

Identification of Southern Ocean acoustic targets using aggregationbackscatter and shape characteristics

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Woodd-Walker, R. S., Watkins, J. L., and Brierley, A. S. 2003. Identification of Southern Ocean acoustic targets using aggregationbackscatter and shape characteristics. – ICES Journal of Marine Science, 60: 641–649.

Acoustic surveys for biomass estimation require accurate identification of echoes from the target species. In one objective technique for identifying Antarctic krill, the difference between mean volume-backscattering strength at two frequencies is used, but can misclassify small krill and other plankton. Here, we investigate ways to improve target identification by including characteristics of backscattering energy and morphology of aggregations. To do this, multi-frequency acoustic data were collected concurrently with target fishing of Antarctic krill and other euphausiid and salp aggregations. Parameter sets for these known aggregations were collated and used to develop empirical classifications. Both linear discriminant-function analysis (DFA) and the artificial neural network technique were employed. In both cases, acoustic-backscattering energy parameters were most important for discriminating between Antarctic krill and other zooplankton. However, swarm morphology and other parameters improved the discrimination, particularly between krill and salps. Our study suggests that for krill-biomass estimates, a simple DFA based on acoustic-energy parameters is a substantial improvement over current dB-difference acoustic methods; but studies requiring the discrimination of zooplankton other than krill must still be supported by target fishing.

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Keywords: acoustics, artificial neural network, *Euphausia superba*, krill, linear discriminant analysis, South Georgia, Southern Ocean, zooplankton.

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Introduction

Acoustic surveys are conducted throughout the Southern Ocean to determine standing stock estimates of Antarctic krill (*Euphausia superba* (Dana)) and to investigate aspects of the distribution and ecology of the species (e.g. Watkins *et al.*, 1992; Trathan *et al.*, 1995; Hewitt *et al.*, 2002). Traditionally, Antarctic krill were distinguished from other scatterers using a range of subjective methods (e.g. Kalinowski and Witek, 1985; Murray *et al.*, 1995). Subjective classifications require validation through target-fishing representative examples of each grouping. However, target fishing is time-consuming and therefore costly, and classification may vary between acousticians. With the advent of multi-frequency echosounders, and developments in acoustic models, more objective methods have been developed. Madureira *et al.* (1993b), for example, used the difference in mean volume-backscattering strength (S_v) at

two frequencies to differentiate krill from other scatterers. Krill were identified as having a difference in S_v between 120 and 38 kHz ($\delta S_{v120-38}$) of 2–12 dB, whereas larger organisms tended to have a lower $\delta S_{v120-38}$ and smaller zooplankton a higher $\delta S_{v120-38}$. With some modifications, this method has been widely adopted by the international community (e.g. Brierley and Watkins, 1996; Brierley *et al.*, 1997; SC-CAMLR, 2000). However, evidence from both modelling and empirical studies suggests that $\delta S_{v120-38}$ for small krill may be greater than 12 dB and that other scatterers may fall within the $\delta S_{v120-38}$ 2–12 dB range (e.g. Watkins and Brierley, 2002; Demer, 2003; Ward *et al.*, 2002).

In an alternative approach to distinguishing between species, and one that has been applied extensively with regard to schooling fish (Reid, 1999), a single-frequency echosounder is used to characterize physical features of

each shoal or school (e.g. Weill *et al.*, 1993; Scalabrin *et al.*, 1996). Some fish shoals have distinct forms of aggregation, e.g. cod, capelin, and mackerel (Rose and Leggett, 1988). Others have distinct distributions within the water column (e.g. Richards *et al.*, 1991). Barange (1994) developed a range of acoustic-swarm features to distinguish between fish and zooplankton swarms. These features fall into two broad categories: first, morphological characteristics such as length, height, and area of swarms (see Figure 1 in Haralabous and Georgarakos, 1996); and, second, the distribution of acoustic-backscattering energy (energetic parameters) within the swarm (variance, “roughness”, and mean acoustic intensity). Lawson *et al.* (2001) used these and other swarm criteria to distinguish between schools of co-occurring fish species.

Most krill biomass is concentrated into near-mono-specific aggregations or swarms, particularly during the day (Watkins *et al.*, 1986). Other Antarctic zooplankton also form monospecific aggregations or layers (e.g. Brierley *et al.*, 1998). They are thus good candidates for differentiation using swarm-shape characteristics. In this study, we combine the use of multi-frequency acoustic techniques

with the characterization of swarm morphology to improve the discrimination between Antarctic krill and co-occurring Southern Ocean zooplankton, namely salps and another euphausiid *Thysanöessa* sp.

Method

The data described here were collected during four cruises on RRS “James Clark Ross” and during the CCAMLR 2000 synoptic survey on RV “Atlantida”, “Kaiyo Maru”, and “Yuzhmorgeologiya” (Hewitt *et al.*, 2002) around the sub-Antarctic Island of South Georgia and in the Atlantic sector of the Southern Ocean.

Acoustics

Data were collected using a SIMRAD EK500 echosounder operating hull-mounted, split-beam 38 and 120 kHz transducers and a single-beam 200 kHz transducer. The echosounder was configured to ping simultaneously at each frequency every 2.5 s on all cruises except one where it pinged once a second, with pulse lengths of 1.0, 1.0, and 0.6 ms, respectively. The performance of the echosounder was monitored at least once every cruise using standard-target, calibration techniques (Foote *et al.*, 1987). Data were recorded on a computer using Echolog (SonarData Pty Ltd 1996–2000) and viewed using Echoview.

Net sampling

Most of the net samples were taken with a multiple-opening and closing, 8 m², rectangular, midwater trawl (RMT8; Roe and Shale, 1979) with a 4.5-mm mesh. Some samples were collected with a five-net, multiple-opening and closing device, Antarctic multiple plankton sampler (AMPS). AMPS has a fixed-frame net with a mouth area of 1 m² and a 1.5-mm mesh. The five opening and closing codends, with 1-mm mesh, are mounted 1.5 m behind the mouth of the net. For RRS “James Clark Ross” cruises, both net systems were controlled and logged through the conducting towing cable by a shipboard PC.

Net sample analysis

On retrieval, net samples were either sorted immediately onboard or were preserved in 4% buffered formalin. Volumes of the total catch and of the dominant component species were recorded. Preserved samples were analysed on return to the UK. Total lengths of 100 Antarctic krill per sample were measured from the tip of the telson to the front of the eye (Morris *et al.*, 1988).

Reconstruction of net trajectories

The net trajectory was determined relative to the acoustic transducers by trigonometry. The “net depth” and “length-of-cable-out” were used to calculate the distance of the net

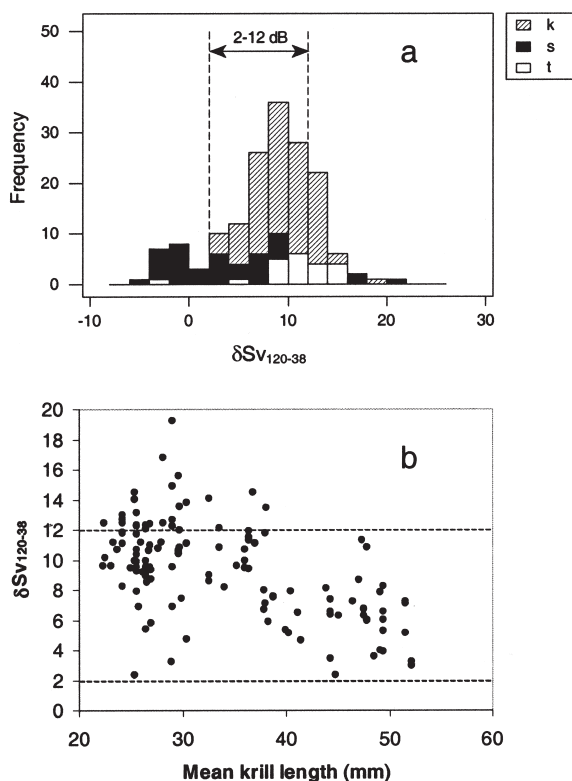


Figure 1. $\delta S_{V120-38}$ for the different swarm taxa. (a) A histogram of the distribution. (b) The relationship between the mean length of *E. superba* in net catches and $\delta S_{V120-38}$ for corresponding swarm. The dotted lines represent the boundaries of the 2–12 dB range for *E. superba*.

behind the transducers (cf. Zhou *et al.*, 1994). The ship's speed was used to convert this distance into a time offset that, with "net depth", was used to reconstruct the position of the net relative to the echogram.

Acoustic data processing

Acoustic data were calibration corrected and edited to remove erroneous points due to surface noise, bottom integration, or false-bottom detection. Echosounder data were integrated over 2.5-s and 1-m intervals to standardize the resolution between cruises, whilst maintaining as much detail as possible. TVG-amplified noise was masked out from each frequency using Echoview (SonarData Pty Ltd 1996–2000).

The 120-kHz echogram was used to identify acoustic targets and extract the parameters of the aggregations. To reduce the effects of beam spreading and absorption at depth, only those targets in the top 100 m of the water column were considered. The "Schools" module in Echoview was used to identify swarms and layers using a background threshold of -80 dB, minimum school-length of 10 m, school-height of 3 m, minimum connected length 15 m, minimum connected height 3 m, and a maximum horizontal linking-distance of 15 m. For each identified aggregation the mean volume-backscattering strength (S_v), the distribution of backscatter, and the various shape descriptors were calculated (Table 1). The S_v of these same aggregations was calculated from the 38- and 200-kHz echograms. Aggregation detection and description was repeated using a lower background threshold (-85 dB) so that the difference in swarm properties at the two thresholds could be compared (Lawson *et al.*, 2001).

Finally, acoustically detected aggregations that were likely to have been sampled with the net were determined with reference to the corrected net trajectory, and those with greater than 90% by volume of the dominant species were assigned to that species.

Statistical analysis

The discrimination currently used to determine krill was tested for its reliability by calculating $\delta S_{v120-38}$ for each of the swarms, and the proportion between 2 and 12 dB was calculated for each of the three species identified. This was used as a baseline to compare with more complex discrimination functions.

Many of the parameters had highly skewed distributions and so were \log_{10} transformed (Table 1). The data from all cruises were standardized to zero mean and unit standard deviation. Several of the swarm features were highly correlated. Therefore, to reduce the number of factors, principle component (PC) analysis was carried out on groups of factors from the training set: size, shape, δS_v , variation in acoustic energy (Var_en) (Table 1), and changes in these variables with the detection threshold (Δ size, Δ Var_en).

Table 1. Swarm parameters used in analysis.

PC category	Energetic parameters	PC category	Morphometric parameters	Additional information
—	S_v mean at 120 kHz dB, (S_{v120}) ^a	Size	Corrected length (L_c) ^{a,b}	Depth of aggregation (D_m) ^a
Var_en	Standard deviation of acoustic energy (s.d.) ^{a,b}	Size	Corrected height (H_c) ^{a,b}	Day/night
Var_en	Skewness of acoustic energy (Skew) ^{a,b}	Size	Corrected perimeter (P_c) ^{a,b}	
Var_en	Kurtosis (Kurt) ^{a,b}	Size	Corrected area (A_c) ^{a,b}	
Var_en	Horizontal roughness (HR) ^{b,c}	Shape	Image compactness (IC) ^{b,d}	
Var_en	Vertical roughness (VR) ^{b,c}	Shape	Fractal dimension (FD) ^{b,c}	
δS_v	$\delta S_{v120-38}$ ^e			
δS_v	$\delta S_{v200-120}$ ^e			
δS_v	$\delta S_{v200-38}$ ^e			

^aSee Lawson *et al.* (2001) for definitions.

^b \log_{10} transformed.

^cSee Barange (1994) and Nero *et al.* (1990).

^dSee Weill *et al.* (1993).

^e δS_{vf1-f2} is the difference in the mean volume backscatter (S_v) at f_1 and f_2 kHz.

The data set was split into a training set and a testing set consisting of 80 and 20% of the known swarms, respectively, with the same proportion of each group (Antarctic krill, salps, and *Thysanöessa*) in each data set. The training set was used to develop empirical discrimination models.

Initially, linear discriminant-function analyses (DFA) based on Mahalanobis distances were carried out using Minitab 13. This was performed on the training set using cross-validation to improve the generalization capabilities of the model. We first included all three discriminant categories (krill, salps, and *Thysanöessa* sp.) for swarm parameters related to the backscattering energy (S_{v120} , PC1 and 2 δS_v , PC1 and 2 Var_en). The process was repeated using only morphological principle component (PC1 and 2 size, PC1 and 2 shape). Next, energetic and morphological swarm parameters were combined, and additional information such as swarm depth and day and night differences were included. Finally, we included the PC from the change in threshold (ΔS_{v120} , PC1 Δ Var_en, PC2 Δ Var_en, PC1 Δ size, PC2 Δ size). At each stage the discrimination function was optimized by adding and removing different parameters to give maximum accuracy in the discrimination. The final optimized model based on all parameter types was then tested for its generalization capabilities using the validation data set.

The DFA was repeated using salps and krill only because the distinction between krill and salps was less clear than with *Thysanöessa*, and this has been identified as a problem in previous studies (Demer, 1994, and references therein). In addition, the limited number of *Thysanöessa* sp. swarms may reduce the power of the discriminant analysis.

An analysis using an artificial neural network (ANN) was also carried out, although *Thysanöessa* spp. were excluded from this analysis as there were not enough swarms sampled. Unlike a discriminant analysis, the ANN does not have any underlying assumptions of linearity in the data. The ANN analysis (SAS, version 8, SAS Institute Inc., 1999–2000) was based on a simple feed-forward network with one hidden node. With such a small training set ($n = 166$), more nodes were likely to reduce the generalization capabilities of the network. The “training set” used for the linear-discriminant analysis was split into two parts with 75% used for training the network and 25% for testing the network. A Levenberg–Marquardt training technique was used to optimize the network (Hagan and Menhaj, 1994), which was done in the same way as the linear-discriminant model, taking into account the performance of the testing as well as the training part of the data set. Once the model was optimized, it was tested for its generalization capabilities using the separate validation data set.

Results

Baseline acoustic classification

Over the seven cruises, analysis of the net samples indicated that 145 swarms were Antarctic krill (*E. superba*), 59 salps, and 21 the small euphausiid *Thysanöessa* sp. Using $\delta S_{v,120-38}$ values of 2–12 dB as our baseline acoustic discrimination (Madureira *et al.*, 1993b) to identify krill, over 75% of net-identified krill swarms were correctly identified as krill using the acoustic technique. However, more than 50% of the salp and *Thysanöessa* sp. aggregations were incorrectly identified as krill (Table 2, Figure 1a). This baseline acoustic classification improved when considered in terms of biomass, thus 94.4% of krill biomass was correctly assigned. However, approximately 85% of salp and 23% of *Thysanöessa* biomass were still classified

Table 2. A classification of swarms using the method of Madureira *et al.* (1993a) ($\delta S_{v,120-38}$ 2–12 dB for krill) (bold denotes correct classification).

	Krill ($2 < x < 12$ dB)	Non-krill ($2 > x > 12$ dB)	Total	% Correct	% Correct by mass
Krill	117	28	145	80.6	94.4
Salps	30	29	59	49.2	15.5
<i>Thysanöessa</i>	12	9	21	42.9	76.9
Overall correct	117	38	226	68.8	79.8

as krill. Most of the krill misclassifications were juvenile krill (mean length <30 mm, Figure 1b).

Principle component analysis

PC analysis of the groups of standardized parameters shows that there is high covariance between the variables within each group, with the first PC accounting for most of the variation (70–96%), and combined with the second component over 96% of the variation is accounted for. Thus, use of the PC has provided a powerful way of reducing the number of parameters used in the DFA without reducing the information content.

Separation by linear discriminant-function analysis

Linear DFA, using acoustic-energetic parameters alone, provided a good separation of *Thysanöessa* sp. from krill (Table 3a). However, salps were frequently misclassified as krill or *Thysanöessa* sp. Swarm morphology (shape and size) criteria were less effective overall in distinguishing the three species, and particularly for *Thysanöessa* sp. (Table 3b). However, salps were correctly classified more frequently. Combining energetic and swarm morphology parameters improved the overall correct classification to 75% of swarms (Table 3c). Salps again were least consistently classified correctly. Including the change in threshold improved the classification of krill and therefore the overall results slightly, with the overall classification rate approaching 80% (biomass 99%) (Table 3d). In this final model, all groups of parameters are represented, suggesting that extra types of data contain useful information. Testing the model on the validation data set showed reasonable discrimination for krill and *Thysanöessa* sp. (70 and 100%, respectively), but poor discrimination for salps (40%), although sample sizes were small for salps and *Thysanöessa* sp. (Table 3e).

Repeating the analysis, but discriminating only between krill and salps, showed that although the discrimination was improved, similar factors were significant (Table 4). The test of the final model also showed improved performance over the equivalent model for three species (Tables 3e and 4b). However, note that the number of salp aggregations in the validation data set is small and so differences between these test results may not be significant.

Inspection of the distribution of the aggregations within the parameter space provides useful information on the properties of the different species. Thus, in contrast to krill, both *Thysanöessa* sp. and salp aggregations generally had relatively low S_v and a low variation in energy within each aggregation (high PC1 Var_en; Figure 2a). *Thysanöessa* sp. and salp aggregations differed, however, in terms of shape and δS_v . Thus the difference in backscatter at higher frequencies ($\delta S_{v,120-38}$ and $\delta S_{v,200-120}$) is much larger in *Thysanöessa* sp. aggregations than in salps (PC1 δS_v ; Figure 2a). The change with threshold parameters is close

Table 3. DFA of the training set carried out with cross-validation and optimized from different parameter sets. Bold represents correct assignment.

	True group			Total	% Correct	% Correct by mass
	Krill	Salps	<i>Thysanöessa</i>			
(a) Energetic parameters: PC1 δS_v , PC1 Var_en. (optimized from S_{v120} , PC1 δS_v , PC2 δS_v , PC1 Var_en, PC2 Var_en)						
Krill	82	19	11	112	73.2	
Salps	6	27	9	42	64.3	
<i>Thysanöessa</i>	0	2	15	17	88.2	
Overall correct					72.5	
(b) Shape parameters: PC1 size, PC1 shape, PC2 shape (optimized from PC1 size, PC2 size, PC1 shape, PC2 shape)						
Krill	59	26	33	118	50.0	
Salps	2	37	7	46	80.4	
<i>Thysanoessa</i>	7	4	6	17	35.3	
Overall correct					56.4	
(c) Energetic, morphological, and other parameters: PC1 δS_v , PC1 Var_en, PC1 size, PC1 shape, PC2 shape (optimized from S_{v120} , PC1 δS_v , PC2 δS_v , PC1 Var_en, PC2 Var_en, PC1 size, PC2 size, PC1 shape, PC2 shape, day/night, Dm)						
Krill	84	17	11	112	75.0	
Salps	7	29	6	49	69.0	
<i>Thysanöessa</i>	1	1	15	17	88.2	
Overall correct					74.9	
(d) All classes of parameters including change with threshold: PC1 dB, PC1 Var_en, PC1 shape, PC2 shape, S_{v120} mean with threshold (optimized from: S_{v120} , PC1 ΔS_v , PC2 δS_v , PC1 Var_en, PC2 Var_en, PC1 size, PC2 size, PC1 shape, PC2 shape, day/night, Dm, change with threshold: ΔS_{v120} , PC1 ΔVar_{en} , PC2 ΔVar_{en} , PC1 $\Delta size$, PC2 $\Delta size$)						
Krill	89	13	9	111	80.2	99.4
Salps	13	28	6	49	68.3	48.7
<i>Thysanöessa</i>	1	1	15	17	88.2	75.0
Overall correct					78.1	98.8
(e) Testing of the final model (all classes of parameters including change with threshold. Parameters included in the discrimination PC1 δS_v , PC1 Var_en, PC1 shape, PC2 shape, ΔS_{v120})						
Krill	19	5	3	27	70.3	86.4
Salps	4	4	2	10	40.0	14.3
<i>Thysanöessa</i>	0	0	4	4	100.0	100.0
Overall correct					65.9	83.9

to 1, suggesting that detection threshold makes little difference to the swarm attributes (see Figure 2c for instance).

For salps, there is no single defining characteristic, but salps do have a high δS_{v120} (Figure 2c), suggesting that a reduction in threshold of backscatter reduces the S_v at 120 kHz, i.e. more low-backscatter areas are being included. PC1 Var_en is also high. However, in contrast to *Thysanöessa* sp., this is associated with a low PC1 δS_v (Figure 2a), and with a high PC2 shape (Figure 2b) suggesting a high fractal dimension compared with compactness. Salp swarms also have high PC1 shape for their size (Figure 2d). Many of the salp swarms which have been misclassified as krill have low PC1 shape relative to PC1 size (Figure 2d), and low PC2 shape and PC1 Var_en (Figure 2b). Large salp aggregations (low PC1size) have been misclassified as krill when their PC1 Var_en has been low, i.e. when there is high variability in the backscatter within the swarm. Such a result suggests that there is considerable heterogeneity within the large aggregations.

Krill swarms tend to cover a wide range of the parameter space and have been misclassified when their swarm type is similar to salps and *Thysanöessa* sp. However, if the mean backscatter is examined with size (Figure 2e), it can be seen that the misclassified krill swarms tend to be low density (low S_{v120}) and small or just small. Therefore, the effect on biomass estimates is relatively low.

Separation using ANN

The ANN was optimized with parameters of mean backscatter (S_{v120}), change in mean backscatter with threshold (ΔS_{v120}), first and second PCs of shape, and the first PC of size. This model performs well for classifying krill, but less well for salps, particularly on the validation data set (Table 4). Krill that were misclassified tended to have high PC2 shape, whereas misclassified salps had low PC2 shape and relatively high S_{v120} . PC2 shape is low when image compactness is high relative to fractal dimension. Comparing S_{v120} with \log_{10} (swarm area) (Figure 3) shows that the krill which were misclassified tended to be low

Table 4. The results of ANN discrimination for krill and salps using all classes of parameters including change with threshold. Significant parameters: S_{v120} , PC1 size, PC1 shape, PC2 shape, Δ_{v120} mean with threshold (from S_{v120} , PC1 δS_v , PC2 δS_v , PC1 Var_en, PC2 Var_en, PC1 size, PC2 size, PC1 shape, PC2 shape, day/night, swarm depth, change with threshold: ΔS_{v120} , PC1 Δ Var_en, PC2 Δ Var_en, PC1 Δ size, PC2 Δ size, PC1 Δ shape, PC2 Δ shape). In parentheses are the results for DFA of krill and salps only, derived from the same parameter set (significant parameters: PC1 δS_v , PC1 Var_en, PC1 shape, PC2 shape, ΔS_{v120}). Bold represents correct assignment.

	True group			% Correct	% Correct by mass
	Krill	Salps	Total		
(a) Training set					
Krill	110	10	120	91.7 (87.4)	99.9 (97.0)
Salps	12	34	46	73.9 (85.4)	3.4 (29.4)
Overall correct				86.7 (86.5)	98.4 (96.1)
(b) Validation dataset					
Krill	27	2	29	93.1 (80.8)	87.5 (94.9)
Salps	6	6	12	50.0 (60.0)	84.6 (17.3)
Overall correct				80.4 (75.0)	87.5 (92.5)

density and therefore would lead to quite a small effect on biomass estimates. However, the misclassified salp swarms were those with high density (S_{v120}) and large area or just large area (Figure 3), and so the estimates of salp abundance would not be accurate. However, because the salp densities are lower than those of krill, the effect of including salps within krill would have a minor effect on the apparent krill density.

Discussion

The classification or identification of pelagic aggregations by acoustic means alone is a major goal for acousticians worldwide. Work in the Antarctic has shown that under ideal conditions it is possible to use multi-frequency acoustics to identify a number of different species (Brierley *et al.*, 1998). However, the general utility of such techniques to work under a wide range of conditions rather than

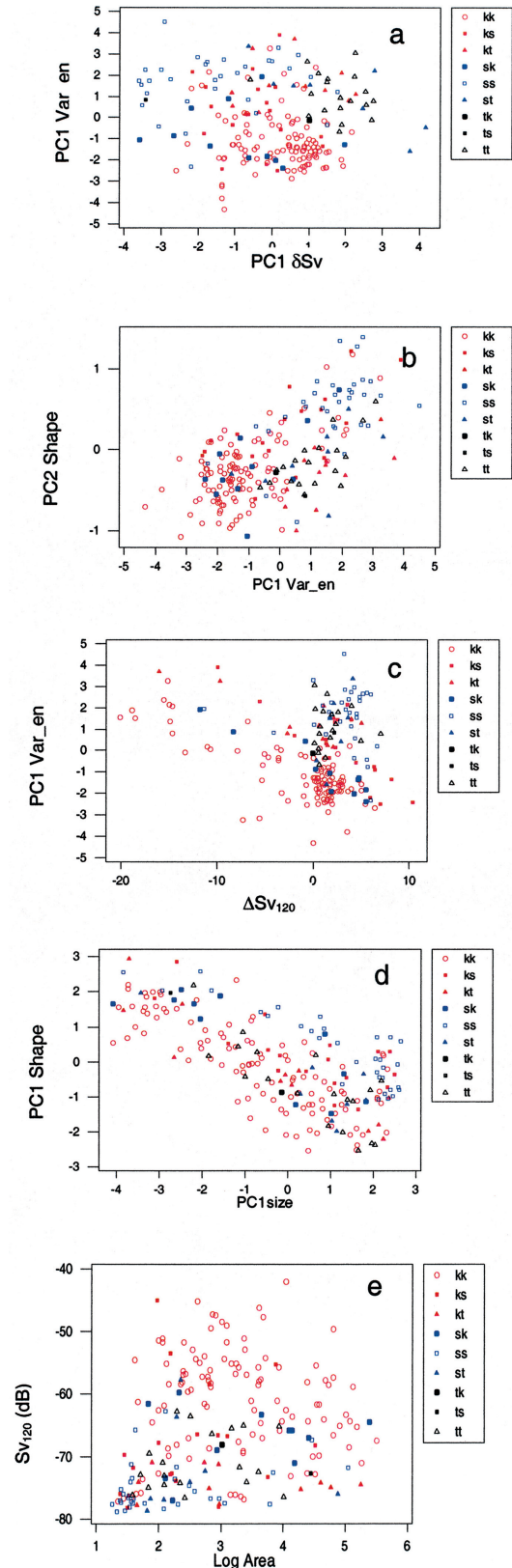


Figure 2. Scattergrams of the correct and misclassified swarms from the final DFA model, including all swarms (testing and training sets). (a) PC1 δS_v and PC1 Var_en. (b) PC2 shape and PC1 Var_en. (c) PC1 Var_en and ΔS_{v120} . (d) PC1 shape and PC1 size. (e) S_{v120} and log area. In the key, the first letter refers to the actual swarm type and the second to the predicted swarm type. The colour represents the actual swarm type (Krill red, Salps blue, and *Thyasnoessa* black) and the shape of the predicted swarm type (Krill circles, salps square, and *Thyasnoessa* triangles). Filled symbols are misclassified swarms.

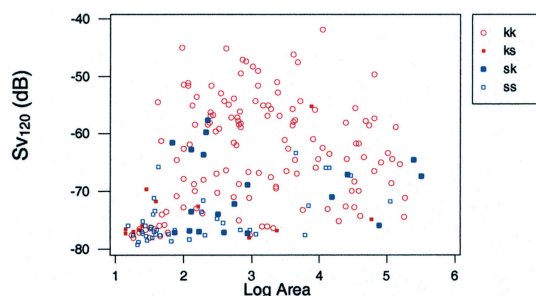


Figure 3. Scattergrams of the correct and misclassified swarms from the final ANN model, including all swarms (testing and training sets). S_{v120} vs. log area. In the key, the first letter refers to the actual swarm type and the second to the predicted swarm type (see Figure 2).

just the specific conditions encountered during a particular study is yet to be demonstrated.

Comparison of classification techniques

In this study, we have taken a selection of acoustically-derived parameters and used these in various combinations to derive more rigorous techniques for identifying or classifying acoustic targets. Using the simple technique ($\delta S_{v120-38}$ range 2–12 dB) to discriminate Antarctic krill is reasonably reliable for large krill (length >30 mm), but in the present study approximately 60% of the salp and 50% of the *Thysanöessa* sp. swarms sampled were included as krill. In studies where the dB-difference range has been extended (e.g. CCAMLR-2000 data; SC-CAMLR, 2000) even more non-krill zooplankton will be included in the krill fraction.

Adding additional acoustic parameters to the two-frequency dB difference provided an improved classification. Used alone, the morphometric descriptors provided only a low level of discrimination. This is in marked contrast to the level of discrimination obtained in studies on schooling fish (Scalabrin *et al.*, 1996). However, this may be a reflection of the irregularity of some of the aggregation types with the apparent shape and size of swarms perhaps being very sensitive to the direction and line along which they were sampled. Aggregation shape and size may vary in response to time of day or location; for instance, on or off the continental shelf (Miller *et al.*, 1993; Watkins, 2000) and the inclusion of such information is likely to improve classification. Morphometric and acoustic-energy information used together did result in improved discrimination over that of just acoustic energy.

In this study, we have used both linear (DFA) and non-linear (ANN) techniques to classify the acoustic targets. The ANN shows similar discrimination abilities to the DFA (Table 4). However, slightly different parameters were used in the models. Because of the non-linear nature of the ANN model, it was possible to use S_{v120} in the discrimination process. Theoretically, this should lead to improved discrimination between krill and salps. However, in our

particular case further improvement in the model may have been limited because the small number of swarms did not provide adequate coverage of the parameter space. In addition, a very simple network had to be used and this limited the interaction between variables and the non-linearity that could be encapsulated by the model.

Krill and *Thysanöessa* appear to be relatively easy to separate from each other, but salps are not so easy to distinguish, particularly if only acoustic-energy traits are used. The distinction between salps and euphausiid species is ecologically important because they occupy very different niches and play different roles in the transfer of energy within the Southern Ocean ecosystem (Voronina, 1998). Recent modelling and target-strength estimates of salps (David *et al.*, 2001) have shown that not only is the size of salps within an aggregation more variable than is typical for krill but also that scattering may be dominated by either the dense small nucleus or by the larger diffuse body, depending on the size of the salp and the ensonifying frequency. This results in variable target strength and inconsistent dB differences between frequencies. Salps tend to be less patchily distributed than krill and form lower density swarms (Figure 3 and Foxton, 1966). Thus, the shape and the difference in S_v on the threshold of the aggregation appear to be important indicators of salps. Another problem with salps is that at times they are found within layers that contain high- and low-density regions. Net sampling indicates that such layers often contain both krill and salps, but it is difficult to determine the degree of mixing within the layer. Thus krill and salps may occur discretely, for instance with krill in the dense regions and salps in the low-density regions, or may occur as a more homogeneous mixture within the layer. If layers have areas of salps separate from areas of krill, net samples may be dominated by one or the other, and therefore the initial identification of the layer may be incorrect.

Implications for biomass assessment of krill and identification of Antarctic zooplankton

We have shown that use of DFA or ANNs on an acoustic-parameter set that combines energetic and morphometric values provides the best discrimination. However, it must be noted that this improved discrimination comes with an additional analysis cost. While school or swarm recognition can be automated to some degree, there is still a requirement to define and extract swarm descriptors. It is therefore important to ensure the correct balance between analysis effort and the level of discrimination required. On the basis of the present work we can make some recommendations about the level of effort required to achieve adequate species discrimination for two different objectives. The first objective is to achieve an adequate discrimination between Antarctic krill and other zooplankton, such that reasonable acoustic-biomass assessments of krill may be made. The second objective is to achieve robust identification of

major zooplankton groups for studies of pelagic ecology (Constable *et al.*, 2000).

The results show that in terms of our first objective the use of a simple discriminant function produces a reasonable separation and an improvement over the more frequently used dB-difference technique. One significant advantage of the DFA is that misclassified krill tend to be from low-density, small swarms or simply from small swarms *per se*, whereas the dB-difference technique excludes swarms of small krill that may, of course, be high-density aggregations. The implication for biomass assessments of krill can be seen clearly; correctly apportioned biomass increases from 94% to approximately 99%. We therefore suggest that these relatively simple discrimination techniques are entirely adequate for estimating krill biomass. Under limited circumstances, salps could lead potentially to overestimates of krill biomass where krill biomass is low and salp biomass is high. It would not, however, lead to high biomass estimates of krill such as are commonly found around the Antarctic Peninsula and South Georgia (SC-CAMLR, 2000).

In contrast, for the second objective aimed at zooplankton ecology, we find that although the discriminant function and ANN are significant improvements over the simple dB-difference techniques, there are still large proportions of some of the species, in this case salps, that are incorrectly classified. In more complex ecosystems, these problems are likely to be worse and so ecological studies must depend to a large extent still on the right balance of acoustic sampling and net sampling to ensure adequate species identification.

Acknowledgements

We thank the Chief Scientists (Drs Hewitt, Naganobu, and Tchernyshkov) for permission to use the acoustic data collected by the acousticians Drs Hewitt, Demer, Takao, Kasatkina, and Malyshko and the net data collected by Drs Loeb, Kawaguchi, Litvinov, and Siegel from the CCAMLR-2000 Synoptic Survey. We also thank colleagues at BAS, particularly D. Bone, who assisted with the acoustics and net sampling during the RRS "James Clark Ross" cruises, and N. Crisp, A. Harris together with Professors G. Griffiths and H. Roe for assistance with the project. Funding for RWW was provided by the UK's Natural Environment Research Council Antarctic Funding Initiative Grant (AFI GR3/G0010).

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