Sensitivity analysis and parameter selection for detecting aggregations in acoustic data

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A global sensitivity analysis was conducted on the algorithm implemented in the Echoview ® software to detect and describe aggregations in acoustic backscatter. Multiple aggregation detections were performed using walleye pollock (*Theragra chalcogramma*) data from the eastern Bering Sea. Walleye pollock form distinct aggregations and dense and diffuse layers. In each aggregation detection, input parameters defining minimum size, density, and distance to other aggregations were selected at random using a Latin hypercube sampling design. Sensitivity was quantified by testing for correlation among input parameters and a series of aggregation descriptors. In all, 336 correlation tests were performed, corresponding to a combination of seven detection input parameters, eight aggregation descriptors, and six transects. Among these, 181 tests were significant, indicating sensitivity between input parameters and aggregation descriptors. The aggregation-detection algorithm is sensitive to changes in threshold and minimum size, but less sensitive to changes in the connectivity criterion among aggregations.

Keywords: aggregations, echo-trace classification, sensitivity analysis, walleye pollock.

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Introduction

Echo-integration trawl surveys are conducted routinely to map distributions and obtain abundance estimates of aquatic organisms (Simmonds and MacLennan, 2005). Aggregations (i.e. areas with multiple, non-resolved organisms) are evident features when high-resolution acoustic data collected from these surveys are displayed in echograms. Echo-trace classification (ETC, Reid *et al.*, 2000), defined as the detection and description of aggregations in acoustic data, can be used to study behavioural and ecological processes in aquatic environments that occur at relatively small (tens to thousands of metres) spatial scales (ICES, 2000). ETC is based on the use of detection algorithms that recognize and quantify aggregations and has been used to characterize fish aggregations (Coetzee, 2000; Iglesias *et al.*, 2003; Wilson *et al.*, 2003), their spatial distribution (Swartzman, 1997; Bahri and Freón, 2000; Petitgas, 2003), their relationship to environmental variables (Barange, 1994; Swartzman *et al.*, 1994a; Soria *et al.*, 2003), and diel changes in aggregation structure and location (Freón *et al.*, 1996; Gauthier and Rose, 2002). ETC has also been used to study shoaling behaviour (Nøttestad *et al.*, 1996), migration (Rose, 1993), and predator–prey interactions (DeBlois and Rose, 1995; Mackinson *et al.*, 1999; Axelsen *et al.*, 2000).

Several algorithms have been developed to detect aggregations in acoustic data. Most work in a similar way, searching for adjacent pixels with density values above a threshold, then applying a minimum size criterion to groups of adjacent pixels. Some algorithms also include a connectivity criterion, where nearby groups of pixels are joined in a single aggregation. All calculate and export spatial, morphological, and energetic descriptors from each detected aggregation (Barange, 1994). Algorithms used to detect and describe aggregations include SCHOOL (Georgakarakos and Petrakis, 1993), SHAPES (Coetzee, 2000), MOVIES–B (Weill *et al.*, 1993), and applications developed by Reid and Simmonds (1993) and Swartzman *et al.* (1994b). The SHAPES algorithm has been incorporated in the school-detection module of Echoview (SonarData, 2004), a software package that processes acoustic data.

In all aggregation-detection algorithms, the acoustic threshold (AT), minimum aggregation size, and the amalgamation distance are parameters defined by the user. We observed that these parameter values were typically chosen in an *ad hoc* manner. In some cases, parameters were iteratively selected so that detected aggregations matched those observed on echograms (Wilson *et al.*, 2003), or parameter selection was based on biological information, such as expected fish sizes and densities (Coetzee, 2000). It is likely that the characteristics of detected aggregations are dependent on the values of the input parameters used in the aggregation-detection algorithm. The sensitivity of aggregation descriptors to the choice of input parameters has not been quantified. Only Petitgas *et al.* (1998) reported changes in the number and characteristics of aggregations detected when using different ATs. Other aggregation-detection parameters were not examined.

The objective of this paper is to quantify the effect of varying input parameters when using the aggregation-detection algorithm implemented in Echoview. We followed a global sensitivity analysis approach, using multiple aggregation detections on the

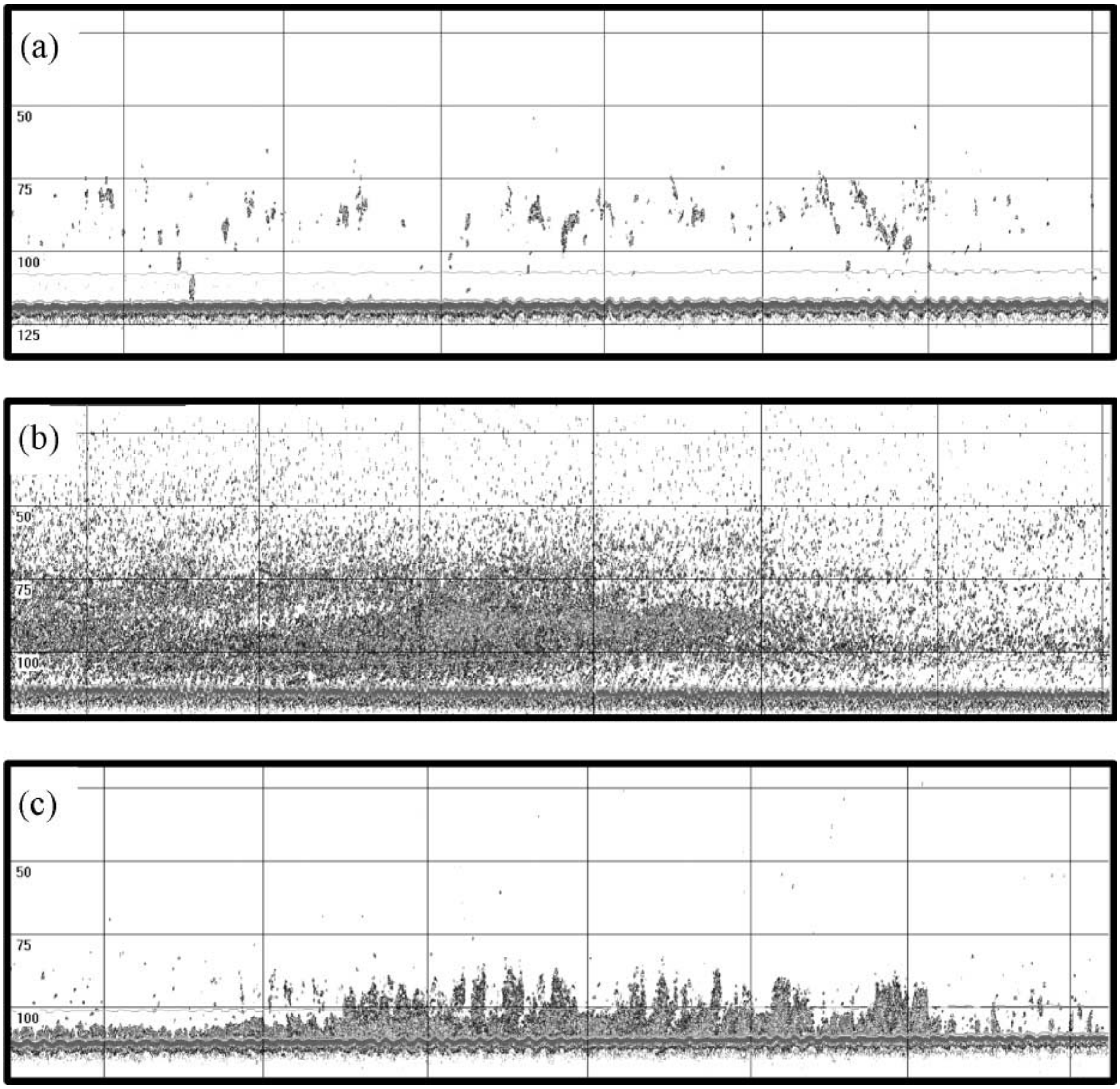

Figure 1. Echograms (depth, distance) illustrating examples of the patterns of walleye pollock distribution observed in the eastern Bering Sea: (a) well-defined schools, (b) diffuse midwater layer, (c) benthic “carpet”. The grid resolution is 0.5 nautical miles horizontal and 25 m vertical.

same data, varying all input parameter values simultaneously, and measuring correlations among parameter values and aggregation descriptors over their entire range (Campolongo *et al.*, 2000). We used acoustic data collected during echo integration and trawl surveys of walleye pollock (*Theragra chalcogramma*), a commercially important species in the Bering Sea. Examination of the data collected in these surveys shows that walleye pollock form spatial patterns typical of semi-demersal gadoids: large pelagic shoals, benthic layers, and discrete aggregations (Figure 1). This diversity in aggregation patterns allows us to generalize the results of this study to other semi-demersal fish species.

Material and methods

The National Oceanic and Atmospheric Administration’s (NOAA) Alaska Fisheries Science Center routinely conducts echo-integration and trawl surveys to estimate walleye pollock (*T. chalcogramma*) biomass on the eastern Bering Sea shelf. The data selected for this study were collected during winter (late February to early March 2000) and summer (June–August 2000) surveys by NOAA’s RV “Miller Freeman”. Three transects in an area north of Unimak Island (Figure 2) were analysed from each survey. Transect length ranged between 244 and 339 km in summer and between 71 and 107 km in winter. The area contained relatively high densities of walleye pollock, and the observed aggregations were characteristic of other regions on the eastern Bering Sea shelf (Honkalehto *et al.*, 2002). Acoustic data were collected following established survey methodology (Anon. 1990; Honkalehto *et al.*, 2002) using a calibrated (Foote, 1983) Simrad EK 500 echosounder operating at 38 kHz. The data were initially processed using the Simrad BI500 echo-integration software (Foote *et al.*, 1991), at a volume-backscattering strength (Sv) threshold of −70 dB, a horizontal resolution of

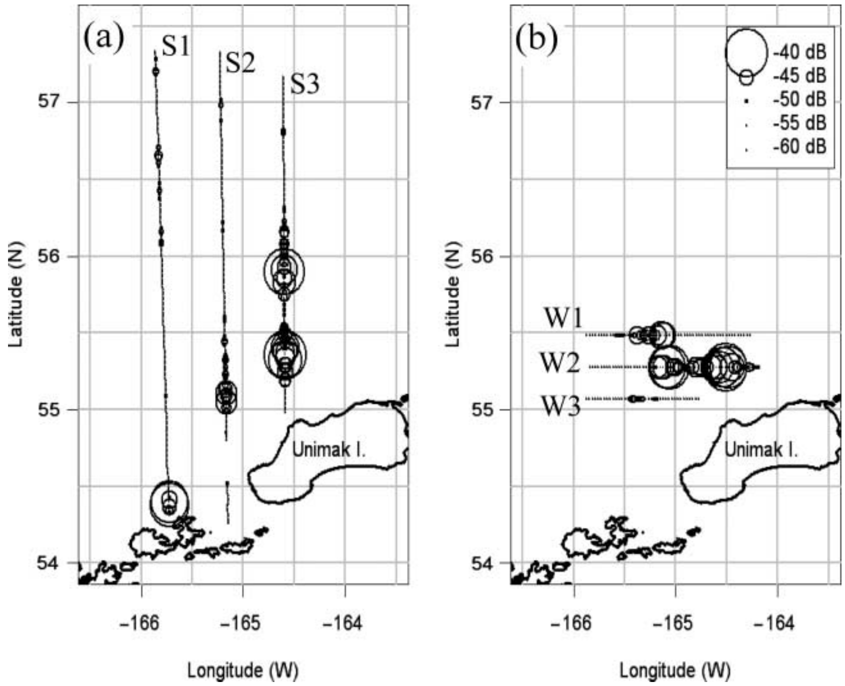

Figure 2. Walleye pollock acoustic density distributions along selected transect lines from (a) summer and (b) winter 2000 echo integration trawl surveys on the eastern Bering Sea shelf. Circles are proportional to the area-backscatter strength (dB re 1 m^2 m^{-2}) in transect segments of 1 nautical mile.

approximately 10 m, and a vertical resolution of 0.2 m. Acoustic backscatter patterns were categorized by NOAA personnel as adult walleye pollock, juvenile walleye pollock, and other species. Only backscattered energy from 14 m from the surface to 0.5 m off the bottom and echogram regions corresponding to adult walleye pollock were used in this analysis. Transects from the summer survey are labelled S1, S2, and S3 and from the winter survey W1, W2, and W3.

Walleye pollock aggregations were detected and characterized using the SHAPES algorithm implemented in Echoview. We used Echoview version 3.10, but the same algorithm is available in later versions. The algorithm requires six input parameters: minimum candidate length (MCL), minimum candidate height (MCH), minimum school length (MSL), minimum school height (MSH), maximum vertical linking distance (MVLD), and maximum horizontal linking distance (MHLD). The algorithm first generates a matrix of Sv values for the section of echogram being analysed. Matrix columns correspond to each ping, and rows to each vertical sampling interval (Barange, 1994). The matrix is filtered by setting the cells with Sv values below a selected AT to zero. In the next step, candidate schools are identified. These are groups of adjacent pixels whose length and height are larger than the minimum candidate length and height parameters. Next, a connectivity criterion is applied. A search ellipse is moved around the perimeter of each candidate school. The axes of the ellipse are defined by the maximum vertical- and horizontal-linking distance parameters. Nearby groups of pixels that fall partially or completely within the search ellipse are connected and considered to be part of the same aggregation. Finally, connected aggregations with dimensions smaller than the minimum school length and height parameters are discarded (SonarData, 2004).

We tested the global sensitivity of aggregation descriptors to changes in seven input parameters (AT and the six parameters of the aggregation-detection algorithm), using a Monte Carlo sampling-based method (Helton and Davis, 2000). During each Monte Carlo run, aggregations were detected in each transect using a set of input parameter values selected at random using a Latin Hypercube sampling (LHS) design (McKay *et al.*, 1979). LHS is a stratified sampling design in which the probability density of each input parameter is divided into a number of intervals equivalent to the number of runs performed. The interval of each input parameter is randomly assigned to each run so that each interval appears in just one run (Rose, 1987). In each run, a single value is selected at random for each input parameter from the intervals assigned. This approach ensures that the entire parameter range is tested (Megrey and Hinckley, 2001). Values of all input parameters are simultaneously changed, which incorporates potential parameter interactions (Rose, 1987).

When using an LHS sampling design, the number of Monte Carlo runs required is independent of the number of parameters in the algorithm being tested. In this study, 350 Monte Carlo runs were performed for each transect. Rose (1982) concluded that an LHS design with 200 runs provided stable results (i.e. sensitivity tested with a larger number of runs provided similar results). The number of runs in this study was set at 350 to accommodate potential differences in the stability of the analyses results relative to Rose's (1982) experiments.

Input parameter values were selected using the widest possible range of values, at the same time minimizing the number of Monte Carlo runs that did not detect aggregations. Acoustic threshold values were set between −70 and −60 dB re 1 μPa @ 1 m. The lower limit of the range corresponded to the threshold used during data acquisition. The upper AT was recommended by

Petitgas *et al.* (1998) as an appropriate threshold for aggregation detection. This range includes −65 dB re 1 μPa @ 1 m, considered by ICES (2000) to be an adequate threshold for school detection. The lower bound of horizontal variables (i.e. MSL, MCL, and MMLD) was set at 10 m, which corresponds to the horizontal resolution of the data. To avoid vertically splitting aggregations, MHLD should be larger than the distance between pings, because the algorithm considers pixels to be adjacent in the horizontal direction only if the distance between pings is smaller than the MHLD value. For input variables that control aggregation detection in the vertical direction (i.e. MSH, MCH, and MVLD), a value of 6 m was selected, corresponding to the minimum value accepted by Echoview version 3.10: later versions accept smaller values. Except for AT, the upper bound of all input values varied among transects. To select these values, an aggregation detection was performed in each transect using an AT of −70 dB re 1 μPa @ 1 m and the lower limit of each input parameter, i.e. 10 m for horizontal and 6 m vertical parameters. The objective was to detect all possible aggregations using a low threshold. The upper limits selected for horizontal and vertical variables corresponded to the 90th percentile of the length and height of aggregations detected using these parameters (Table 1). The input parameter values for aggregation detection runs were selected from uniform distributions, because there was no *a priori* reason to select otherwise.

Several methods can be used to analyse the global sensitivity of an algorithm, including linear regression, correlation, and stepwise regression analysis (Helton and Davis, 2000). We evaluated the sensitivity of the aggregation-detection algorithm using rank correlation tests based on Spearman's ρ statistic (Sokal and Rohlf, 1981). The premise of a correlation test is that the index measures the influence of the input variable on each descriptor (Rose *et al.*, 1991; Campolongo *et al.*, 2000). We selected the rank correlation specifically because a preliminary analysis using local polynomial regression suggested non-linear trends in the aggregation descriptor values with varying values of input parameters. Whereas simple correlation measures linear dependency, rank correlation is a measure of general association between two variables (Sokal and Rohlf, 1981). Although the output of an LHS sampling design does not satisfy assumptions for testing significance, correlation tests can be used to indicate whether an algorithm output is affected by a particular input parameter (Helton and Davis, 2000). In our study, we considered that rank correlation tests significant at the $\alpha = 0.05$ level indicated that an aggregation descriptor was influenced by an input parameter.

The sensitivity of eight aggregation descriptors was measured. Six of the descriptors were calculated individually for each aggregation: aggregation length and height, mean and standard deviation of the volume-backscattering strength (Sv, MacLennan *et al.*, 2002) of pixels in each aggregation, line-backscattering coefficient (s_L), and aggregation depth in the water column, measured from the water surface to the centre of the aggregation. The line backscattering coefficient is s_L, a measure of the aggregation's total backscatter, is the volume-backscattering coefficient integrated over the sectional area of the aggregation (MacLennan *et al.*, 2002). Diner's (2001) corrections were applied to all descriptors to compensate for beam-effect distortion (Reid and Simmonds, 1993; Barange, 1994). Detected aggregations too small for an accurate size correction were eliminated from further analysis. Two additional aggregation descriptors were calculated in each transect: the total number of aggregations detected in each transect and the sum of their volume-backscattering coefficients.

Results

In all, 18 280 walleye pollock aggregations were identified in 2100 detection runs, corresponding to 350 runs in six transects. Aggregations were detected in 97.5% of the runs. The number of aggregations detected in each transect ranged from 1 to 85 with a median of 7 aggregations.

Rank correlation tests indicated that the aggregation-detection algorithm is sensitive to changes in input parameter values. A total of 336 rank correlation tests was performed: seven input parameters, eight aggregation descriptors, and six transects. Among these, 181 tests indicated significant correlation between input parameters and aggregation descriptors at the $\alpha = 0.05$ level (Table 2). The aggregation-detection algorithm was sensitive to changes in AT (41 of 48 correlation tests were significant) and, as expected, AT was negatively correlated with the number of aggregations detected. Increasing the AT eliminates pixels with low Sv values, and aggregations with low acoustic density are not formed. The reduction in the number of pixels included in each aggregation explains the negative correlation between acoustic threshold and total s_L. When threshold was increased, the mean Sv value increased in the remaining aggregations. This accounts for the positive correlations observed between threshold and mean Sv, as well as between threshold and s_L. An additional effect of a higher mean Sv is that there was a significant positive correlation between AT and the standard deviation of Sv values within aggregations, despite the fact that the range of Sv values within each aggregation decreased. Aggregation length and height were negatively correlated with AT,

Table 1. The range of input parameter values used for sensitivity analysis of the aggregation-detection algorithm implemented in Echoview®.

Transect	AT		MCL, MSL, and MHLD		MCH, MSH, and MVLD	
	Minimum (dB)	Maximum (dB)	Minimum (m)	Maximum (m)	Minimum (m)	Maximum (m)
S1	−70	−60	10	346	6	16
S2	−70	−60	10	266	6	16
S3	−70	−60	10	211	6	19
W1	−70	−60	10	268	6	18
W2	−70	−60	10	526	6	43
W3	−70	−60	10	131	6	20

Input parameters include acoustic threshold (AT), minimum candidate length (MCL) and height (MCH), minimum school length (MSL) and height (MSH), maximum horizontal-linking distance (MHLD), and maximum vertical-linking distance (MVLD). Sensitivity was tested in three transects from summer 2000 (S1, S2, and S3) and winter 2000 (W1, W2, and W3) echo-integration trawl surveys.

Table 2. Spearman's ρ correlation coefficients among input variables and aggregation descriptors obtained using Echoview's school-detection algorithm on three transects from summer 2000 (S1, S2, and S3) and winter 2000 (W1, W2, and W3) echo-integration trawl surveys.

Input parameter	Aggregation descriptor	S1	S2	S3	W1	W2	W3
Acoustic threshold	Number	−0.484***	−0.606***	−0.257***	0.043	−0.199***	−0.805***
	Total s_L	−0.672***	−0.698***	−0.236***	−0.798***	−0.992***	−0.848***
	s_L	0.164***	0.262***	0.325***	0.177***	−0.093***	0.046
	Mean Sv	0.214***	0.420***	0.356***	0.357***	0.060***	0.504***
	Sv s.d.	0.130***	0.223***	0.007	0.134***	−0.141***	0.050
	Length	−0.116***	0.009	−0.211***	−0.177***	−0.104***	−0.199***
	Height	−0.107***	−0.192***	0.014	−0.310***	−0.206***	−0.175***
	Depth	−0.008	0.070***	−0.113***	0.258***	0.107***	0.210***
MSL	Number	−0.137	−0.194***	−0.145**	−0.318***	0.025	0.094
	Total s_L	0.042	−0.153***	−0.056	0.042	−0.008	0.097
	s_L	−0.006	0.009	−0.081***	0.059***	0.047	0.008
	Mean Sv	−0.016	0.006	−0.125***	0.006	0.004	0.024
	Sv s.d.	−0.020	0.000	0.212***	0.040	0.015	−0.006
	Length	0.251***	0.243***	−0.089***	0.209***	0.038	0.085***
	Height	0.108***	0.089***	0.241***	0.147***	0.047	0.053**
	Depth	0.057***	0.083***	0.100***	0.014	0.028***	0.036
MSH	Number	−0.391***	−0.350***	−0.118	−0.256***	−0.492***	−0.284***
	Total s_L	−0.281***	−0.248***	−0.059	−0.093	−0.055	−0.199***
	s_L	0.027	0.148***	0.164***	0.031	0.254***	0.184***
	Mean Sv	−0.008	0.058***	0.094***	−0.004	0.123***	−0.085***
	Sv s.d.	0.020	0.093***	0.220***	0.000	0.148***	−0.094***
	Length	0.091***	0.125***	0.021	0.113***	0.234***	0.291***
	Height	0.244***	0.323***	0.167***	0.127***	0.278***	0.383***
	Depth	−0.158***	−0.138***	−0.097***	−0.041	0.117	0.116***
MCL	Number	−0.295***	−0.302***	−0.300***	−0.319***	0.039	−0.102
	Total s_L	−0.259***	−0.244***	−0.471***	−0.288***	−0.002	−0.047
	s_L	0.002	0.065***	0.008	0.168***	−0.003	0.024
	Mean Sv	−0.031	−0.019	−0.067***	0.065***	−0.013	0.011
	Sv s.d.	−0.047***	−0.042**	0.232***	0.007	−0.013	−0.022
	Length	0.149***	0.221***	−0.123***	0.099***	0.007	0.023
	Height	0.037	0.014	0.233***	0.007	−0.011	−0.030
	Depth	0.023	0.140***	0.099***	0.092***	0.008	0.054**
MCH	Number	−0.349***	−0.410***	−0.216***	−0.297***	−0.447***	−0.273***
	Total s_L	−0.411***	−0.400***	−0.283***	−0.352***	−0.085	−0.311***
	s_L	0.118***	0.237***	0.237***	0.062***	0.280***	0.191***
	Mean Sv	0.061***	0.074***	0.159***	−0.053***	0.128***	−0.222***
	Sv s.d.	0.082***	0.090***	0.080***	−0.052**	0.138***	−0.200***
	Length	−0.082***	0.080***	0.107***	0.030	0.216***	0.144***
	Height	0.188***	0.320***	−0.005	0.110***	0.288***	0.317***
	Depth	−0.103***	−0.119***	−0.120***	−0.088***	0.129***	0.157***
MVLD	Number	−0.019	0.016	−0.023	0.041	−0.020	−0.069
	Total s_L	−0.005	0.015	−0.039	−0.060	−0.008	−0.075
	s_L	0.037	0.022	0.038	0.007	−0.012	0.027
	Mean Sv	0.034	0.002	0.051	0.031	0.007	−0.010
	Sv s.d.	0.024	0.007	−0.008	0.006	0.006	0.002
	Length	−0.005	0.014	−0.015	−0.034	−0.006	0.027
	Height	−0.014	0.024	−0.004	−0.034	−0.010	0.023
	Depth	0.014	0.006	−0.002	0.011	−0.018	−0.009

MHLD	Number	−0.078	−0.013	−0.080	−0.354***	−0.165***	−0.017
	Total s_L	0.035	0.047	−0.026	0.119	−0.039	0.044
	s_L	−0.001	0.014	0.045	0.000	−0.048	−0.005
	Mean Sv	0.009	0.032	0.039	0.018	0.006	−0.011
	Sv s.d.	0.005	0.051***	0.091***	0.047	0.001	−0.004
	Length	0.091***	0.096***	0.030	0.183***	0.088***	0.103***
	Height	0.062***	0.089***	0.109***	0.114***	−0.015	0.046
	Depth	0.042**	−0.033	−0.006	0.011	−0.033	0.012

Symbols indicate *p*-values of significance of the correlation tests: *** < 0.005 < ** < 0.05.

because increasing the threshold removes low Sv pixels located at the periphery of most aggregations. Threshold was positively correlated with aggregation depth in four transects, indicating an increasing fish density with depth.

The aggregation descriptors were also sensitive to changes in parameter values that define minimum aggregation sizes. The aggregation-detection algorithm was sensitive to changes in MCL and MCH. Aggregation detection was more sensitive in the vertical dimension (MCH; 45 of 48 tests were significant; Table 2) than in the horizontal (MCL; 24 of 48 tests were significant). Aggregation detection was also sensitive to changes in values of MSH (35 significant tests), but less sensitive to MSL (22 significant tests). In general, changes to MCL and MCH, and to MSL and MSH, had a similar effect on the output of the aggregation-detection algorithm: a negative correlation with the number of aggregations detected and a positive correlation with aggregation length and height. Increasing the minimum size criterion reduces the number of detections and increases their average size. The patterns observed in the sensitivity of minimum aggregation size parameters and minimum candidate size parameters were similar. Correlation results, either positive, negative, or non-significant, were consistent between MCL and MSL in 35 of the 48 tests performed, and no test yielded contradictory results (i.e. positive and negative correlation values) in the same aggregation detection run. Similarly, correlation results between MCH and MSH were consistent in 45 of 48 tests, only one test resulting in contradicting values.

The aggregation-detection algorithm was less sensitive to the size of the search ellipse than to other input parameters. The search ellipse is defined using the MVLD and the MHLD parameters. The horizontal parameter had a greater influence than the vertical parameter. Changes in MHLD yielded 14 of 48 tests as significant, whereas changes in MVLD resulted in no significant tests.

Discussion

Aggregations of walleye pollock detected using the algorithm implemented in Echoview are sensitive to AT, minimum aggregation size and, to a lesser degree, the connectivity criterion. We believe that these results are applicable to similar aggregation-detection algorithms (e.g. MOVIES–B, Weill *et al.*, 1993) and to other fish species that aggregate in large pelagic shoals, benthic layers, and discrete aggregations. Changes in the detection input parameters were expected to influence the characteristics of detected aggregations, given that the detection process delimits regions of the echogram that satisfy acoustic density, size, and connectivity constraints defined by input parameter values.

Aggregation descriptors are very sensitive to changes in AT. In most studies, a single AT is selected to eliminate background noise, returns from non-target species, and returns from targeted individuals smaller than those of interest. The AT can be selected empirically by comparing empty regions of the echogram with regions that contain multiple targets (e.g. Richards *et al.*, 1991). Threshold selection can also be based on the target strength and density of the species of interest (Coetzee, 2000). As an example, Freón *et al.* (1996) used a threshold of 100 mV^2 to detect clupeoid schools. During post-processing, schools with Sv values lower than −44 dB were eliminated. In walleye pollock studies, two different ATs have been used for aggregation detection. During NOAA walleye pollock surveys, acoustic data are collected using a threshold of −70 dB re 1 μPa @ 1 m. This value was selected because lower thresholds did not significantly increase overall acoustic density in each transect (N. Williamson, pers. comm.). Wilson *et al.* (2003) used this threshold when detecting walleye pollock aggregations. In contrast, Swartzman *et al.* (1994a) selected a threshold of −55 dB re 1 μPa @ 1 m to eliminate samples with low acoustic density and small organisms such as zooplankton. It is likely that acoustic data collected at a threshold of −70 dB re 1 μPa @ 1 m contained returns from small organisms. These returns could introduce bias in aggregations detected using echo-trace classification, because every non-zero pixel is a candidate to be included in an aggregation by the detection algorithm. Low Sv pixel values can introduce bias in the results of ETC by increasing the number, size, and shape complexity of aggregations detected and by decreasing their mean Sv value. Additional aggregations detected or pixels added to aggregations will introduce spatial variability in the observed distribution of the target species. To reduce these potential biases, a threshold should be selected to minimize the number of pixels with non-target backscatter.

One approach to the selection of an AT is to estimate the mean volume-backscatter strength produced by a single animal within the volume represented by each pixel in an echogram. This threshold can then be used to eliminate pixels with lower Sv values. The mean volume-backscatter strength produced by a single scatterer can be calculated as

$$\mathrm{Sv} = 10\ \log\left(10^{\mathrm{TS}/10}\mathrm{Vp}^{-1}\right),$$

where TS is the target strength and Vp the volume represented by a pixel. For walleye pollock, target strength (in dB re 1 μPa @ 1 m) is quantified as a function of length using

$$\mathrm{TS} = 20\ \log\left(\mathrm{FL}\right) - 66.0,$$

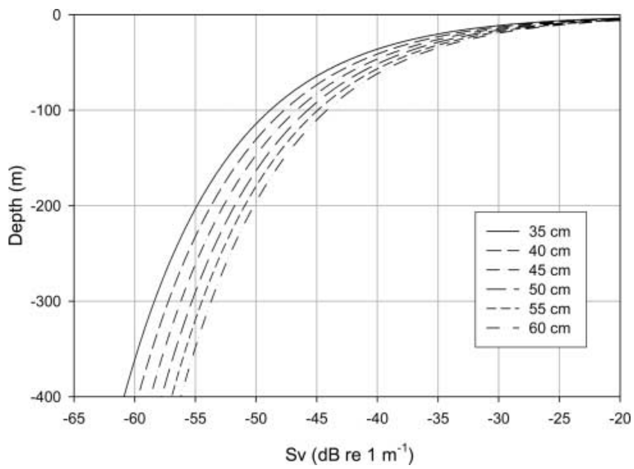

Figure 3. Estimated volume-backscatter coefficient (Sv) of a single walleye pollock as a function of depth and fish size.

where FL is fork length in cm (Foote and Traynor, 1988). We approximated the volume represented by each pixel in an echogram using

$$\mathrm{Vp} = \left(\frac{1}{3}\right)\pi h \tan^2\left(\frac{\theta}{2}\right)\left(3r^2 + \frac{h^2}{4}\right),$$

where θ is the beam angle at the half power points (i.e. −3 dB re 1 μPa @ 1 m), r is the range between the transducer and the centre of the pixel, and h is the height represented by each pixel. In our data, the beam angle was 7° and the height of each pixel was 0.2 m. The estimated Sv value of a single walleye pollock as a function of range and fish length is shown in Figure 3. For fish sizes between 35 and 60 cm, estimated Sv values ranged between −56.2 and −60.9 dB at a range of 400 m from the transducer, increasing to −42.8 to −38.1 dB at a range of 100 m. Given that the mean bottom depth in transects used in this study varied between 92 and 112 m and that trawl data in our study area indicated that most walleye pollock were between 35 and 60 cm FL, it is safe to assume that pixels with Sv values lower than −55 dB do not represent returns from walleye pollock in this area. A more conservative threshold of −60 dB could be used in deeper water or in the presence of smaller (e.g. juvenile) fish.

An additional consideration in the selection of an AT is the use of AT for school geometry and density. It is well known that horizontal dimensions of aggregations detected using echosounders suffer from beam-effect distortion (Reid and Simmonds, 1993; Barange, 1994). This distortion is based on the apparent increase in aggregation length attributable to the increase in beam diameter with range. As a consequence, average fish density and other derived aggregation descriptors (e.g. area, perimeter) may have systematic errors. To reduce bias in aggregation descriptors, Diner (2001) recommends the use of an AT sufficiently large to minimize aggregations detected in the side lobes of the acoustic beam. Diner's (2001) algorithms also provide more accurate corrections when the processing threshold is between 10 and 30 dB lower than the average Sv value of the detected schools. In our study, the average Sv value for detected schools in each transect using a threshold of −55 dB varied between −45.2 and −48.2 dB. Therefore, an AT between −60 and −55 dB is appropriate when using Diner's (2001) correction for the detection of walleye pollock aggregations in Bering Sea backscatter data.

Most studies use a fixed AT value, but other approaches are possible. Nero and Magnuson (1989) and Benoit-Bird *et al.* (2001) defined aggregations as adjacent elements (pixels) whose density was higher than an adaptive threshold based on two-dimensional smoothing within a rectangular window. Baussant *et al.* (1993) used eigenvector filtering to determine the two-dimensional trend in acoustic density, then defined patches as groups of pixels with density values higher than this trend. Additional effort is required to quantify possible differences among aggregations detected using fixed and varying ATs.

The school-detection algorithm is sensitive to changes in the minimum height of aggregations (MCH and MSH parameters), but less sensitive to changes in minimum length (MCL and MSL parameters). In principle, any group of contiguous pixels with non-zero values can be considered to be an aggregation. The size of the smallest aggregation detected is a function of the horizontal and vertical resolution of the data. The use of correction algorithms also limits the minimum aggregation size, because corrections can only be calculated accurately for schools with lengths 1.5 times wider than the beam width. Given this constraint, the selection of a minimum aggregation size is arbitrary. In some studies, minimum size parameters are selected to eliminate small patches and isolated echo returns. For example, Barange (1994) limited the minimum length of patches to values between 21 and 35 m. Freón *et al.* (1996) set the minimum length and height of detected pilchard (*Sardina pilchardus*) aggregations to 31 and 10 m. Coetzee (2000) used a minimum length of 10 m and a minimum height of 2 m to detect sardine (*Sardinops sagax*) schools. Minimum size parameters, or any other input parameter, may be iteratively selected to match aggregations observed when inspecting the echograms. Wilson *et al.* (2003) used this approach to detect walleye pollock aggregations using a minimum length of 40 m and a minimum height of 5 m.

A universal set of criteria to select minimum aggregation sizes does not exist. Petitgas *et al.* (1998) suggested eliminating small aggregations that do not contain a significant amount of fish biomass, but did not provide a method to select the minimum size. One objective approach to address this omission is to select a minimum aggregation size that includes a fixed fraction of the total acoustic density in each transect. A potential weakness of this approach is that a varying and sometimes large proportion of the total acoustic density could be located in numerous small patches. To illustrate this point using the walleye pollock data, aggregations were detected using the following input parameters: −70 dB AT, 10 m MSL and MCL, 3 m MSH, MCH, and MVLD, and 40 m MHLD. The total line-backscatter coefficient (s_L) of aggregations detected in transect W2 was just 7.47% of the total line backscatter within the transect. In contrast, an aggregation detection in transect W1 using the same input parameters included almost 80% of the total line backscatter within the transect. Because aggregation-detection algorithms do not export descriptors from patches smaller than the selected minimum size, we recommend that the minimum size parameters should be selected iteratively, starting with a small minimum size to maximize the number of aggregations detected. The importance of small patches can then be assessed by calculating the fraction of the total acoustic density included in aggregations as a function of the aggregation length or height. Minimum size parameters can then be selected to include a fixed fraction of the total acoustic density in the study area.

The objective of the study should also be considered when selecting minimum aggregation-size values. In studies describing spatial distributions of aquatic organisms, it may be important to quantify and characterize small aggregations and backscatter from organisms not included within aggregations. Small patches or dispersed individuals may not contain a large proportion of the biomass, but may be ecologically important. As an example, small aggregations are often located higher in the water column and, therefore, more accessible to shallow-diving predators. Speckman (2005) observed that the feeding activity of kittiwakes (*Rissa tridactyla*), a shallow diver, was better correlated with the acoustic biomass in the top 30 m of the water column than with the biomass in the top 100 m. Alternatively, when the objective is to characterize the spatial distribution of a population using geostatistical or point-process models (e.g. Petitgas, 2003), the detection of small patches may mask characterization of the population spatial structure and introduce bias in model parameter estimation.

Some school-recognition algorithms include a connectivity criterion that joins non-contiguous groups of pixels to an existing aggregation. MOVIES−B (Weill *et al.*, 1993) allows the user to define the horizontal and vertical spacing between patches, where vertical spacing is defined in metres and horizontal spacing by a number of pings. In Echoview, the connectivity criterion is defined using two parameters: maximum vertical- and horizontal-linking distances (MVLD and MHLD). These parameters define the axis of a search ellipse that is moved around the perimeter of each candidate school. The lack of sensitivity to MVLD is probably a result of the minimum value (6 m) used in this analysis. The selection of a maximum linking distance is also somewhat arbitrary. Two-dimensional sections depicted in echograms may not adequately portray the complex shapes and other features (e.g. vacuoles, gaps, protuberances) found in three-dimensional fish aggregations (Gerlotto and Paramo, 2003). Patches or groups of pixels that appear separated in two dimensions may be parts of the same three-dimensional structure. Larger connectivity distances reduce the number of detected aggregations and increase aggregation size and shape complexity. Increasing connectivity distance also confounds the spatial location and other properties of merged aggregations. If connectivity distances are kept small, these effects are minimized, while still allowing patches separated by small distances to be merged. One possible approach to selecting connectivity distances is to perform a preliminary aggregation detection using the smallest connectivity distance allowed by the software. A connectivity distance can then be set as a fixed quantile (e.g. 5% or 10%) of the length and height of the detected aggregations.

When using echo-trace classification, we recommend that all input parameter values are reported. In the past, aggregation-detection parameters were not listed or not explained when reported (Scalabrin and Massé, 1993; Haralabous and Georgakarakos, 1996; Soria *et al.*, 2003). Explicitly stating the threshold, minimum size, and connectivity criterion used to detect aggregations, as well as the rationale for their selection, facilitates evaluation of results and comparison with other studies.

Aggregation-detection algorithms may not adequately characterize small-scale spatial distributions of species that do not form aggregations with well-defined boundaries. Reid *et al.* (2000) recognized that spatial patterns such as loose aggregations, pelagic layers, and benthic layers cannot be characterized using aggregation-detection algorithms, and suggested that the presence or absence of these structures should be assessed visually at the elementary sampling data unit (ESDU) level. A further step to quantifying these spatial patterns would be to define a set of patch-based parameters that describe patch characteristics (i.e. groups of non-zero pixels) in each ESDU, including their number, size, and acoustic density; and a set of ESDU-based metrics, e.g. aggregation index or other indices from landscape ecology, that describe the overall spatial configuration of acoustic density within the ESDU. This combination of metrics may be more appropriate to describing fully the small-scale distributions of pelagic organisms and can be related to other biological or environmental variables to provide a better understanding of the processes that influence the distribution patterns of aquatic organisms.

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