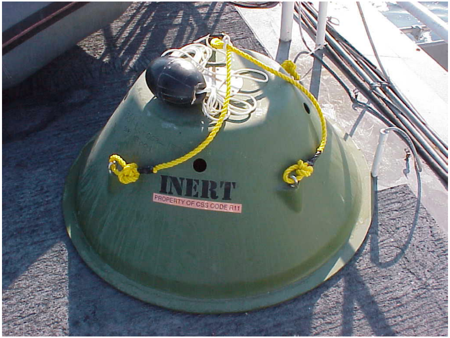
Outline

Outline

Objectives

- Detection of shallowly-buried objects using wideband FM sonar
- Classification of objects into mines or non mines
- Characterization of types of mines



(a) Manta

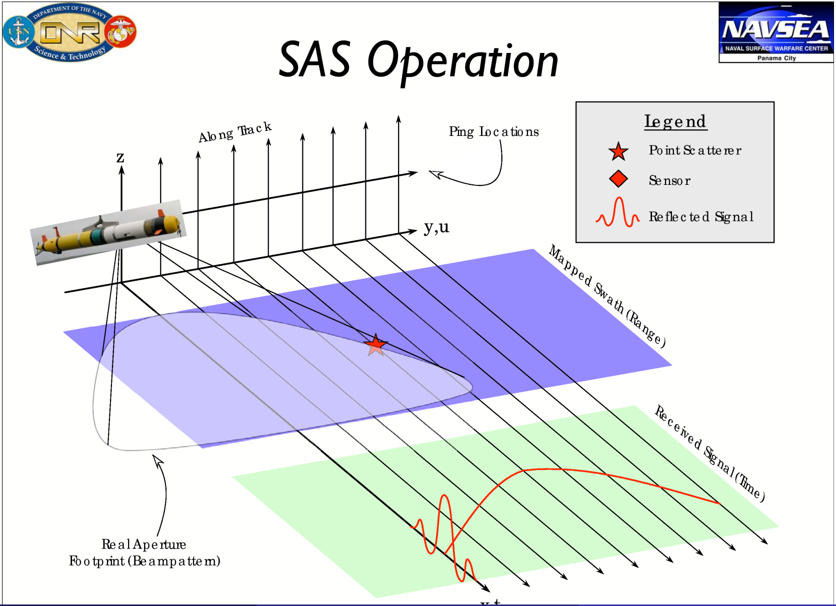
(b) Pdm1

Concept

- Synthetic Aperture Sonar (SAS) for wide range survey
- Buried Object Scanning Sonar (BOSS) for the detailed check

Outline

SAS Photos


SAS Operation
Legend
Point Scatterer
Sensor
Reflected Signal
Along Track
Ping Locations
z
y,u
Mapped Swath (Range)
Received Signal (Time)
Real Aperture
Footprint (Beampattern)
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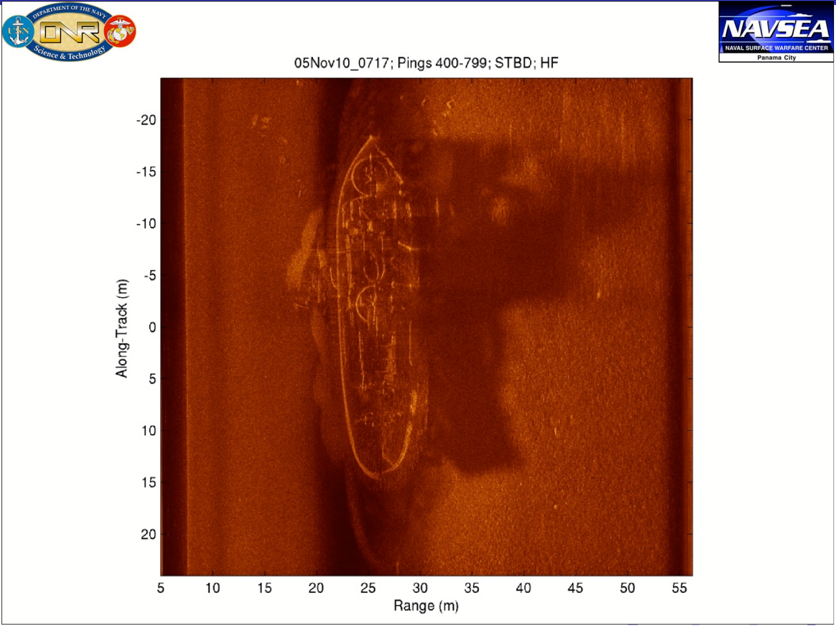
SAS Imagery



05Nov10_0717; Pings 400-799; STBD; HF
Along-Track (m)
-20
-15
-10
-5
0
5
10
15
20
Range (m)
5
10
15
20
25
30
35
40
45
50
55
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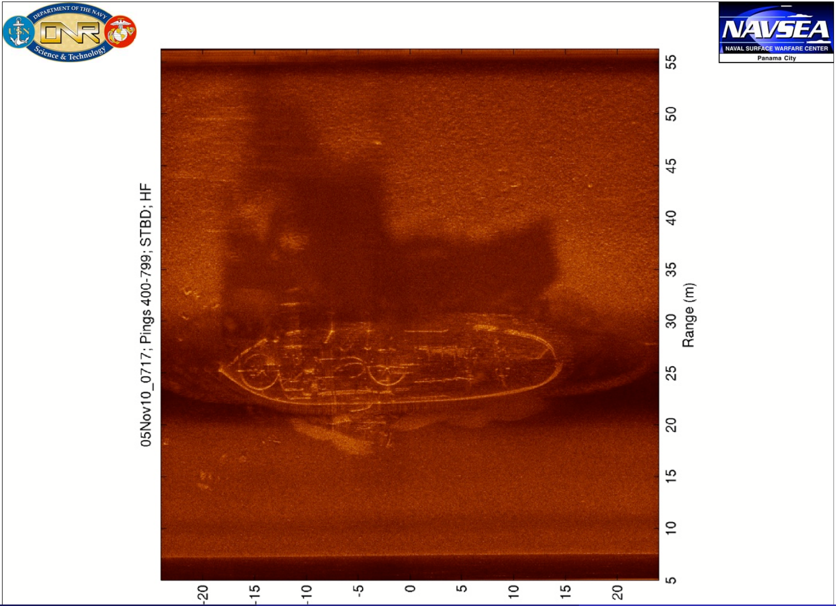
SAS Imagery . . .



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Panama City
05Nov10_0717; Pings 400-799; STBD; HF
Range (m)
55
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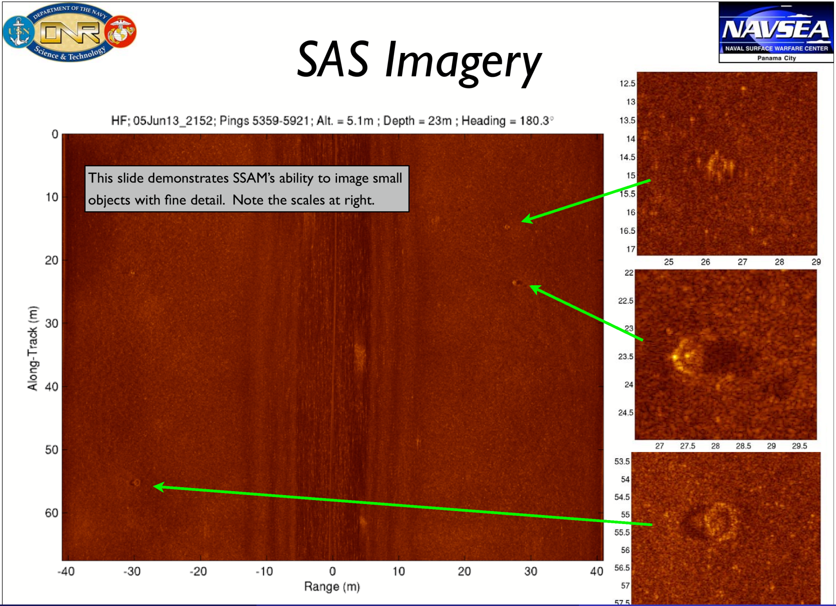
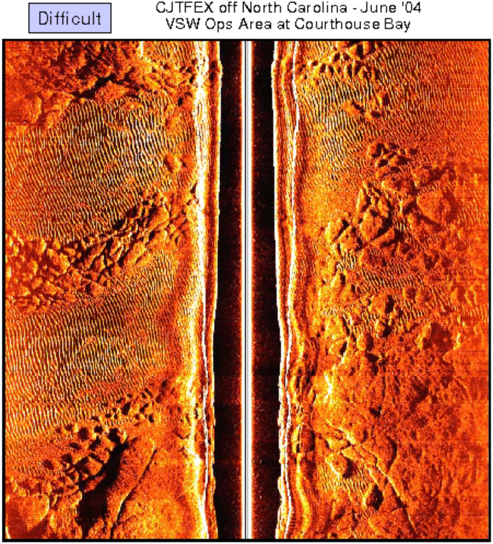
An Easier Example



A Tough Example



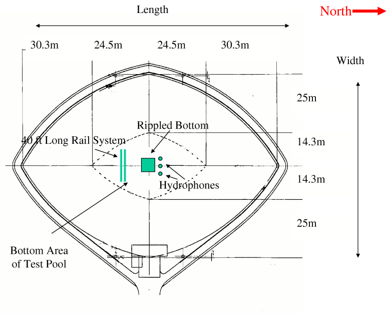
Outline

Our Overall Strategy

- Two important problems: Detection and Classification
- We tackle the classification problem first.
- We cast the detection problem later as a clustering problem.
- In both cases, shape information alone obtained from reconstructed images from sonar is often ambiguous even after improving image resolution using sophisticated interpolation algorithms
- Hence, we examine the part of the recorded raw waveforms scattered from the objects that are responsible to form the imaged object of interest.
- We will examine whether we can distinguish material content inside of suspicious objects from waveforms $\Longrightarrow$ acoustic impedance of material
- We first examine the experimental data obtained in a pond at Naval Surface Warfare Center (NSWC), Panama City, FL.

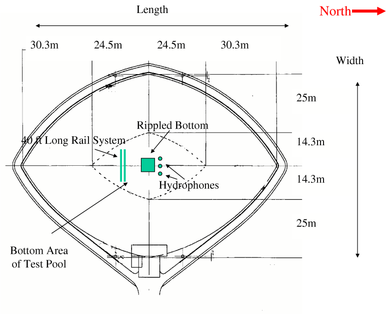
Outline

Experiment Setup

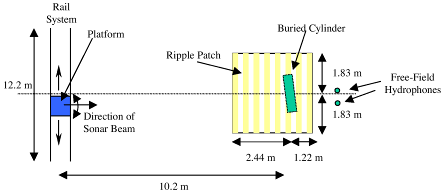


(a) Pond

Experiment Setup



(a) Pond



(b) Zoom up

Experiment Setup

(a) Rail system

(b) Sonar tower

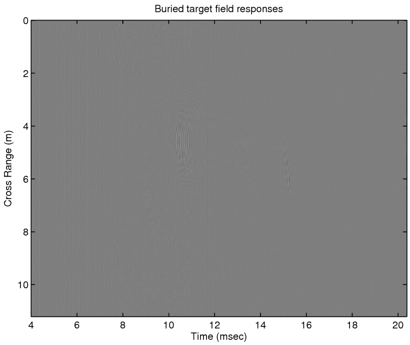
Experiment Setup . . .

- Source: 10 kHz – 50 kHz sinusoids; 0.2 msec duration
- Fast-time sampling rate: 500 kHz, i.e., $\Delta t = 2\,\mu\text{sec} \Longrightarrow \Delta x = 0.15$ cm
- Along-track sampling distance, $\Delta u = 2.54$ cm
- Sonar height above bottom $= 3.8862$ m
- Grazing angle $= 20$ degree
- Sound velocity in the pond water $= 1503$ m/s
- Ping rate: about 6–10 pings/sec
- Average 32 pings at each position

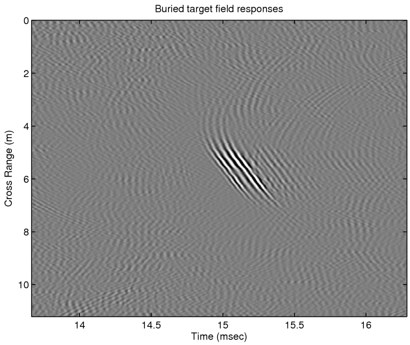
Experiment Setup . . .

We have three different sets of experiments:

- Experiment 1: Buried
  - Target: a solid aluminum cylinder (diameter: 30.5 cm; length: 1.52 m)
  - Target location: $x = 10.3$ m (or $t = 14.8$ msec), $y = 4.0 - 5.5$ m; buried about 10 cm below the rippled interface
  - A steel sphere (filled with air) of diameter 25.4 cm was placed in front of the target.
- Experiment 2: Proud
  - Target: a solid aluminum cylinder (diameter: 30.5 cm; length: 1.52 m)
  - Target location: the same as above
  - A sphere (filled with silicone oil) of diameter 35.6 cm was placed in front of the target.
- Experiment 3: Proud Short
  - Target: a shorter solid aluminum cylinder (diameter: 30.5 cm; length: 60 cm)
  - Target location: the same as above
  - A sphere (filled with silicone oil) of diameter 35.6 cm was placed in front of the target.



(a) Data



(b) Zoom up

Outline

Our Classification Strategy

Step 0: Reconstruct reflectivity images/scenes from SAS data

Step 1: Select objects of interest (at this point manually using a pointing device)

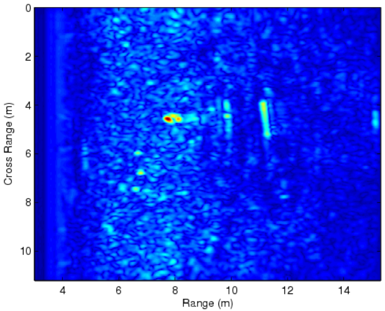
Step 2: Extract raw waveforms corresponding to the selected objects and align/straighten them

Step 3: Apply Local Discriminant Basis (LDB) algorithm to the waveforms

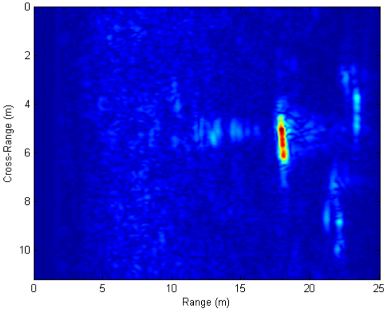
Step 4: Supply top k LDB coordinates to a classifier of one's choice (e.g., linear discriminant analysis, decision tree, support vector machine, ...)

Step 5: Validate the classification rule using test datasets

An Example in a Pond; Step 0: Reconstruct an Image

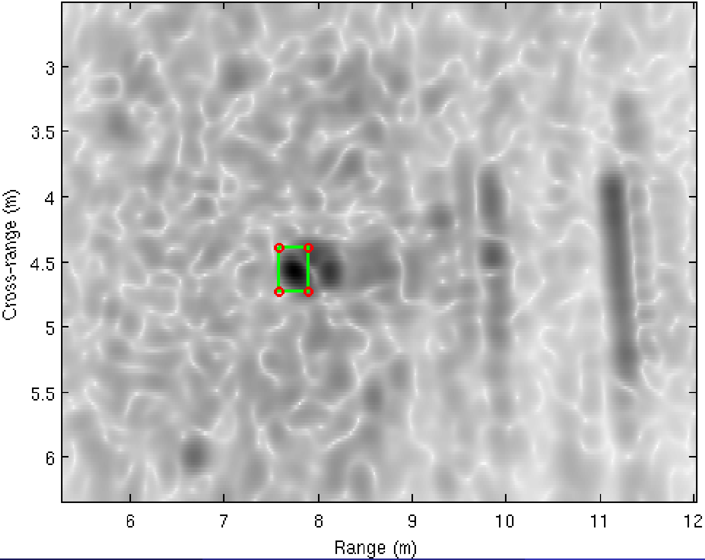


(a) Buried Cylinder (C1)

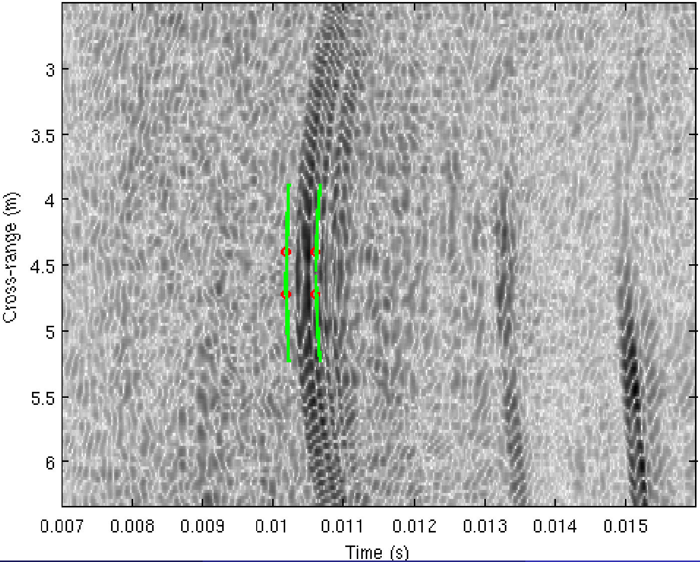


(b) Proud Cylinder (C2)

An Example in a Pond; Step 1: Select objects



An Example in a Pond; Step 2: Extract data



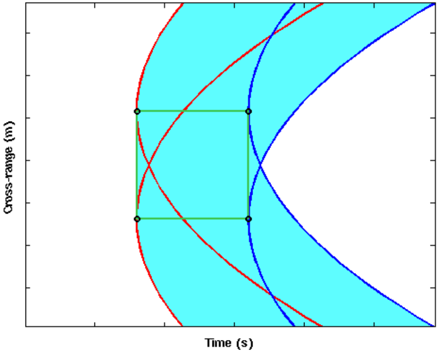
Step 2 details: Extraction/Alignment Algorithm

- Indicate the four points of rectangle. (Rectangle shown in green. Point shown in black.)
- Calculate dispersion of four points using dispersion relation

$$\left(\frac{ct}{2}\right)^2 = x_0^2 + (y - y_0)^2$$

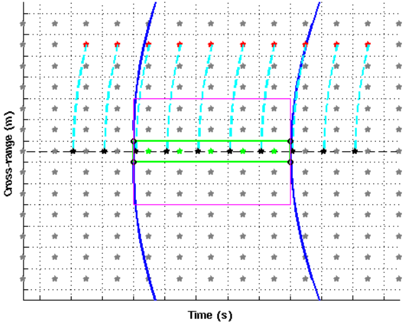
y - cross-range location of the transmitter/receiver
t - two-way travel time of the signal
(x_0, y_0) - location point source
c - speed of sound through water
(red and blue lines show dispersion of points)

- Use the union of the dispersed points corresponding to all the points in the rectangle to form envelope (indicated in cyan).

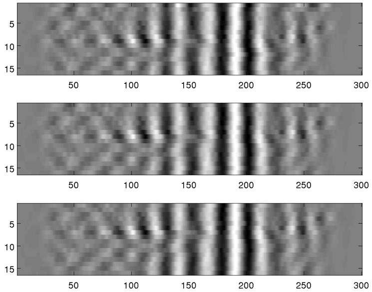


Step 2 details: Extraction/Alignment Algorithm . . .

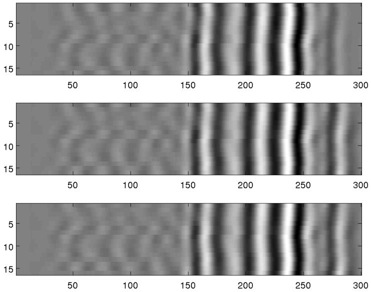
- Assume the object to be extracted consists of a collection of horizontal lines (e.g., a magenta rectangle);
- Construct a rectangular envelope for each horizontal line segment (green points);
- Extract waveform samples contained in envelope and within half of signals wavelength of envelope (red points);
- Using the dispersion relation, map extracted points to their location if dispersed from the center line (black points);
- Interpolate these mapped points to find the values of waveforms at the desired time locations (the same as the center line time samples);
- Repeat this procedure for all the horizontal line segments in the object.



An Example in a Pond; Step 2: Extract data . . .



(a) Cylinder Waveforms

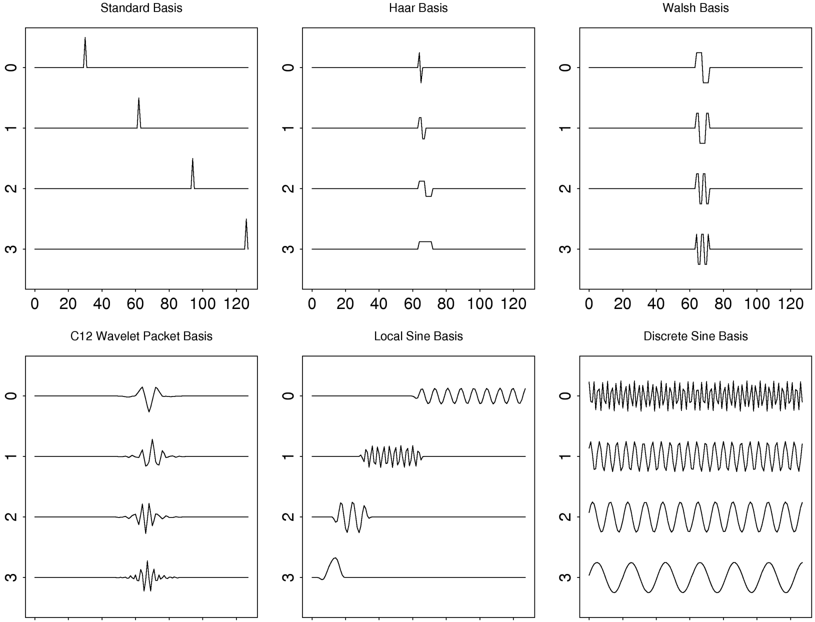


(b) Sphere Waveforms

Step 3: Apply Local Discriminant Basis (LDB) Algorithm

- Developed by Saito and Coifman (1993–5) for extracting localized discriminant features from data using various basis dictionaries (e.g., wavelet packets, local cosines, etc.)
- Selects a complete basis from a specified dictionary by optimizing some discriminant measure of the basis coordinates
- Top few coordinates in terms of the discriminant measure are then fed to any classifier of one's choice (Linear Discriminant Analysis, Decision Trees, Support Vector Machine, . . .)
- LDB and its variants have been applied to: geophysical signal/image classification; noise reduction in hearing aids; diagnostics of mammography; radar target discrimination; neural spike detection and sorting; face detection, etc.
- Searching the keyword "local discriminant basis" in **google.scholar.com** immediately shows its impact

Examples of Basis Dictionaries



An Example in a Pond; Step 3: LDB

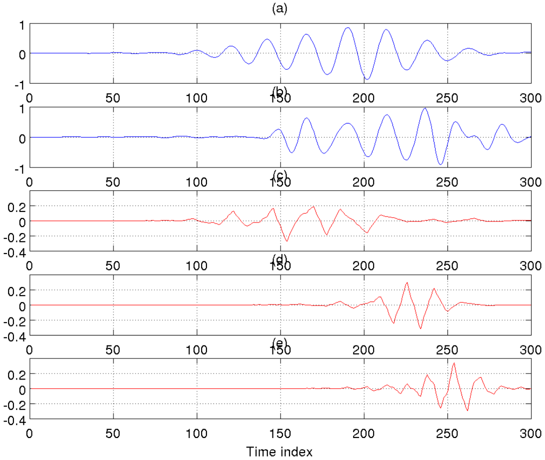


Figure: (a) Average $C1$ waveform; (b) Average $S1$ waveform; (c) The LDB vector #1 trained on $(C1, S1)$; (d) The LDB vector #2 trained on $(C1, S1)$; (e) The LDB vector #3 trained on $(C1, S1)$.

An Example in a Pond; Step 3: Top 3 LDB coordinates

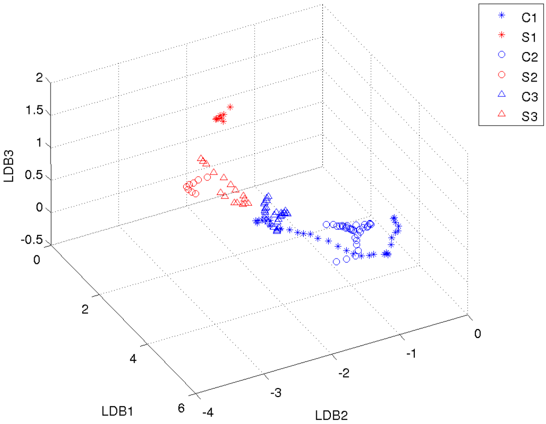


Figure: Extracted waveforms projected onto the top 3 LDB coordinates. Each point represents a single waveform. The LDB was computed on the $(C1, S1)$ dataset.

Outline

Future Plan

- Examine the robustness of the extracted LDB features
- Investigate a new and robust discriminant measure based on Earth Mover's Distance (EMD), which is related to optimal transport (or the Monge-Kantorovich) problem
- Modify LDB to accept complex-valued signal or phase information

References

- The following articles are available at
  http://www.math.ucdavis.edu/~saito/publications/
  - B. Marchand, N. Saito, and H. Xiao: "Classification of objects in synthetic aperture sonar images," *Proceedings of 14th IEEE Workshop on Statistical Signal Processing*, pp. 433–437, 2007 (a bit obsolete).
  - N. Saito and R. R. Coifman: "Local discriminant bases and their applications," *J. Mathematical Imaging and Vision*, vol. 5, no. 4, pp. 337–358, 1995 (Invited Paper).
  - N. Saito, R. R. Coifman, F. B. Geshwind, and F. Warner: "Discriminant feature extraction using probability density estimation and a local basis library," *Pattern Recognition*, vol. 35, no. 12, pp. 2841–2852, 2002.
- C. L. Nesbitt and J. L. Lopes: "Subcritical detection of an elongated target buried under a rippled interface," *Oceans '04, MTS/IEEE Techno-Ocean '04*, vol. 4, pp. 1945–1952, 2004.

Thank you very much for your attention!

Acknowledgment

- Dan Cook (formerly NSWC-PC)
- Gerry Dobeck (NSWC-PC)
- Carrie Dowdy (formerly NSWC-PC)
- Richard Holtzapple (NSWC-PC)
- Joe Lopes (NSWC-PC)
- ONR
- NSF