Broadband Fish Identification of Laurentian Great Lakes Fishes

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***Abstract*— Broadband acoustic echoes were collected on free-swimming alewives *Alosa psuedoharungus*, rainbow smelt *Osmerus mordax*, and bloaters *Coregonus hoyi*. Concurrent midwater trawls were used to determine species composition. A genetic neural network was trained on broadband echoes from each species to an overall correct classification rate of 91%. Tests of the trained network suggested an overall expected correct classification rate of 80-85% and indicated rainbow smelt and alewife echoes were less likely confused as compared to bloater. Application of the trained network to recorded echo data resulted in predicted species compositions that did not correspond well to those observed in the trawls. The classifiers may have been confounded by inclusion of echoes from various species, especially for bloater. A restriction to echoes collected concurrent to trawls or other controlled situations (e.g., pens or smaller lakes with single species) may be needed for building 'clean' classifiers.**

Keywords* – *Broadband, Sonar, Fish Identification, Classification

I. Introduction

In mixed species situations, species discrimination has been particularly challenging in fisheries acoustics [16, 8, 12]. Apportionment of acoustically derived estimates of total abundance into subsets of a particular species or life stage of interest is typically dependent on net captured organisms. Reliance on supplemental trawl sampling as part of acoustic surveys is commonplace but capture techniques can often be subject to biases (e.g. [29, 13]), at times missing classes of targets that comprised part of the acoustic signal. In general, the spatial and temporal resolution of net sampling is often not fully comparable with the more comprehensive acoustic data. This incompatibility, as well as the need to dedicate additional time and effort to deploy fishing gear, can often compromise many of the advantages of the application of acoustics to fishery surveys. The benefits of a reliable, acoustically-based species discrimination technique are obvious.

Two direct acoustic target identification approaches are currently practiced. Mean target strength can be used to differentiate between species whose acoustic sizes differ, on average, by more than a factor of two [16]. Rose and Leggett [16] also used shoal characteristics to develop multivariate discrimination functions for shoals of Atlantic cod, capelin, and mackerel. Signal descriptors known to have discriminatory power include shoal position in the water column (depth, distance from bottom), gross shoal measures (dimensions and shape), and measures of the signal pattern from within the shoal (measured in time or frequency domain) [18]. Quantitative descriptors of fish aggregations (schools, shoals, assemblages) can be calculated for signals derived from single of averaged echosounder pings [31] and from echogram images [15].

In the Great Lakes and Lake Michigan in particular, acoustic surveys have been implemented to quantify prey fish abundance, principally the alewife *Alosa psuedoharungus*, rainbow smelt *Osmerus mordax*, and bloater *Coregonus hoyi* (e.g., [2, 3, 5, 9]). These surveys are critical to fisheries managers making decisions on stocking rates of salmonine predators and on allowable harvests of these valuable fish by commercial fishing operations. The overlap in range of sizes and in spatial distributions of the major prey fishes and the lack of schooling behaviors to form 'shoals' renders the previously mentioned acoustic identification techniques unsuitable [3]. Due to temperature and bathymetric preferences (e.g., [4]), some physical environment features can be used to predict prey species composition [3], but enough similarity in the distribution of the various species and their different life stages still requires the use of pelagic trawling to classify the echoes. Another acoustic method that shows a potential to directly identify echoes is broadband echo sounding. However, this emergent technique is thought to be too technically demanding to be practical for acoustic surveys (e.g. [19, 20, 21]).

The objective of this study was to investigate and evaluate the ability to reliably identify key Great Lakes fishes, specifically in Lakes Michigan and Huron, using broadband acoustics in combination with neural network classification. The first known use of neural networks for species identification was performed by Ramani and Patrick [14]. The technique developed for this study represents the application and combination of three elements: broadband transmission, echo spectral representation, and neural network identification.

II. Methods

Broadband acoustic echoes were collected on free-swimming fish in Lakes Huron (1998) and Michigan (2000 and 2001) aboard the USGS *R/V* Grayling. The surveys were conducted during late summer (i.e., August) and at night, to take advantage of the nocturnal vertical migrations that positioned the fish throughout the thermally stratified water column. The transducer was attached to a towfish and deployed abeam the vessel at depths of 1-1.5 m depth below surface and towed at speeds of 2-3 m/sec. Fish aggregations, as revealed by the acoustics, were subsequently sampled by midwater trawling in the fashion described by Fleischer et al. [7]. Trawl netsondes were used to accurately position the net and monitor the net during the tows. All fish caught were individually measured to the nearest millimeter (total length) and weight in species aggregate. Large catches (> 500 fish) were subsampled and total counts expanded to total catch.

Our sampling efforts were focused on finding monotypic *in situ* aggregations of each species. Due to their recognized thermal and depth preferences, some degree of predictability in the distributions of each of the three species was anticipated. Variations in extant thermal conditions plus changes in species dominance due to year-class fluctuations over the duration of the study period, however, made the task of collecting echoes from each species challenging. Our sampling strategy was to search as wide an area as possible and to collect fish from any detected aggregations. Upon finding single-species aggregations in the trawl catches, we re-traversed the area to collect additional echo data. Echoes from these areas, both those collected during the trawl and in subsequent transects, were extracted for use in training and testing the neural network classifiers. This sampling strategy for free-swimming fishes was somewhat 'hit-or-miss'. However, our previous experience with tethered fish experiments indicated that well-trained classifiers from these fish did not result in reliable extrapolation to testing on echoes from free-swimming fish [3]. We concluded that reliable training of the neural network, especially for application to *in situ* fish aggregations, required the collection of echoes from free-swimming fishes.

A. Broadband Sonar Transceiver

The broadband transceiver used was designed to maximize acoustic bandwidth while maintaining functionality in terms of output power, beam pattern characteristics, noise immunity, and deployment capability. In this prototype system, the transducer was a modified version of a standard Acoustic Doppler Current Profiler (ADCP) transducer with custom electronics in the transducer housing and in the topside vessel-mount chassis. The disc-shaped ceramic transducer, whose center frequency is 153.6 kHz, produced a cone-shaped beam with a nominal 3 dB beam width of 5 degrees (3.5 to 7 º). A wide absolute bandwidth was required so a high operating center frequency was chosen since fractional bandwidths above 0.5 (Q's below 2.0) are difficult to realize in ceramic transducers. As delivered, the 3 dB receiver bandwidth was about 80 kHz (110 kHz to 190 kHz), with -6 dB pass-band flatness. The higher center frequency also generates a narrower beam for a given size transducer and reduces concern over common background noise sources in the lower bands (e.g., waves and shipping).

Output power used was 40 to 250 W and maximum source level of 216 dB 2 µPa at 1 m. Possible receiver gain settings ranged 20-83 db in 23 dB increments on this prototype. For most of our experimental work, the gain was set to 43 or 66 dB. Pulse lengths ranged 1-2 m (c = 1500 m/sec). Though the 3 dB bandwidth of the sonar is 80 kHz, there was adequate signal-to-noise ratio for a bandwidth of 80 to 100 kHz. The standard active sonar equation [30] showed a maximum allowable range of 250 m for a 40 dB signal-to-noise ratio (SNR) for –40 dB targets on the maximum response axis (MRA). For targets outside the 5 degree beam width, the echo level will fall off rapidly and this analysis becomes invalid. But, for insonification of schools of fish where at least some targets are likely to fall on the MRA, this analysis shows that the system has useful range for a full 80 kHz bandwidth. With matched filtering for increased detection of signal characteristics embedded in noise, the effective range could perhaps be doubled. The principal transmit waveform used was pseudo-random noise (PRN). The transmit waveform's pseudo-noise (implemented as a phase shift keyed –PSK- code) sequence was modified from the standard RDI codes so that the first 13 elements transmitted represent a barker code for maximal bandwidth energy and autocorrelation. The PRN mode is meant to impart maximum spectral energy into the water column for a given pulse length.

B. Echo Detection

We applied a pulse compression technique known as a matched filter to recognize individual targets. A matched filter is a member of a general class of Weiner filters in which the filter output is maximized for signal-to-noise ratio. The receiver structure is a specialized correlation receiver where the received signal, such as voltage, varying in time is compared to the impulse response of the output signal, yielding a correlation output proportional to how well the received signal looks like the input signal. A correlator is an optimum way of detecting the signal. The Wiener-Khinchine theorem shows that we can shift between time (or time delay) and frequency domains for implementation, an ability that can have computational savings. The transformations themselves are done via Fourier Theory, implemented as Discrete Fourier Transforms (DFTs) via a Couley-Tukey algorithm. The correlation is obtained as a convolution of the transmit pulse (the filter) with the received signal. In the time case, the time series of the transmit pulse is reversed and point-by-point multiplied to segments of the received signal then summed. The process is moved 1 point and repeated. In implementing the scheme in the frequency domain, the complex conjugate of the transmit pulse spectrum is multiplied to spectrum of the received signal. The correlation time series is then the inverse transform of the convolution output, showing correlation as a function of time (or range). The ability to do large DFTs (>65000 point) allows the frequency case to be significantly faster and more computationally efficient.

Echoes were extracted from those strata where the tows revealed the individual species were found and the spectra of each echo stored for classification. In order to filter out smaller echoes (young-of-year fish and invertebrates), especially in the shallower strata, we used minimum target strength criteria during the extraction process: typically we applied minimum values of -45 dB, and in some cases where larger targets were collected, we applied a maximum of -30 dB threshold. We define target strength, in broadband terms, as the echo energy returned relative to total returned energy compared to the total transmitted energy across the band.

C. *Acquisition and Processing Software*

Broadband echo acquisition, storage, and playback were performed using SciFish 2000 software. This software, a Windows® NT application developed by the Scientific Fishery Systems, Inc., provided the graphical user interface for both sonar controls and for the extraction of targets for classifier construction. In addition, the program accepts completed classifiers for application to real-time or playback echo data. A separate set of routines were used to condition the echo data for submission to training and testing in a neural network. The software saves each sonar configuration at time of the survey and can save the raw data for future playback via a database. The echo data were sampled at 770 KS/s and the entire ping is saved, so acquired data files can become quite large (e.g., 80-90 kbyte/ping).

Echoes were extracted during subsequent playback by a user-defined subset of all echoes that meet the range, target strength, and ping number criteria observed in a file. These data were edited for any obvious outliers before exporting to the neural networks. The extracted echo data included the target's position in space and time, correlation, target strength, and the signal strength (volts squared) by each desired spectral bin from the DFT of the return. A fixed length DFT operates on a segment of data whose position in the raw data stream is determined by the output of the threshold-applied matched filter.

The echo data were conditioned by first normalizing the spectral bin values between 0 and 1 and then averaging these over 5 consecutive echoes. Previous studies [23,24] have indicated averaging between 5 and 10 of either independent or overlapped spectra improve classification accuracy by 10-15%. The data were constrained to only average within a given ping and/or within set range bounds (e.g. 82 ± 3 m). These conditioned echoes were used as the training and testing data for the neural network classifier.

D. *Neural Network Classifier*

We used a neural network technique, specifically a genetic algorithm (GA), to develop echo classifiers based on the spectral composition of the echoes. A genetic algorithm solves optimization problems by creating a population or group of possible solutions to the problem and offers the advantages of automatic model construction (i.e., no need for an explicit model of the problem), potential massive parallelism, robustness, and can capture nonlinear relationships. We relied on the NeuroShell® 2.0 Classifer neural network software. The genetic estimator applied in the NeuroShell® Classifier is based upon Specht [25-27], specifically the Probabilistic Neural Nets (PNN) classifier. There are random processes in the GA: crossover process, where pairs of variable values are randomly picked and exchanged, and mutation processes, where variable values are randomly changed [11]. For comparison to the neural network, the echo spectra data were also analyzed by the more conventional discriminant analysis multivariate technique.

A fixed number of randomly-selected echoes for each species were used to train and test the neural net. Owing to the need for balanced numbers, we were constrained by the lower number of rainbow smelt echoes, we used 75 exemplars to train and 150 exemplars to test each species. The spectral response was stratified into 66 individual 'bins', which gave the measured relative strength of the returning echo by frequency bin. Validation of constructed neural network included application of network to additional randomly selected conditioned echoes and by comparisons of species composition observed in midwater trawls and predicted by application of neural network classifier to broadband echoes collected concurrent to hauls. Echoes used for this analysis were not included in the training set.

III. RESULTS

A total of 2,966 alewife, 2,966 bloater, and 315 rainbow smelt conditioned echoes were extracted from the echo files for input into a neural network. The majority of the bloater and alewife echoes were collected in 2001 in Lake Michigan; technical problems in the broadband hardware corrupted most of the recorded data from collections in 2000. The rainbow smelt echoes were collected exclusively in 1998 in Lake Huron. These imbalanced numbers of echo data reflect the dynamics of these species: rainbow smelt populations have recently declined in Lakes Michigan and Huron and were more difficult to locate during the study period.

The genetic neural network trained in 343 generations to an overall correct classification rate of 91% and tested at an overall correct classification rate of 82% (Table I). Performance by species in rank order of correct classification during the training session was rainbow smelt (96%), alewife (92%), and bloater (84%). The relative importance of each of the spectral bins in formation of the neural network was not strongly dominated by any distinct band of frequencies within the full width of frequencies applied. By comparison, the jackknifed discriminant analysis classification matrix indicated only a 57% correct classification rate, with a similar rank order of correct classification by species: rainbow smelt (70%), alewife (64%), and bloater (47%).

Our validation of the trained neural network included further testing against a different random set of the conditioned echoes for application of the classifiers to broadband echo data. The network correctly classified 85% of 600 (200 of each three species) randomly chosen echoes from the conditioned echoes (Table II). Again, rainbow smelt were the most correctly classified (91%), followed by alewife (89%) and bloater (76%). In combination, the two tests of the trained network suggested an overall expected correct classification rate of 80-85%. From these test trials, rainbow smelt and alewife echoes are less likely confused as compared to bloater (Tables I and II). The spectral composition of bloater echoes appears to have been similarly less discriminating between the other two species.

TABLE I. CONTINGENCY TABLE (NUMBERS ABOVE AND PROPORTIONS BELOW) SHOWING INITIAL TEST CLASSIFICATION RESULTS FOR NEURAL NETWORK TRAINED ON ALEWIFE, BLOATER, AND RAINBOW SMELT BROADBAND ECHOES. HIGHLIGHTED CELLS IN LOWER TABLE INDICATE PROPORTIONS OF CORRECT CLASSIFICATION RATES BY SPECIES FOR ECHOES NOT UNIDENTIFIED.

		Actual			
		Alewife	Bloater	Rainbow Smelt	
Classified	Alewife	115	9	1	125
	Bloater	33	122	19	174
	Rainbow Smelt	2	18	129	149
		150	149	149	448

		Actual			
		Alewife	Bloater	Rainbow Smelt	
Classified	Alewife	0.77	0.06	0.01	
	Bloater	0.22	0.82	0.13	
	Rainbow Smelt	0.01	0.12	0.87	
					0.82

TABLE II. CONTINGENCY TABLE (NUMBERS ABOVE AND PROPORTIONS BELOW) SHOWING ADDITIONAL VALIDATION TEST FOR NEURAL NETWORK APPLIED TO RANDOMLY SELECTED ECHOES FROM ALEWIFE, BLOATER, AND RAINBOW SMELT. HIGHLIGHTED CELLS IN LOWER TABLE INDICATE PROPORTIONS OF CORRECT CLASSIFICATION RATES BY SPECIES FOR ECHOES NOT UNIDENTIFIED.

		Actual			
		Alewife	Bloater	Rainbow Smelt	
Classified	Alewife	177	24	4	205
	Bloater	23	151	14	188
	Rainbow Smelt	0	23	181	204
		200	198	199	597

		Actual			
		Alewife	Bloater	Rainbow Smelt	
Classified	Alewife	0.89	0.12	0.02	
	Bloater	0.12	0.76	0.07	
	Rainbow Smelt	0.00	0.12	0.91	
					0.85

Application of the trained network to recorded (i.e., unconditioned) echo data resulted in predicted species compositions that did not correspond well, at least as expected from the testing trials, to those observed in the trawls (Table III). Alewife, highly dominate in hauls 2 and 3, were predicted to be the most numerous from the broadband echoes, but at much lower proportions than observed (Table III). In these same trawls, bloaters were not found, yet the echo classifiers predicted substantial numbers of this species. In haul 1, the observed and predicted proportions of alewives were similar (Table III), however bloaters were predicted but not observed, and rainbow smelt were underrepresented by the classifier as compared to observed. In haul 4, which was predominated by bloaters, the classifiers erroneously assigned many of the echoes to alewife and overrepresented the proportion of rainbow smelt (Table III). This lack of fit in each instance could be due to the confusion of bloater echoes with the other species, as was suggested in the test trial results (Tables 1 and 2).

TABLE III. COMPARISON OF SPECIES COMPOSITION OBSERVED IN MIDWATER TRAWLS AND PREDICTED BY APPLICATION OF NEURAL NETWORK CLASSIFIER TO BROADBAND ECHOES COLLECTED CONCURRENT TO HAULS. ECHOES USED FOR THIS ANALYSIS WERE NOT INCLUDED IN TRAINING SET. UNKNOWN VALUES REPRENT PROPORTION OF ALL ECHOES UNCLASSIFIED BY NEURAL NETWORK AND OTHER PREDICTED VALUES ARE PROPORTION BY SPECIES OF ALL CLASSIFIED ECHOES.

		Species Composition			
		Unknown	Alewife	Bloater	Rainbow Smelt
Haul 1	Predicted	0.64	0.56	0.25	0.19
	Observed		0.59	0.00	0.41
Haul 2	Predicted	0.60	0.40	0.30	0.30
	Observed		0.91	0.00	0.09
Haul 3	Predicted	0.56	0.34	0.47	0.19
	Observed		0.91	0.00	0.09
Haul 4	Predicted	0.58	0.20	0.42	0.38
	Observed		0.00	0.99	0.01

Generally, about 60% of the echoes were not classified by the neural network. This rate of unidentifiable echoes was much higher than seen previously in the neural network testing, and may represent juvenile fishes or invertebrates that would be found in the water column, but not sampled by the trawl, or those echoes that did not fit the pattern of dominant spectral features developed as part of the conditioning procedure. We attempted to minimize the impact of such outlier echoes by filtering out smaller echoes during playback and classification.

IV. DISCUSSION

The differences seen in the predicted and observed species compositions do not indicate that the neural network technique developed here is, at this time, completely reliable for fish species discrimination in the Great Lakes. Though fully trained and tested, the network did not perform satisfactorily on application to *in situ* fish. One potential source of error may be related to our ability to gather echoes from monotypic *in situ* aggregations. We assumed the trawl catches truly represented the particular species compositions and, further, that the subsequent echo collections from these areas were also represented by the same species in the preceding trawl. It is possible that owing to spatial variability in fish distributions, the classifiers may have been confounded by inclusion of echoes from different species. This problem may be especially prevalent in those echoes classified as bloaters. The bloater is the dominant deep water prey fish species [3, 7], but is not exclusive to these areas [3]. Our inability to fish all portions of the deeper strata to document the source of echoes necessitated that we assume all echoes in the deeper area be classified as bloater. This assumption may have been faulty. In the future, the restriction of echo extractions to only those strata concurrently fished may be needed, though this would limit greatly the number of echoes collected in any given survey. Otherwise, identification of other areas (e.g. inland lakes, holding pens) with known species composition may be needed for building 'clean' classifiers to reduce the chances of mixed echoes.

The large number of unclassified echoes may be the result of our practice of echo conditioning, which was needed to improve the training and testing of the neural network. This smoothing procedure is designed to eliminate all but dominant spectral features of the extracted echoes. This conditioning does not truly mimic the possible variation in the field situation. Further study on the benefits of this procedure should be undertaken with the intent to examine the results in terms of application to free-swimming fish, and not just the network testing and training.

Our results also suggest that overlap in the broadband echo spectral representations alone may render neural network identification unreliable. Discrimination by broadband acoustic analyses may also need to include additional features. As example, Haralabous and Georgakarakos [10] have applied a discrimination technique to the identification of sardine, anchovy, and horse mackerel using several parameters extracted from detected schools: morphological, bathymetric, and energetic characteristics. Inclusion of similar ecological and habitat features (e.g., spatial and thermal characteristics) might improve species composition prediction in Great Lakes fishes.

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