A multi-angle acoustic scattering apparatus for zooplankton and fish

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Outline

• Background and motivation
  – Previous studies, backscatter modeling, and the application to in situ systems.

• Design of a multi-angle laboratory scattering system
  – Tank, acoustics, reverberation, calibration, animal behavior.

• Preliminary data.

• Work for future.
Background: Motivation

- Use acoustics to survey marine animal populations.
- Empirical forward modeling for target strength estimation.
- Acoustic classification studies.
- How can we solve the inverse problem?
Background: Forward modeling experiments

Measure scatter from animals and build a model

Reeder et. al 2004
FIG. 2. Schematic drawing of the Friday Harbor Experimental Chamber. The enclosure was deployed off the laboratory dock. See text for details.

Wiebe et. al 1990

Traykovski et. al 1998
Background: Acoustic Classification
Multiple angles

- More observations of scattering could reduce uncertainty about scatter size, shape and taxa.
- In some cases, the additional observations can be obtained without substantial cost (just add a few more transducers and channels).
- Current surveys limited in many cases (fish, krill) by scatterer orientation.
Motivation: Time varying scatter

- Previously all studies have only considered stationary targets.
- For classification, including the dynamics could be helpful (different swimming speed, behavior).
- This requires the ability to track multiple targets, as well as good calibration.
Previous multi-angle studies

Incorporating additional angles can improve estimates of animal length, or taxa.

Estimating fish bladder length

Classifying zooplankton
Experimental overview

- Test simulation results on live animals.
- Collect the first multi-angle data set for zooplankton and fish.
- Observe dynamic animals (minimal thethers).
- Study realistic scattering environments (multiple targets, water motion).
- Ground truth with stereo video.
Experiment concept

- Transducer array
- Interrogation volume
- Down looking camera
- Side looking camera
Elliptical tank:
8 feet deep, 14 feet long, 10 feet wide. Interogration volume is 4 feet above the tank bottom.

Transducer array is mounted on a sliding rail system to avoid long term sea water exposure after alignment.

One camera images through a side viewport, while the other images though an open ended water tight housing with viewport.

Sony Hi-Res SPT-M320 0.07lux CCD cameras
Tamron 70-300mm zoom lenses

Matrox Meteor II Framegrabber x2
NTSC 10fps

PC running:
Windows XP
NIL-Lite
Image storage/display

ENI 240
Power Amplifier

Standford Research
DS-345

Preamplification:
Olympus 5670 x8
0.05-10 MHz 40dB

Data Acquisition:
NI PXI-6115 x2
4 channel 10MS/s simultaneous.
Features of the system

- One transmitter, eight receivers.
- Rigid array on sliding rail system.
- Cameras mounted on three-axis telescope mounts.
- Broad band transducers (0.25-3.5MHz).
- Arbitrary waveform generation.
- Laser Illumination.
Array Alignment

- Initial alignment using a laser pointer.
- Tank filled half way, and the system turned on.
- With real-time display of data, rotate each receiver until max return.
- Rotate transmitter to max all returns.
Reflection data from cal sphere
System Calibration (first try)

- Estimate 3D location of scatterer from image pair.
- Map the acoustic field into image planes.
- Convert echo voltage to target strength at each frequency.
Calibration concept

Calibrated target positions

Echoes on each receiver

3D space in the sample volume

Projection of target into each image
Calibration Movie
3D Target localization using image data

From the image data, and grid points, extract mapping functions from 3D to each image

\[ X^1 = F^1(x) \quad \quad X^2 = F^2(x) \]

Mapping functions computed using a neural network built using Netlab

\[ X^j_i = \hat{F}^j_i (x) = U \left( \sum_{k=0}^{K} \hat{\omega}_{i,k} V \left( \sum_{l=0}^{3} w_{k,l} x_l \right) \right) \]

Then use both mapping functions and a very fine grid in 3D space to build a lookup table approximation to the inverse function

\[ \hat{x} = F_{F_1,F_2}^{-1} (X_1, X_2) \]
Issues with calibration

- Hanging ball method is too coarse for estimating body pose from images.
- Sample grid is too small.
- Effect of the tether may bias target strength estimates.
- Like to have more automation.
An improved calibration?

Rigid 3D points
Dealing with live animals

• A big tank with a small field of view means big problems!
• For the small scatterers, tethers typically corrupt the echo.
• For larger scatters, behavior will typically keep them away from the field of view.
• Two different solutions were developed to solve these issues.
Plankton Pump

- Realistic data, with water motion, free swimming animals, diverse scatterers.
- Easy and relatively fast.
- Dramatically increases encounter rate.

- Bubbles entrained in pipe system.
- To keep flow rate low, need to have a wide output, many animals lost.
- Strong swimmers typically swim away before being insonified.
Tethers

- Nylon monofilament or various diameters.
- Braided silk suture.
- Single silk strands.
- Thin slices of polyurethane.
- Thin Human hair.
Tether methods

Static no swimming tether

- Nearly constant artifact from tether.
- Control over the animal's orientation.
- Full length of the tether must be in beam.
- No behavior.
- Animals may die quickly.

Quasi-free swimming tether

- Animal can swim around.
- Main tether can be outside beam.
- Get some behavior.
- Tether is dynamic.
- Can wind up with a lot of the same views.
Tether based methods

- Very hard to get an acoustically transparent tether at Mhz frequencies.
- Tethering animals is difficult.
- Cause atypical behavior.

- Good localization.
- One scatter in the volume at a time.
- Much higher encounter rate.
Preliminary data

- Movies of animals moving through the field of view.
- Examining the variation in echo across the array.
- Ping series for zooplankton and fish data.
Data Pre-processing

Signal Model $s_0[n]$ → Matched Filter $p[n] →$ Peak Detect $→$ Window $→$ Pressure time series on each element

Pressure time series on each element

Raw Echo

Windowed filter output

Spectral smoothing
Data view software (matlab)
Zooplankton movie
Interesting variations across the array
Ping series from a swimming fish
Ping series from a rotating fish
Ping frames from swimming fish
Ping series from swimming fish
Ping series from swimming fish
Ping series from swimming fish
Ping series of per frequency energy
Ping series of per frequency energy (swimming fish)
Looking towards the future

- What kind of algorithms are appropriate?
- How can the system perform well without excessive training?
- What type of features are uniformly best for representing these data.
- What are the limitations on discrimination capability.
Summary

- A multiple angle scattering apparatus has been constructed and tested.
- Improved image calibration is needed for pose estimation.
- Preliminary data shows important advantages of using additional angles.
- Future algorithm development should aim to use time varying scatter, regional data for priors, and multiple classification paradigms.
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Previous approaches to the problem

• Sequential state estimation
  – Robinson, Dasgupta, Runkle, Carin.

• Neural networks, support vector machines, nearest neighbor
  – Azimi-Sadjadi, Yu, Roberts.
State estimation methods

- What should the state be?
- How to estimate emission probabilities?
- How to model state transitions?

Physics based state decomposition

\[ p(y_n | s_m, T_k) = \sum_{i=1}^{L} w_i g_i(y_n | s_m, T_k), \quad \sum_{i=1}^{L} w_i = 1. \]

Block diagram of the HMM/MLP system for local probabilities.
Non-parametric methods

Data Pre-processing and filtering

Feature extraction

Pick best features

Classify using training data.
Limitations of current methods

- Only process spatial data, either from simultaneous views of a dynamic target, or for sequential views of a static target.
- Heavy dependence on training data, which is expensive to obtain.
- Unclear how these methods will generalize to new target types.
Improving existing methods

Regional Data → Simulated Data → Adaptive Classes

Classifier Bank

Expert Feedback / Training

Temporal sequence of multiview data: $\ldots, p_{t-1}[n], p_t[n]$