Modeling Statistics of Fish Patchiness and Predicting Associated Influence on Statistics of Acoustic Echoes

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LONG-TERM GOALS

To accurately describe the statistics of acoustic echoes due to the presence of fish, especially in the case of a long-range active sonar. Toward this goal, fundamental advances in the understanding of fish behavior, especially in aggregations, will be made under conditions relevant to the echo statistics problem.

OBJECTIVES

To develop new models of behavior of fish aggregations, including the fission/fusion process, and to describe the echo statistics associated with the random fish behavior using existing formulations of echo statistics.

APPROACH

Several interrelated components of research are conducted in parallel and in a synergistic way: One important component of the research is the development of new advanced models of fish behavior inspired by, and grounded by, 3-D images of fish aggregations. These images are derived by multi-beam acoustic systems. Key parameters to be observed and modeled are the fission/fusion rate of the aggregations. Concurrent with the modeling of fish behavior, observed statistics of fish aggregations, as they become available, will be incorporated into an existing general formulation for echo statistics, as well as being used to parameterize previously published, and the newly developed, behavior models. The results of these latter efforts will, in turn, help to drive further development of the fish behavior model. Some of the fish aggregation data comes from NOAA/Fisheries, as they conduct these measurements as part of their routine surveys. The Stanton/Weber/Grunbaum group participated in planning their experiments which yielded data that reveal key aspects of fish behavior and, in turn, contributes to the modeling.

Stanton oversees the entire project as well as works on predicting echo statistics from fish in an ocean waveguide and applying existing fish behavior models to existing 3-D images of fish aggregations. Weber analyzes images of fish aggregations that he and NOAA/Fisheries have recently collected for parameterization and incorporation into new theoretical models. Grunbaum develops the new fish behavior models and parameterizes them with data analyzed in this project. The work also involves informal collaborations with Chris Wilson of NOAA Alaska Fisheries and Ben Jones of NPS.

WORK COMPLETED

Major milestones were reached this year including one new paper that was submitted to a refereed journal, a previously submitted paper that was published in a refereed journal, and a previously submitted paper that was revised and submitted to a refereed journal. The newly submitted paper involved predicting animal behavior associated with a plume. The published paper predicted echo statistics due to a long-range sonar insonifying schools of fish in an ocean waveguide. The paper that was resubmitted involved comparing past models of fish behavior with published 3-D multi-beam acoustic data. In addition, a new paper is currently being drafted which describes empirical parameters of fish behavior (fission/fusion rates) that were extracted from recently collected 3-D multi-beam acoustic data.

1. Comparing previous competing behavior models with 3-D multi-beam data

In previous years on this project, we compared published competing models with published 3-D multi-beam data. The Niwa and Anderson models were compared with 3-D multi-beam data collected by Paramo and Gerlotto. The data were consistent with the Anderson model in that both the data and model had a mode in the statistics of fish school dimensions (whereas the Niwa model does not have a mode). Based on the reviews of our paper that summarized our analysis and that was submitted in a previous year, we revised the analysis by also analyzing the statistics of the volume of the fish schools (which is uniquely provided by the multi-beam data). The statistics of the fish school volume are also consistent with the Anderson model. This new observation strengthens previous years' conclusions that the assumptions in the Anderson model on fish dynamics apply to these fish—the rate at which fish exit the school is proportional to school size. This fiscal year, the results and paper were finalized and the revised paper was re-submitted for consideration of publication (Stanton et al, submitted).

2. Extracting fish-behavior parameters from high resolution images of fish aggregations derived from acoustic multibeam data

In a previous year, we focused on analyzing and interpreting a subset of data collected in the summer of 2012 using a Simrad ME70 multibeam echosounder data as part of the NOAA Alaska Fisheries Science Center acoustic/trawl walleye pollock survey in the Gulf of Alaska. The data concerned repeated transects over the same discrete aggregations of pollock that were approximately 1 nmi long and collected at approximately 15 minute intervals. These data were analyzed to extract metrics describing morphological changes in the fish aggregations that can be used to tune or ground-truth behavioral models. Metrics of particular interest include the size-dependent group speed and bounds on the rate at which aggregations appear to split (a 'fusion' event) or recombine (a 'fission' event).

The analysis of the data provided quantitative metrics describing fish group behavior (e.g., the speed at which groups of various sizes move) that are rarely seen outside of laboratory settings. We have analyzed the group transects to determine group speeds for the unique aggregations that can be clearly identified in subsequent passes. These data ($N = 15$) show wide variation (an order of magnitude), with no apparent dependence on the characteristic group length scale (cube root of volume), as shown in Figure 1a. A subset of these groups were in very close proximity, making it possible to also assess their relative group speed (e.g., the speed of group A relative to the speed of group B). The observed relative speeds are approximately a factor of 2 smaller than the absolute speeds, but with similar variation (Figure 1b).

The detection of fusion/fission events in fish groups is rare even for repeat pass surveys, but when they are observed they help to further bound the space/time scales at which information is passed (i.e., remains coherent) within the school. In the repeat-pass multibeam echosounder data, three fission and two fusion events have been identified. With each of these events the relative speed at which the aggregations are separating/joining, as a function of group size, has been estimated from the multibeam echosounder data.

These results, which were initially reported in last year's report, were further advanced and presented this year in the Spring, 2014 scientific meeting of the Acoustical Society of America in Providence, R.I.. A manuscript based on the final results described here is currently being drafted at the time of writing this progress report.

3. Parameterizing and optimizing recent model for fish school behavior

This year, we continued our focus on estimating parameters of the new fish schooling model using individual-level and population-level fish schooling data. The individual-level data are 10-minute-long 3-dimensional-trajectory sequences of all individuals within small schooling and milling aggregations in the laboratory. The population-level data were collected in field surveys of Alaska pollock being analyzed by Weber and Stanton. The model and its application to schooling analysis involve a relatively large number of parameters, which must be constrained and optimized with respect to the available data. Therefore, much of the effort this year also involved building computational and statistical machinery to execute this optimization. Both the number of parameters and the relatively high computational demands of large-scale spatially-explicit schooling models make effectiveness and efficiency key to successful parameter-fitting. This year's principal modeling accomplishments are summarized:

(a) We developed computational infrastructure to extract cognitive behavior and other parameters from the NOAA Alaska Fisheries Science Center acoustic/trawl walleye pollock survey data. The central challenge in parameter estimation from data of this type is that data have incomplete spatial coverage and, at any given spatial position, are irregular in time. A consequence is that, within a set of repeated surveys, each acoustic transect reflects an unknown fraction of fish that were previously detected, that moved into the survey area since the last transect, or that left the survey area since the last transit.

Our approach to estimating parameters utilizes iterated simulations of behavioral models, maximizing statistical similarities between predicted and observed data where observations are available. The gist of this approach is that a model provides a means to accumulate information between intermittent and probably sparse data. The combination of data and movement mechanisms embedded in the equations enable the model to "learn" as much as possible about the state of the system. A necessary element in this maximization is as unbiased as possible a “null” population distribution for areas in which no observation data are available.

An example of this approach is given in Fig. 2 which shows estimates for the walleye pollock survey data using an advection-diffusion process as the underlying movement mechanism for fish populations. The analysis goes through the entire sequence of recent surveys, and determines the advection velocity and diffusion that yield the best matches between model and data (according to one of a number of statistical metrics; the figure reflects a correlation metric). In these data, the best-fit advection velocity for fish signals likely is dominated by the ambient current velocity. The diffusion coefficient reflects movement and fission/fusion of fish schools, possibly with contributions from other sources. With an estimate of the current velocity, we can remove water movement from the geo-referenced survey data to quantify how the fish are moving relative to the water in which they are immersed, reflecting the true school movement dynamics. The work now in progress is to implement this approach in more sophisticated behavioral models.

(b) Because cognitive schooling models have not been developed previous to this project, statistical methods for estimating cognitive behavioral parameters do not yet exist. To develop statistical tools for inferring these parameters, we considered a simpler spatial memory/cognition problem, which is the odor source location problem, applicable to many engineering and environmental problems of interest to the Navy. We had access to trajectories of male moths finding a pheromone-emitting female; our goal was to quantify the mate-seeking behavior of these male moths in a cognitive behavioral framework. This is a simpler parameter estimation problem because ways in which the geometry of plumes transported by turbulent environmental flows might be statistically summarized are known from fluid physics.

Using the moth dataset, we developed new biomimetic cognition-based algorithms for odor source location, and mapped out strategies for estimating parameters of models of spatial memory and cognition (Fig 3). We assumed that cognitive parameters were structured so as to estimate and respond to plume geometry in the most efficient way. The guidance to parameterizing behavioral parameters provided by this assumption was central to obtaining parameter estimates that explain large fractions of variance in observed movements. This work is described in a manuscript in collaboration with a chemosensory ecologist and was submitted to the Journal of Movement Ecology (Grunbaum and Willis, 2014). As with fish schooling, this is an entirely new approach to assessing this biological phenomenon, which will be stimulating and useful to a wide range of future investigations.

Armed with this understanding of how parameter estimation for these kinds of models works, we are currently refining and expanding parameter estimation schemes for acoustic surveys and fish trajectory data.

4. Echo statistics due to various aggregations of fish detected by a mid-frequency long-range sonar

In a previous year, as part of the goal of characterizing echo statistics due to aggregations of fish detected by a long-range sonar, we made calculations involving several simple cases as illustrated in last year's report. Reverberation was predicted for a mid-frequency sonar deployed near the surface in an ocean waveguide (many km long). Two sets of calculations were made, one with the community standard PE code, and the other with a numerically efficient code that we developed. Several example calculations were made with 1, 2, 5, and 10 identical small aggregations of fish in the waveguide. The calculations demonstrate the degree to which the statistics are non-Rayleigh, with the "tail" of the echo probability density function (PDF) increasing with decreasing numbers of aggregations. Last year, those results, as well as predictions involving a wide range of realistic waveguide conditions (randomized environment with internal waves), were completed and submitted for publication. This year, the paper was revised based on reviews, then accepted and published (Jones et al., 2014).

RESULTS

Our key advances this year involved multiple aspects of continuing to ground our new theoretical behavior model with experimental data. Recently collected 3-D data concerning a time series of aggregations of fish are providing a rare assessment of the fission and fusion rates of fish and provide critical information on fish behavior in their natural environment. These group-level ocean data, coupled with our laboratory data involving individual fish, are being instrumental in enabling the model (through experimental parameterization) to make realistic predictions.

Our results are further illustrating the great complexity of fish behavior, which is important at scales relevant to both the individual and group level. Our simulations show that our cognitive schooling model can exhibit a wide variety of population-level behaviors, and these are typically strongly sensitive to the timescale of spatial memory. For example, the modal group size shifts to larger groups when the memory timescale is increased, all other parameters held constant. The strong effects of spatial memory, cognitive algorithms and memory timescale on group-size distributions and other population-level characteristics suggest that mechanistic models are likely to have better predictive capabilities if they incorporate cognitive behavioral algorithms. Behavioral parameters that we are extracting from laboratory and field data are helping us to ground key aspects of the model. Our predictions of echo statistics due to a long-range sonar for simple aggregations of fish show that the degree to which the echoes are non-Rayleigh depends upon the number of fish (or fish aggregations). The behavior modeling is working toward making predictions of echo statistics due to realistic aggregations of fish.

IMPACT/APPLICATIONS

The modeling and observations of fish behavior represent an advancement of the fundamental understanding of fish behavior. Integrating the data with the model is creating a powerful tool for making realistic predictions of fish behavior. The modeling of echo statistics from a mid-frequency sonar with several simplistic examples of fish aggregations demonstrates the fish clutter characteristics relevant to Navy ASW applications. The observed speeds of fish schools yields information on the degree to which fish impact Doppler-sensitive sonars. Once the advanced behavior model is incorporated into the echo statistics model, we will have a significant tool for predicting sonar performance associated with the presence of fish.

TRANSITIONS

The 3-D fish shoal data, provided by NOAA Fisheries and analyzed in this project, were the basis for a transition last year of the HiFAST biologic simulations in the CASE (NAVAIR) sonar trainer. In addition, transition of the shoal data into the SAST ACB15 (NAVSEA) sonar trainer was approved last year and is currently being incorporated into the system at the time of this writing.

RELATED PROJECTS

Parts of this project fed into the ONR HIFAST FNC program last year in which fish echoes were simulated for use in Navy sonar trainers (SAST-NAVSEA and CASE-NAVAIR) (see update on related "Transitions" above). The 3-D multi-beam data involving fish shoals from the Eastern Bering Sea, provided by NOAA Fisheries and analyzed in this project, were used in the HiFAST program to predict echoes from shoals.

PUBLICATIONS

Grünbaum, D. and M. A. Willis. (2014) Spatial memory-based behaviors for locating sources of odor plumes. Movement Ecology. [submitted, refereed].

Jones, B.A., J.A. Colosi, and T.K. Stanton (2014), "Echo statistics of individuals and aggregations of scatterers in the water column of a random, oceanic waveguide," J. Acoust. Soc. Am., DOI 10.1121/1.4881925 [published, refereed]

Stanton, T.K., Bhatia, S., J. Paramo, and F. Gerlotto (submitted), "Comparing modeled group size distributions to 3-D multibeam sonar data on fish school dimensions," Can. J. Fish. Aq. Sci. [submitted, refereed]

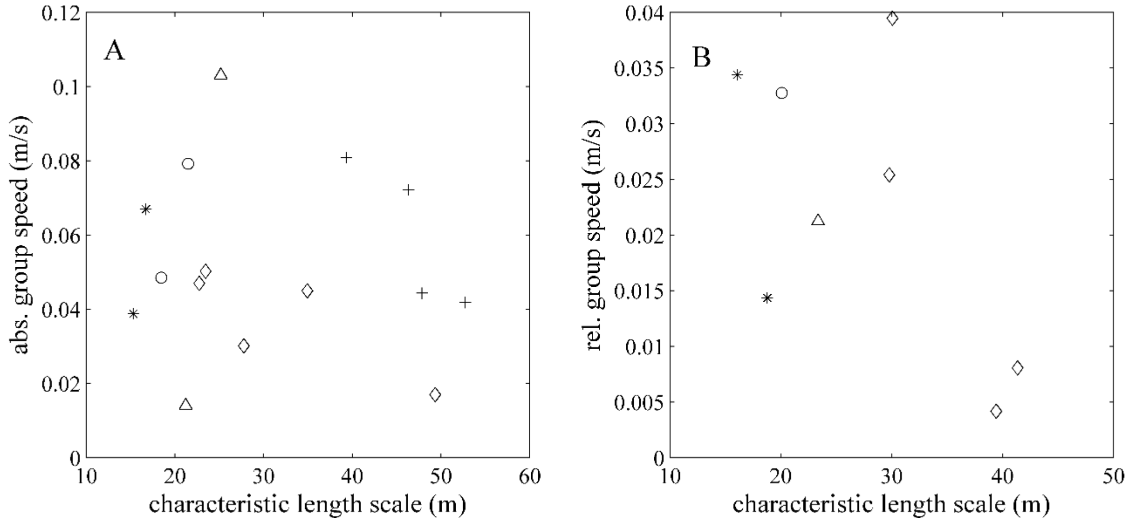

Figure 1. Absolute and relative group speeds as a function of group size observed from repeat-pass multibeam echosounder transects.

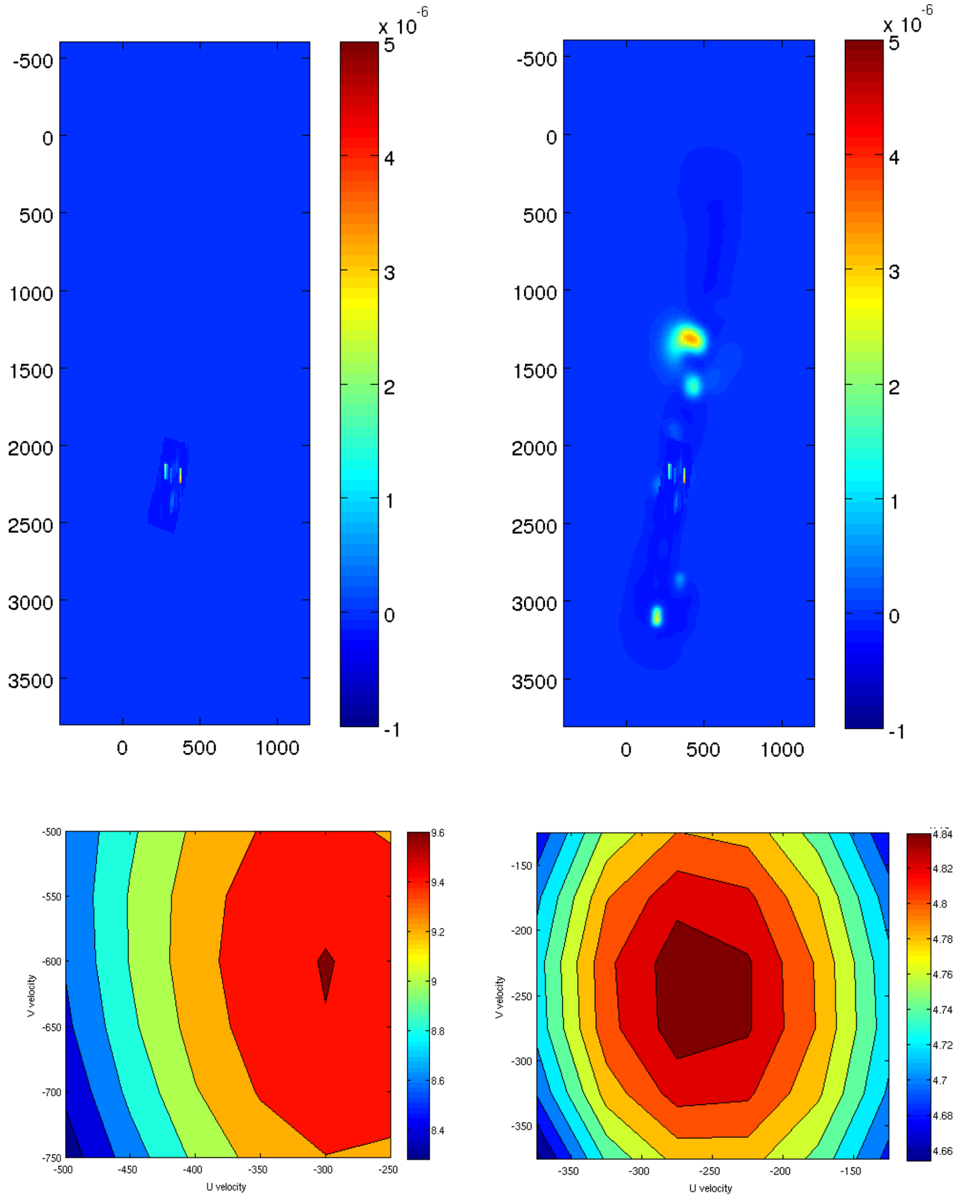

Figure 2. Numerical optimization of fish school movement parameters from NOAA Alaska Fisheries Science Center acoustic/trawl walleye pollock survey in the Gulf of Alaska. The top left graphic shows the observed acoustic backscatter from one section of a repeated survey. The top right graphic shows the simulated fish population distribution, in which location and density of fish schools are projected forward according to an advection-diffusion model. When available, predicted fish densities are replaced by observations, and subsequently carried forward by model dynamics. The bottom left graphic shows the correlation between predicted and observed fish distributions as a function of horizontal velocity in the 50m depth stratum. The strong peak in the middle right of this graphic indicates the estimated ambient current velocity, possibly with a contribution from directional movement of the fish population, within this stratum. The bottom right graphic shows the corresponding estimated velocity in the 90m depth stratum.

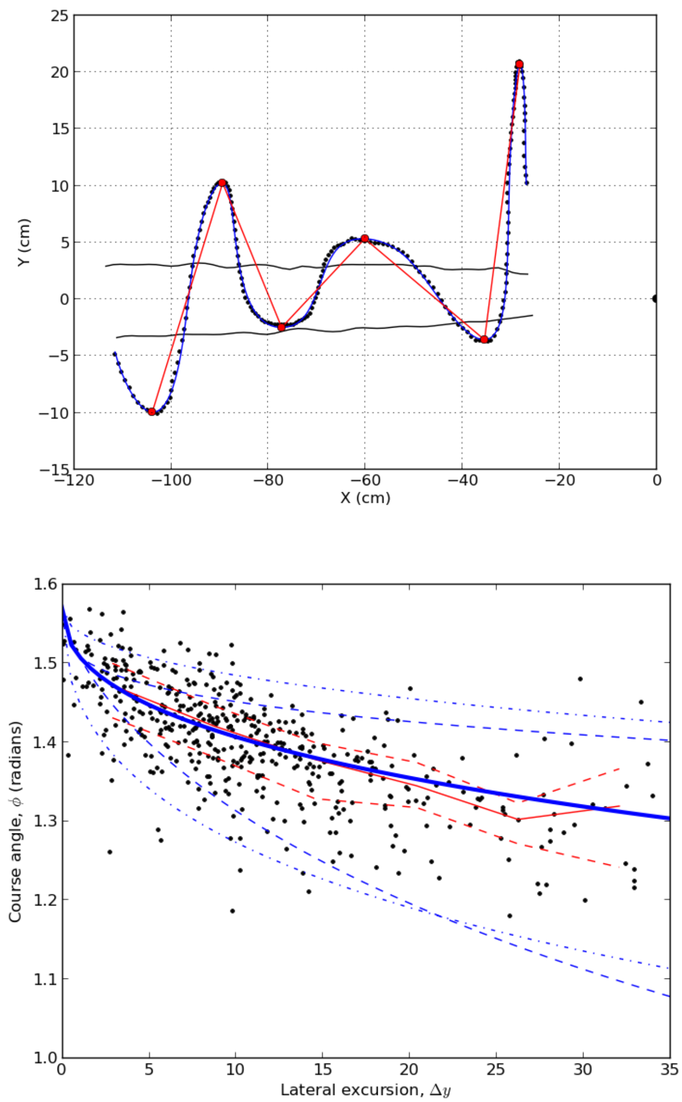

Figure 3. Development of an estimation scheme for cognitive movement behaviors using observed trajectories of a simplified behavior: location of the source of an odorant plume in a turbulent flow. The top plot shows movement of a male moth seeking a pheromone-emitting female, with the odorant source indicated by a black semicircle on the right side. Wind direction is right to left. In this plot, black circles indicate the raw position data; the blue line represents a corrected path after filtering to remove frame rate noise. The red line segments represent straight-line connections between maximum lateral excursions. The bottom plot shows the course angle and lateral excursion of 458 cross-plume transits, aggregated from four flights by each of by 19 moths. The observed data are summarized by the median (solid red line) and 25th and 75th percentiles (dotted red lines). The blue solid line indicates best-fit predictions of a cognitive behavioral model ($p<<0.01$, $r^2=0.43$); dotted blue lines represent a sensitivity analysis for these predictions. These results indicate the methods and results being pursued to estimate fish schooling behavioral parameters from acoustic survey data.