# Acoustic species identification of schooling fish

Rolf J. Korneliussen, Yngve Heggelund, Inge K. Eliassen, and Geir O. Johansen

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The development of methods for the acoustic identification of fish is a long-term objective aimed at reducing uncertainty in acoustic-survey estimates. The relative frequency response $r(f)$ measured simultaneously at several frequencies is one of the main acoustic features that characterize the targets, but the relationship between nearest neighbours, school morphology, and environmental and geographical data are also important characteristics in this context. The number of acoustic categories that can be separated with a high spatial resolution is limited by the stochastic nature of the measurements. Because the acoustic categorization of larger ensembles is more reliable than for single targets, spatial smoothing of the backscattering within the school boundaries before that process allows the separation of more categories than is possible with the raw, highly resolved data. Using the mean $r(f)$ of an entire school gives even more reliable categorization, but determining whether or not the school is monospecific sets a new challenge. This problem is evaluated here. The methods are tested and verified. Identification of acoustic categories with similar acoustic properties is done for schooling fish, although the results have limited spatial resolution. The reliability of the categorization is further improved when knowledge of school morphology and geographical distribution of the species are taken into account.

**Keywords:** categorization, relative frequency response, school morphology.

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*R. J. Korneliussen and G. O. Johansen: Institute of Marine Research, PO Box 1870 Nordnes, N-5817 Bergen, Norway. Y. Heggelund and I. K. Eliassen: Christian Michelsen Research AS, PO Box 6031, N-5892 Bergen, Norway. Correspondence to R. J. Korneliussen: tel: +47 55 23 85 00 (6853); fax: +47 55 23 85 84; e-mail: rolf@imr.no.*

## Introduction

Identification of the particular fish species represented by acoustic data currently depends on a combination of objective visual interpretation of the data, allied with information obtained from biological samples. There is high potential for error with this process and consequently much demand that ambiguity in the interpretations should be reduced to improve acoustic estimates of fish abundance. Species identification is seen by MacLennan and Holliday (1996) as "the grand challenge of fisheries and plankton acoustics". Several attempts have been made to identify species using acoustic data. Horne (2000) and Fernandes *et al.* (2006) summarized various methods developed for this purpose in the period up to 2005.

Species identification based on school morphology represents one type of approach to resolving the identification problem. It depends on the assumption that fish aggregate in monospecific schools. Differences among species regarding swimming speed and prey and water-temperature preference supposedly prevent the formation of multispecies schools. Reid *et al.* (1999) summarized methods for classifying schools and listed the basic morphological parameters to be considered, e.g. the length, height, and perimeter of a fish school. Scalabrin *et al.* (1996) used morphological parameters from single-frequency acoustic data, but admitted that their results were not yet suitable for accurate species identification. Haralabous and Georgakarakos (1996) used morphological and bathymetric details of schools as inputs to their artificial neural network (ANN) and were able to distinguish monospecific schools of some fish species with reasonable success. A general criticism of the ANN approach is that it is difficult to interpret the decision weights and how these are estimated inside the ANN. Therefore, any systematic improvement of the ANN's performance is difficult to achieve.

Species identification based on multifrequency acoustic data is another approach to resolving the classification problem. Multifrequency data have been used since the late 1970s to identify and quantify scattering from zooplankton (Holliday, 1977; Martin *et al.*, 1996), micronekton (Madureira *et al.*, 1993), and fish (Kang *et al.*, 2002; Kloser *et al.*, 2002; Korneliussen and Ona, 2002, 2004; Fässler *et al.*, 2007). Korneliussen and Ona (2002, 2003) drew attention to data-collection procedures, because acoustic-survey data are often collected in a manner optimized for single-frequency applications. Preprocessing of multifrequency data by compensating for transducer positions and transmission delays in the receiver improves the spatial comparability between data collected at different frequencies (Korneliussen *et al.*, 2008). Acoustic records should also be corrected for ambient noise (Korneliussen, 2000) and smoothed to reduce stochastic variation. The preprocessed multifrequency data provide the relative frequency response $r(f)$ for small volumes, which is then used to distinguish various acoustic categories, where $r(f)$ is defined as the ratio of the backscattered energy at frequency $f$ to that at 38 kHz. Hence $r(f) \equiv s_v(f)/s_v(38\text{ kHz})$ (Korneliussen and Ona, 2002). This method has been used with success to distinguish scattering groups with a high spatial resolution (Kloser *et al.*, 2002; Korneliussen and Ona, 2002). A typical example is the grouping of acoustic data into acoustic categories, such as Atlantic mackerel,

which do not have a swimbladder, other fish with swimbladders, resonant scatterers, and zooplankton (Korneliussen and Ona, 2002). However, this approach is limited when trying to distinguish between fish species with similar acoustic properties. For example, it cannot distinguish capelin from polar cod (Fernandes *et al.*, 2006) nor Atlantic herring (*Clupea harengus*) from Norway pout (*Trisopterus esmarkii*; Fässler *et al.*, 2007). Pedersen and Korneliussen (2009) grouped acoustic data from fish tracks that were clearly associated with a single species; hence, they were able to identify species with similar acoustic properties. The challenge then was to identify the species associated with each track and, of course, to identify the track itself.

A novel approach towards better species identification would be to combine the multifrequency analysis with information about the morphology and geographical distribution of fish species. When a fish school contains two species, differences in the swimming speed and prey and temperature preferences support the assumption that the species occupy different regions within the school, rather than it being a fully mixed school. Moreover, it is not always obvious that acoustic records that apparently represent a single school come from a single species. Such records could represent two schools of different species passing each other or it could represent two species schooling together in the same school. In both cases, the uncertainty can be addressed by preprocessing acoustic data, as described above, and generating mean acoustic measures from different cells (segments) of the school. Then, the acoustic properties can be compared with test results to establish whether they belong to the same species. Once monospecificity has been validated, the acoustic variability can be reduced further by averaging the data from entire schools, thereby enhancing the prospect of identifying species with similar acoustic properties. For those schools whose species cannot be identified acoustically, less precise methods, based on school morphology, have to be used.

The aim of this study is to demonstrate that it is possible to distinguish species with similar acoustic properties, provided they occur in monospecific schools. The aim is also to demonstrate that species identification can be improved further by considering the acoustic data in conjunction with information on the morphological properties of schools and the geographical distribution of fish.

## Material and methods

### Data collection

Acoustic data from schools of capelin and juvenile herring were obtained during a survey with the commercial vessels MS "Eros" and MS "Libas" along the Norwegian coast, in the southern part of the Barents Sea, from 2 February to 2 March 2008. No threshold was applied to the echosounder signals. The main purposes of this survey were to estimate spawning-stock abundances, clarify the migration patterns of capelin, and ascertain the distribution of juvenile herring. In addition, the survey provided multifrequency data suitable for training acoustic post-processing systems for species identification. Only acoustic data related to trawl catches dominated by one species were used for the training. Suitable catches had to contain at least 98% of one species by weight, although this proportion was usually 100%. This is a much stronger criterion than using trawl catches within ~50 nautical miles to verify acoustic data, as is done for abundance estimation during routine surveys. Trawl samples were taken with commercial, single-bag pelagic trawls with an opening circumference of 950 m for MS "Libas" and 600 m for MS "Eros". The towing speed was typically 3.5 knots for both vessels.

Acoustic data were collected with a Simrad EK60 echosounder operating at frequencies of 18, 38, 70, 120, and 200 kHz, respectively. The transducers on both vessels were mounted in a close-packing arrangement (Korneliussen and Ona, 2002) on an instrument keel that protruded three metres below the hull to avoid aeration problems during data collection. The beam width of the 18-kHz transducer was 11°, and for the other transducers, it was 7°, as measured at the 3-dB down points.

The echosounders were calibrated according to the methods described by Foote *et al.* (1987). The pulse duration was 1.024 ms for all frequencies. The transmitted power at each frequency was set according to the recommendations of Korneliussen *et al.* (2008).

### Data preprocessing

The volume-backscattering cross sections, $s_v$, were analysed with the large scale survey system (LSSS, Korneliussen *et al.*, 2006; MAREC, Bergen, Norway). The LSSS is convenient for post-processing acoustic data in a similar way to the Bergen Echo Integrator (Foote *et al.*, 1991; Korneliussen, 2004), the MOVIES+ software (Marchalot, 1998), and the EchoView package (Anon., 1999).

To improve data quality before species identification, the following preprocessing steps were performed at all frequencies: (i) remove noise spikes caused by transmission from poorly synchronized acoustic instruments; (ii) correct data for the alongship offset between transducer positions; (iii) correct data for the electronic delay in the echosounder and transducer; (iv) replace any missing pings by interpolation; (v) determine the bottom depth by combining the data from all frequencies; (vi) smooth the data above the detected bottom; (vii) smooth the data below the detected bottom; (viii) quantify the noise, using the data in each ping at a sufficient time after the bottom echo has been detected, if one exists; (ix) remove the noise from the dataset; (x) generate a synthetic data channel; (xi) use this to detect schools; and (xii) remove the synthetic data channel.

The bottom-detection smoothing weights summed to unity and were based on a Gaussian kernel with a relative weight of 1.0 in the centre of the sampled volume and 0.5 at distances of 4 m horizontally off the centre and at 0.25 m vertically of the centre. Restricting the smoothing to regions above the bottom and then below the bottom maintains the detected bottom line without any distortion.

Schools were detected acoustically on a synthetic data channel, where $s_v = (s_{v,38\ \mathrm{kHz}} + s_{v,70\ \mathrm{kHz}} + s_{v,200\ \mathrm{kHz}})/3$, i.e. the mean $s_v$ over the three acoustic frequencies. The schools had to be at least 20 m long, 5 m high, with a vertical-section area of at least 50 $m^2$. Detection was done with a signal threshold of $-60$ dB combined with several filters. Three filters on $3 \times 3$ pixel squares were used to stabilize the data before thresholding, i.e. the median (run three times in sequence), erode, and dilate filters. The last two are commonly used in image analysis to remove large outliers that are likely to be noise. These filters replace the central pixel value with, respectively, the median, minimum, and maximum of the pixel values within the filter squares.

### Training for acoustic species identification

Only acoustic data verified by finding a single (or very dominant) species in the relevant trawl catches were used to train the LSSS for species recognition. These data were $s_v$ values selected from pixels

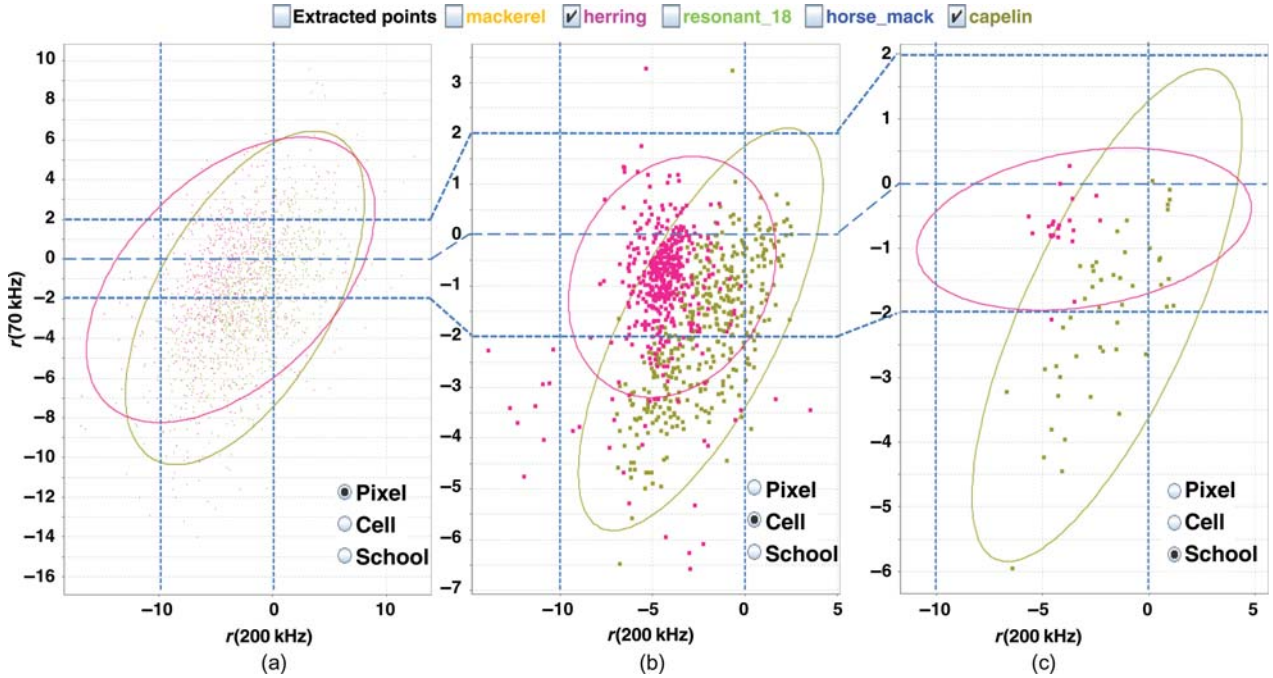


**Figure 1.** The relative frequency response *r*(70 kHz) against *r*(200 kHz) from the training dataset for the categories "herring" and "capelin" at different scales: (a) elementary volumes, (b) cell, and (c) entire schools. The data are taken from the complete library of acoustic data used for the identification of acoustic categories (= "species") and have been verified by biological samples.

in the echogram, i.e. representing small elementary volumes, and preprocessed, as described earlier. The selected $s_v$ had to be greater than $-82$ dB re 1 $m^{-1}$ at all available frequencies to be acceptable for the training process. Moreover, a hyper-ellipsoid, i.e. an ellipsoid with more than three dimensions, was fitted to normally distributed data in each dimension [e.g. *r*(200 kHz)]. Any data outside the 10% percentiles of the hyper-ellipsoid were removed from the training dataset. The remaining data were stored at different resolutions, referred to as either "elementary volume", "cell", or "school". The elementary volumes, sometimes called pixels, represent the original and highest resolution. A cell was defined as 16 pings × 50 pixels vertically, i.e. 800 samples covering ~82 m × 9.5 m, given a ping rate of 1 $s^{-1}$, at a cruising speed of 10 knots and 1 ms pulse duration. The cells were extracted from selected sections of the echogram and had to be at least 50% full, i.e. with 400 samples greater than $-82$ dB being available simultaneously at all frequencies. Figure 1 shows two of the hyper-ellipsoid dimensions—*r*(70 kHz) and *r*(200 kHz)—in the training dataset for the categories "herring" and "capelin" at different scales for the elementary volumes (pixels), cells, and entire schools.

The LSSS can currently recognize fish categories termed "mackerel", "herring", "capelin", "horse mackerel", and "resonant_18" with the training based on Atlantic mackerel (*Scomber scombrus*), herring (*Clupea harengus*), capelin (*Mallotus villosus*), horse mackerel (*Trachurus trachurus*), and pearlsides (*Maurolicus muelleri*), respectively. In addition, it can recognize four zooplankton categories: "siphonophores", "pteropods", "copepods", and "krill or amphipods", for which the acoustic properties are based on modelled backscattering features of the relevant acoustic categories.

Acoustic data on North Sea herring and Norwegian spring-spawning herring, obtained from several surveys and at different locations, were used to train the LSSS to recognize herring. The capelin training data came from the MS "Eros" and MS "Libas" survey. All data were verified by trawl sampling.

The training and testing procedure was as follows. First, half the capelin data suitable for training from MS "Libas" were used to train the LSSS. The training using herring data had already been completed during data selection (see above). Second, the LSSS was run to identify species with the remaining data from the two cruises of MS "Libas" and MS "Eros". Finally, all data suitable for training were used for a further training run, and the species-identification procedure was repeated.

## Acoustic species identification with geographical restrictions

The acoustic properties of the categories "herring", "capelin", and "horse mackerel" are quite similar. Because there were no horse mackerel in the surveyed area, this category was excluded from the list to be identified in the current exercise.

Each category was represented by a Gaussian distribution with parameters estimated from the training data. A cut-off threshold for the probability density function (pdf), corresponding to an outlier fraction of 10%, restricted the acceptable part of the feature space to a hyper-ellipsoid. A two-dimensional projection of this object is displayed in Figure 1. The pixel category was determined by the highest value of the pdf among all the hyper-ellipsoids containing the pixel. Any sample that fell outside all the hyper-ellipsoids was categorized as "unknown".

The larger-scale categories benefitted from the reduced variance and covariance between the samples. Therefore, the "cell" and "school" categories fared better than the "elementary volume" (pixel) category at distinguishing species with similar acoustic properties.

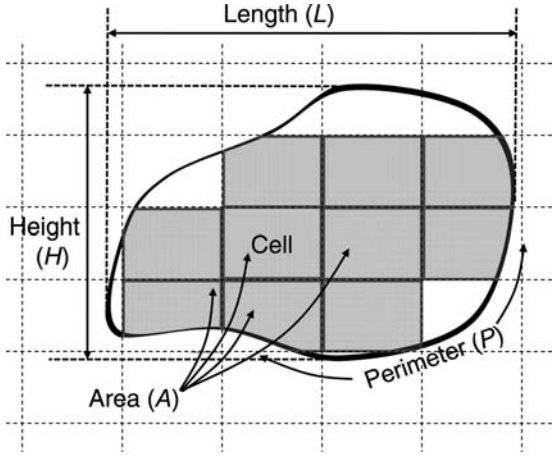


**Figure 2.** Parameters used for school analysis. Length (*L*), height (*H*), perimeter (*P*), and area (*A*) of the cells used in the school-level analysis.

### Detection of one or several species in schools

Unlike the cell placement during training, the placements during detection were precalculated to allow faster processing. Fast computing is necessary for real-time scrutiny of acoustic data during routine surveys. Figure 2 illustrates how the precalculated cells may have been placed within a school. In general, this is done randomly, which results in less cell filling, and the outliers are removed during training, but no data are rejected during the identification process. Therefore, the cells used during analysis had to be 80% full, as indicated by the grey cells in Figure 2 to avoid a concentration of samples on or near the school boundary. Hence, at least 640 samples were required in each 82 m × 9.5 m cell. If a school had no cells meeting this criterion, the cells were merged and the school could then be analysed if it now contained more than 80% of the standard number, i.e. 640 samples in the merged cells.

A species had to be identified in at least half the cells for the school to be analysed further, i.e. in at least five of the ten grey cells in Figure 2, otherwise the school would be marked as "unknown species" and thereafter ignored. Moreover, a school was deemed monospecific only if fewer than 10% of the cells contained a species other than the dominant one. In other words, it was deemed by the cell categorization to contain a different species from the dominant one. Therefore, the school illustrated in Figure 2 would have been rejected if any of the ten cells differed from the others.

### Detection of species in a school

If more than one species were identified in a school, it was marked as "multiple species in school", and no further identification was attempted.

If a school contained a single species, the mean $s_v$ was calculated for the entire school and evaluated against the hyper-ellipsoids for the trained categories (Figure 1c) and eventually a species was assigned to it. In this case, the mean $s_v$ at 38 kHz and the relative frequency responses at 18, 70, 120, 120, and 200 kHz were used. Occasionally, the analysis failed to identify any particular species; then the school was marked as "one species in school, but species not identified". In such a case, other identification methods were used, e.g. those based on morphological considerations.

Various morphological parameters were calculated to quantify the shape of the school in the current analysis. Haralabous and Georgakarakos (1996) identified "rectangularity" (see below) as the most successful parameter for distinguishing the species in schools. Note that the parameters used here follow Haralabous and Georgakarakos (1996), but their inverses are sometimes associated with the same name. For example, the "circularity" is sometimes defined as $4\pi AP^{-2}$ elsewhere in the literature. The morphological parameters used here are

$$\text{elongation:} \quad E = \frac{L}{H}, \tag{1}$$

$$\text{circularity:} \quad C = \frac{P^2}{4\pi A}, \tag{2}$$

$$\text{rectangularity:} \quad R = \frac{LH}{A}, \text{and} \tag{3}$$

$$\text{fractal dimension:} \quad F = \frac{2\ln(P/4)}{\ln(A)}, \tag{4}$$

where $L$ is the school length, $H$ the height, $P$ the perimeter, and $A$ the cell area, as illustrated in Figure 2. These parameters were calculated from the schools observed during the cruises of MS "Libas" and MS "Eros".

## Results

### Biology

The body lengths of spawning capelin were 14–20 and 13–18 cm for males and females, respectively, and 10–30 cm for juvenile herring. The average length varied between schools.

The standard deviation of capelin length was ~1.3 cm in each of the 13 trawl catches of MS "Libas" and MS "Eros" that were selected for verification of the acoustic data, and the mean length in each of those 13 trawl catches varied between 16.0 and 18.1 cm (17.0 ± 0.6 cm).

The mean lengths of capelin in the other trawl catches were similar. The size distribution of herring for all trawls was bimodal, with a mean length of 17 ± 1 cm in a group of four trawl catches and 28.5 ± 2 cm in another group of eight trawl catches.

### Acoustics

Figure 1 illustrates how capelin and herring are identified. The blue lines indicate the same rectangular area in each panel. The results clearly demonstrate that capelin and herring are better separated with the features $r$(70 kHz) and $r$(200 kHz) when they are averaged over a complete school (Figure 1c) than at pixel resolution (Figure 1a). Figure 3 shows slightly smoothed data at 38 kHz in the upper echogram and the results of pixel- and school-based species identification in the middle and lower echograms, respectively. This dataset was not used for training, because nearby trawl samples contained both herring and capelin.

The LSSS had previously been trained to recognize herring, but not capelin. Therefore, half the capelin data from the two surveys were first used for training purposes, then the trained LSSS was run to identify the remainder. Finally, all the data were used for further training, and the identification procedure was repeated. The results indicated no difference in the ability of the LSSS to

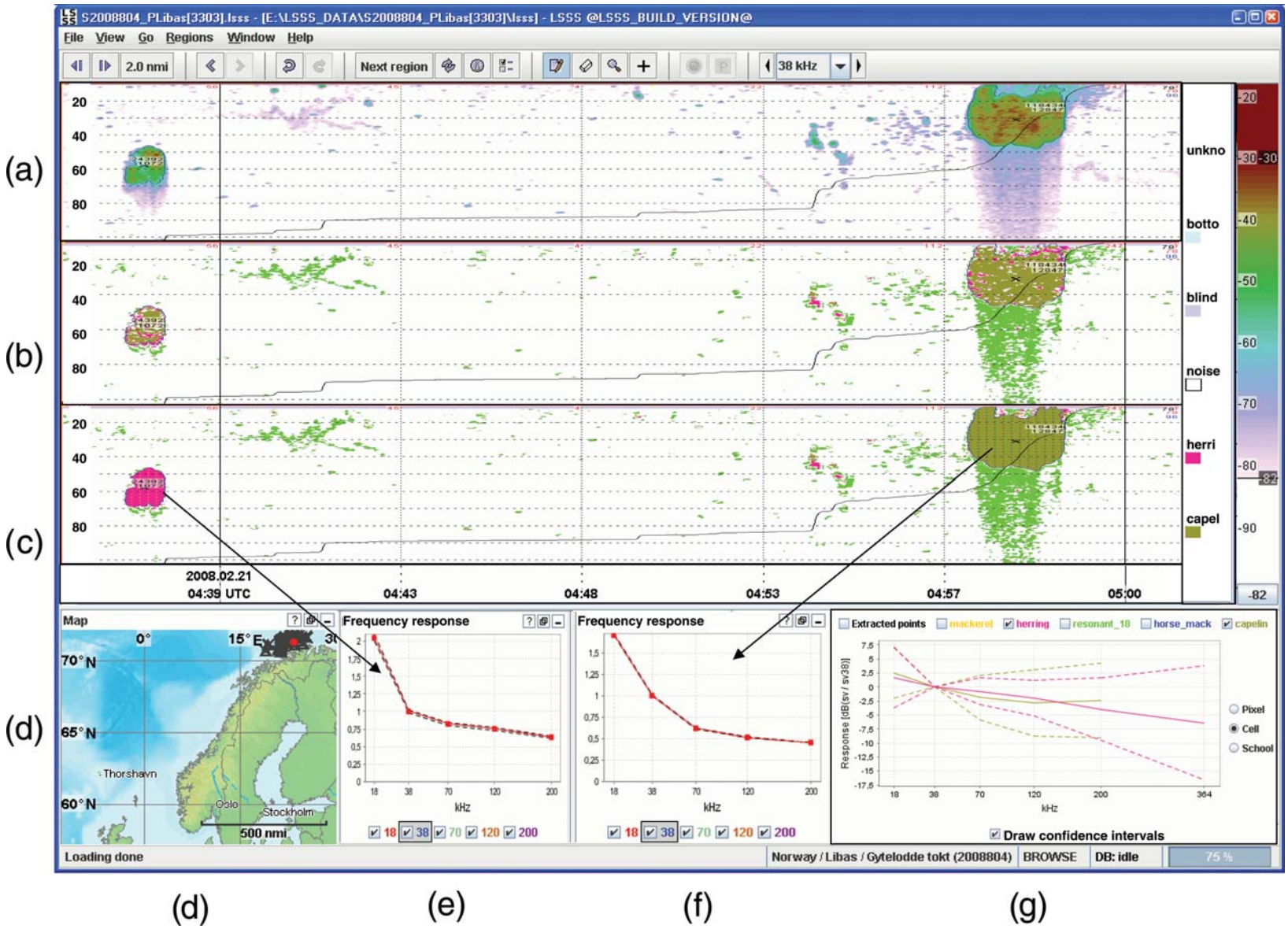


**Figure 3.** Echograms (a–c) and auxiliary information (d–g) used during data interpretation. Colour scales indicating backscattering strength and acoustic categories appear to the right of the echograms. (a) Smoothed and noise-corrected echograms at 38 kHz; (b) pixel- and (c) school-based acoustic identification combined with geographical restrictions; (d) map of the surveyed area; (e and f) relative frequency response of the arrowed schools identified as herring and capelin, respectively; (g) the training database illustrating the relative frequency responses with confidence intervals in school cells for herring and capelin.

**Table 1.** Morphological parameters used to identify the species in a school.

| Species | Area ($10^3$ m$^2$) | Length (m) | Height (m) | Perimeter (m) | *E* | *C* | *R* | *F* |
|---|---|---|---|---|---|---|---|---|
| Herring | 4.6 ± 3.7 | 170 ± 110 | 44 ± 18 | 537 ± 466 | 4.0 ± 1.9 | 5.5 ± 5.4 | 1.7 ± 0.4 | 1.14 ± 0.08 |
| Capelin | 4.0 ± 3.7 | 187 ± 137 | 30 ± 14 | 416 ± 278 | 6.5 ± 3.0 | 4.4 ± 3.1 | 1.6 ± 0.5 | 1.14 ± 0.08 |

*E* is the elongation, *C* the circularity, *R* the rectangularity, and *F* the fractal dimension, as defined in Equations (1)–(4).

**Table 2.** Species identifications of 85 schools using acoustic and morphological data.

| Species | Correct by *r*(*f*) | Correct by *E* | Unidentified | Wrong |
|---|---|---|---|---|
| Capelin | 48 | 12 | 2 | 3 |
| Herring | 10 | 7 | 1 | 2 |

Columns indicate the number of schools.

identify the species of schools after additional training had been done compared with its ability before the additional training.

The analysis of the schools with the LSSS correctly identified the species in 68% of the instances, the other 32% being marked as "unknown species". Hence, the acoustic part of the identification algorithm never incorrectly identified the species for the data tested here.

## Morphology

Table 1 presents the morphological parameters of the schools determined from the two surveys analysed here. Only the elongation differed significantly between herring and capelin. In the analysis, the following limits on $E$ were used to decide whether a school contained only herring or only capelin:

(i) herring: $2.1 < E \leq 4.6$,

(ii) uncertain: $4.6 < E \leq 5.3$, and

(iii) capelin: $5.3 < E \leq 9.5$.

## Species identification

Table 2 presents the results of the species identification based on acoustics and morphology. The species of 68% of the schools in the analysis were correctly identified acoustically, and none was identified incorrectly. The remaining 32% were later input to the morphological module of the LSSS. In total, the species in 77 of 85 schools were identified correctly, and five were assigned to the wrong species. Figure 4 compares the pixel and school categorization of the school selected in Figure 3a. The pixel categorization in Figure 4b is clearly doubtful because of the similar acoustic properties of capelin and herring. The two possible placements of the identification cells in Figure 4b (alt 1 and alt 2) indicate that probably four or five cells were used in the cell-based categorization, because the school categorization in Figure 4c is accepted only if fewer than 10% of the cells indicate a different species than the others, and each of the cells has to be identified as herring in this case. When a single species could not be identified acoustically, the species of the remaining 32% of the schools were identified correctly by the elongation criterion for 22.5% and identified incorrectly for 6% of the schools. For 3.5% of the schools, the species could not be identified or multiple species were indicated. This results in a success factor of 0.85, which is defined as correct identifications minus wrong identifications divided by the number of schools.

## Discussion

Acoustic data were selected to test species identification in a difficult, but realistic situation. The geographic distribution of capelin spawners and juvenile herring overlap in the surveyed area (Dragesund *et al.*, 1980; Gjøsæter, 1998), and adequate separation of the two species during scrutiny of acoustic recordings is a major problem during abundance estimation. The relative frequency response, combined with geographical restrictions, correctly identified the species in two-thirds of the analysed schools, with no species identified incorrectly, despite herring and capelin having quite similar acoustic properties.

Acoustic data should provide more reliable indicators for species identification in a fish school than morphological characteristics, but it remains surprising that neither circularity nor rectangularity, nor fractal dimension of schools could distinguish herring from capelin. The single useful morphological parameter in this context was elongation, as defined in Equation (1). By including elongation, the species were identified correctly for

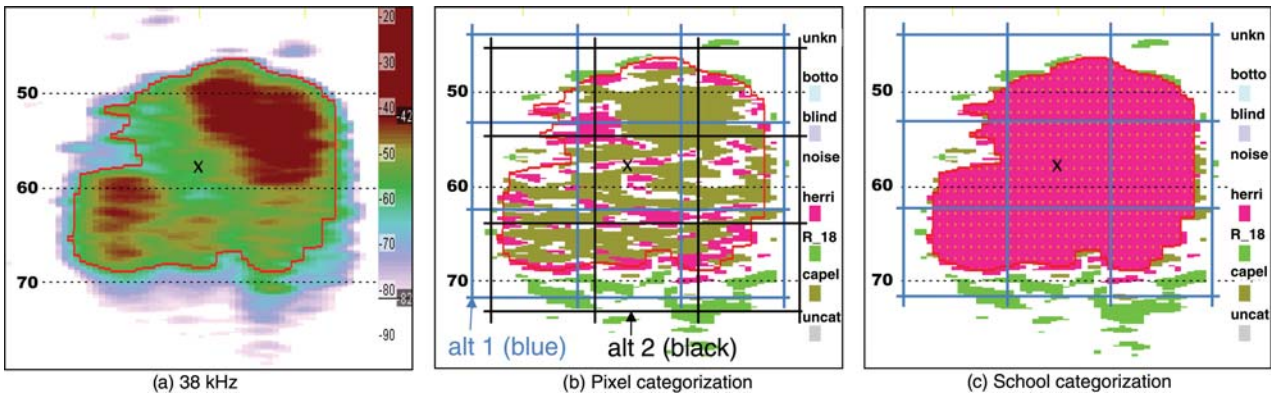


**Figure 4.** Comparison of categorization levels. (a) Echogram at 38 kHz, smoothed $s_v$; (b) the pixel-based categorization displays two alternative placements of the cells; (c) the school-based categorization has a unique result.

70% of the remaining schools, whereas 19% were identified incorrectly and 11% remained uncertain. When elongation criteria were applied in the analysis without reference to the acoustic data, the species were identified correctly for 61% of the schools and identified incorrectly for 27%, whereas the identity of 12% of the schools remained uncertain.

Bathymetry and school depth were not used in the identification process, because herring and capelin display diel and monthly variations in vertical migration patterns that are not fully understood. Diel migrations were not apparent in the data analysed here. Capelin tended to be at depths of 20–75 m and herring at 80–150 m, although both species were sometimes found at other depths. When depth was used for species identification and assigned the same weight as elongation, the success factor, as defined earlier, increased from 0.85 to 0.88, and even further to 0.91, on the assumption that 15% of the cells indicated a different species than the others, instead of the 10% criterion used above.

Although a success factor of 0.85 might be considered acceptable, it can be improved upon. Korneliussen and Ona (2004) were able to identify mackerel with greater success. However, the acoustic properties of mackerel differ markedly from those of fish with a swimbladder. Haralabous and Georgakarakos (1996) distinguished the species in schools with an accuracy of >90% by combining morphological and depth data in a neural-network approach. They did not use multifrequency data, but the species they investigated had different morphological features and did not undertake diel migrations, so school depth could be used in the identification process in addition to morphological features. Their method would probably not have distinguished echotraces of herring and capelin if neither multifrequency data nor school depth had been used in the identification.

## Conclusions

Through a combination of geographical, multifrequency, and morphological data, it is possible to distinguish several species successfully in schools with similar acoustic properties. This approach represents a clear improvement on the pixel-based identification of species, and it should be implemented as an operational system in future. Considering that Haralabous and Georgakarakos (1996) found that the rectangularity had the strongest discriminating power in their study, additional morphological parameters as defined above will have to be used, although these parameters were not effective discriminators in the current study. Species-identification methods need to be tested on data from more surveys than those that have been considered here.

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