Classifying fish schools and estimating their species proportions in fishery-acoustic surveys

Ronan Fablet, Riwal Lefort, Imen Karoui, Laurent Berger, Jacques Massé, Carla Scalabrin, and Jean-Marc Boucher

Fablet, R., Lefort, R., Karoui, I., Berger, L., Massé, J., Scalabrin, C., and Boucher, J-M. 2009. Classifying fish schools and estimating their species proportions in fishery-acoustic surveys. – ICES Journal of Marine Science, 66: 1136–1142.

Automated or computer-assisted tools are needed for estimating the proportion of species and their biomass in echosounder surveys of marine ecosystems. Operational systems rely mainly on school morphologies or the frequency responses of scatterers to identify target species in echograms. This paper presents two complementary methods for classifying schools and estimating their species proportion in a multispecies, pelagic environment. One method relies on the training of probabilistic school classifiers; the other exploits echogram similarities to infer species proportions directly from the proportions known at trawled sites. The methods are demonstrated with empirical and simulated data. School classifications and species-proportion estimates are compared to demonstrate the effectiveness of the proposed methods.

Keywords: fisheries acoustics, multispecies environment, school classification.

Received 8 August 2008; accepted 19 February 2009; advance access publication 19 May 2009.

R. Fablet, R. Lefort, I. Karoui, and J-M. Boucher: Institut TELECOM, TELECOM Bretagne, UMR CNRS 3192 Lab-STICC, Technopôle Brest Iroise CS 83818, 29238 Brest Cedex 3, France, and Université européenne de Bretagne, France. R. Fablet, R. Lefort, L. Berger, and C. Scalabrin: Ifremer/STH, BP 70 29280, Plouzané, France. J. Massé: Ifremer/EMH, Nantes, France. Correspondence to R. Fablet: tel: +33 229 001 287; fax: +33 229 001 012; e-mail: eronan.fablet@telecom-bretagne.eu.

Introduction

Echosounders mounted on oceanographic and fishing vessels provide remote sensing of the spatio-temporal characteristics of pelagic populations (MacLennan and Simmonds, 1992; Petitgas *et al*., 2001; Bertrand *et al*., 2003; McQuinn *et al*., 2005; Johnsen and Godø, 2007). Methods are needed for estimating the proportion of pelagic species in the acoustic data (Korneliussen, 2004). Isolated and aggregated fish and plankton layers can sometimes be classified by their echo amplitudes and their aggregation morphologies (MacLennan and Simmonds, 1992; Haralabous and Georgakarakos, 1996; Scalabrin *et al*., 1996; Doray *et al*., 2006). These methods are based on various school features, including morphology or shape, acoustic energy, and associated habitat, such as depth and seabed type. More recently, features derived from multifrequency echoes have also been used to identify acoustic targets (Kloser *et al*., 2002; Gorska *et al*., 2005; Fässler *et al*., 2007; Jech and Michaels, 2007).

In addition to characteristic features, the classification model and training methods are important. Some classification models include naive Bayes classifiers, linear discriminant models, and neural networks (Haralabous and Georgakarakos, 1996; Scalabrin *et al*., 1996; Hammond and Swartzman, 2001). These methods require "supervised training" with a dataset where all schools have been assigned to a species. However, in a multispecies environment, e.g. in the Bay of Biscay (Petitgas *et al*., 2003), trawl catches generally comprise a mixture of several species, for which an associated fish school cannot be assigned a single species or class. Hence, datasets with validated, single-species school classifications are often not available and supervised classification techniques cannot be applied (Haralabous and Georgakarakos, 1996; Scalabrin *et al*., 1996; Hammond and Swartzman, 2001).

This limitation is mitigated here with new methods for classifying schools and estimating their species proportions in a multispecies environment. As outlined in Figure 1, two complementary approaches are proposed. In both cases, the continuous acoustic record along the survey track was first divided into successive segments 3 nautical miles long, referred to hereafter as echograms. Fish schools are then extracted in all echograms, and each school was characterized by a set of features (Scalabrin *et al*., 1996). The two approaches then differed as follows.

(i) The school-level approach extends school-classification models for application to a multispecies environment. It relies on training these classification models from the data given at trawled sites, i.e. echograms with the associated relative species proportions. Trained classification models can then be applied to classify schools and estimate species proportions in all echograms.

(ii) The echogram-level approach, extended from Petitgas *et al*. (2003), first proceeds to a global characterization of any echogram from school statistics. The similarities between an echogram and the echograms at trawled sites then provide the basis for directly estimating species proportions, without an actual classification of individual schools.

The performances of these two approaches are quantitatively compared here using real and simulated schools datasets.

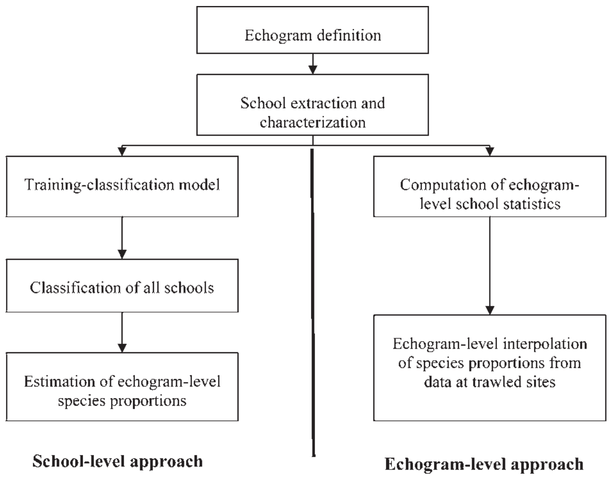

Figure 1. The data-processing steps in the school-based (left) and echogram-level (right) approaches to estimating species proportions.

Methods

This section details the school-level and echogram-level approaches. Let I denote an echogram, SP the associated species proportions, i the index of the schools in the echogram, $\mathbf{X}_i$ the feature vector of school i, Y_i its species or group of species, and k a species index.

School-classification models in a multispecies environment

The training of school-classification models in a multispecies environment was based on methods recently introduced in Bishop and Ulusoy (2005), and Ulusoy and Bishop (2005). Probabilistic models are trained to classify objects according to the presence or absence of each object class in each training image. Similarly, school-classification models can be trained according to the presence or absence of each species in trawl catches. In addition, the training can be improved by substituting the proportions of species for the presence–absence data. Two types of probabilistic school-classification model were considered: a conditional model and a generative model (GM).

The probabilistic-conditional model is an extension of traditional discriminant classifiers, where discrete classifications are replaced by decisions based on probabilities. The classification likelihood $P(Y_i|\mathbf{X}_i)$ is defined as

$$P(Y_i = k|\mathbf{X}_i) = \frac{\exp[W_k^t\mathbf{X}_i + B_k]}{\sum_l \exp[W_l^t\mathbf{X}_i + B_l]}, \tag{1}$$

where W_k and B_k are the model parameters for species k. Equation (1) describes the linear conditional model (LCM) as $W_k^t\,\mathbf{X}_i + B_k$ linear discrimination functions for each class. An extension to a non-linear conditional model (NLCM) was considered (Schölkopf and Alexander, 2002). The original feature space was mapped to a new space, where class separation was improved. In this case, using kernel principal component analysis (details in Schölkopf and Alexander, 2002), the parameterization of $P(Y_i|\mathbf{X}_i)$ is similar to Equation (1), except that the original $\mathbf{X}_i$ is replaced by the corresponding feature vector in the mapped space. The linear and non-linear models are trained with a set of echograms at trawl sites with known SPs; equal catchability being assumed for all species. More precisely, W_k and B_k are calculated by minimizing the error of the estimation of SPs, i.e. the sum over all training echograms of the squared differences between the known and the estimated SP values issued from school-classification likelihoods as follows:

$$\mathrm{SP}(k) = \frac{\sum_i \lambda_k\sigma_{\mathrm{ag}}(i)P(Y_i = k|\mathbf{X}_i)}{\sum_{i,l} \lambda_l\sigma_{\mathrm{ag}}(i)P(Y_i = l|\mathbf{X}_i)}, \tag{2}$$

where $\sigma_{\mathrm{ag}}(i)$ is the acoustic energy of school i (mV^2; Scalabrin *et al.*, 1996) and λ_k a conversion coefficient (kg mV^{-2}) from acoustic energy to biomass. The logarithm of λ is proportional to the target strength.

The second type of probabilistic-classification models, referred to as GMs, uses Bayes' rule to compute the classification likelihood:

$$P(Y_i = k|\mathbf{X}_i) = \frac{P(Y_i = k)P(\mathbf{X}_i|Y_i = k)}{\sum_l P(Y_i = l)P(\mathbf{X}_i|Y_i = l)}, \tag{3}$$

where $P(Y_i = k)$ is the prior likelihood of k, and $P(\mathbf{X}_i|Y_i = k)$ is the distribution of the feature vector $\mathbf{X}_i$ for species k. This model is an extension of the model considered in Hammond and Swartzman (2001) and Hammond *et al.* (2001). The $P(\mathbf{X}_i|Y_i = k)$ are modelled as a Gaussian mixture of, typically, five Gaussian components. The $P(Y_i = k)$ and the parameters of the Gaussian mixture $P(\mathbf{X}_i|Y_i = k)$ are estimated using an adaptation of the expectation-maximization procedure exploiting the information provided by the known SP values in training echograms (Bishop and Ulusoy, 2005; Ulusoy and Bishop, 2005).

Echogram-level inference of species proportions in a multispecies environment

The echogram-level method computes the SP values as a weighted sum of known SP values at trawl sites. For a given I, SP_I are estimated as

$$\mathrm{SP}_I(k) = \sum_j w_j(I)\mathrm{SP}_j(k), \tag{4}$$

where SP_j are the species proportions in trawl j, and $w_j(I)$ the assigned weights of echogram I–j, with $\sum_j w_j(I) = 1$. Quantile-based representations of the school features describe the content of each echogram (Petitgas *et al.*, 2003). In all, 20 school features are used, including geometric, energetic, and positional features (Scalabrin *et al.*, 1996). The dissimilarity D between two echograms is then computed as a Kullback–Leibler distance between the quantile-based distributions of the school features (Kullback, 1951; Karoui *et al.*, in press). To encode both echogram similarities and spatial proximities, the dissimilarity $d_j(I)$ between echogram I and trawl j is defined as

$$d_j(I) = \min_{\Gamma\in\Omega(P(j),P(I))} \sum_{p\in\Gamma} D(I_p, I_j), \tag{5}$$

where $\Omega(P(j),P(I))$ is the set of all paths on the spatial mesh defined by the survey track from the spatial position $P(j)$ of j to the spatial position $P(I)$ of I. I_j is the echogram corresponding to trawl j, p is a point on the survey track Γ in the echogram I_p. Minimum paths are commonly computed in image processing, and efficient numerical algorithms have been developed (Cohen and Kimmel, 1997; Deschamps and Cohen, 2001). The $w_j(I)$ are computed as normalized versions of the inverse of $d_j(I)$ to increase the importance of echograms at trawl sites most similar to I in Equation (4). Using this formulation, $w_j(I)$ is maximal only if there is a spatial path linking I and j such that all echograms along this path are very similar to the I at j. This constraint eliminates spatially incoherent weights that might occur if reliance is placed solely on D. The SP values can vary smoothly, because species habitats can overlap.

Compared with Petitgas *et al*. (2003), the advantages of the proposed interpolation are twofold:

(i) the $w_j(I)$ are not binary and the calculations depend on D, so better account is taken of both smooth and sharp transitions from one SP to another, and

(ii) the $w_j(I)$ account for both echogram similarities and proximities. In contrast, spatial coherence is not required in the method used by Petitgas *et al*. (2003).

Performance evaluation

To evaluate the performances of these methods, the following datasets were considered truthed.

(i) D1: Echograms of monospecific fish schools in the Bay of Biscay collected with a 38-kHz, single-beam echosounder and validated with trawl catches (Scalabrin *et al*., 1996). This dataset comprises 1419 schools: 179 sardine, 478 anchovy, 667 horse mackerel, and 95 blue whiting.

(ii) D2: Echograms of sardine, anchovy, and horse mackerel schools (Gajate *et al*., 2004) simulated with OASIS (Diner, 2001) to resemble the school-feature distributions reported by the SIMFAMI project (EU project QLRT-2000-02054). This dataset comprises 4406 schools: 1187 sardine-like, 1360 anchovy-like, and 1859 horse mackerel-like. The simulated data were from 38- and 200-kHz, single-beam echosounders with 7° beam widths.

School features were extracted by MOVIES+ software (Weill *et al*., 1993). Simulated echograms were generated with randomly selected schools having prescribed SP values for mixtures of one to four species. Using D1, for example, simulated echograms with a two-species mixture were generated by randomly selecting schools from two of the four species, in accordance with the target SP values.

For school-classification experiments, 75% of the schools were used to train the model, and 25% were used to test the model. The training dataset consisted of 18 simulated echograms. The overall procedure (echogram simulation, model training, and model testing) was repeated 100 times.

Three experiments were conducted to evaluate the school-classification models:

1. Using D2, school-classification rates were compared for models trained with presence or absence modes and proportion data (Figure 2). Training echograms with three species ranged from slightly mixed (80% of one species and 10% each of the other two) to highly mixed (33% of each species).
2. Using D1, school-classification rates were compared for one- to four-species echograms [Figures 3 and 4 (top) and Table 1]. Training echograms were uniformly chosen from slightly mixed (90–10, 80–10–10, and 70–10–10–10% for the two-, three-, and four-species mixtures, respectively) to highly mixed (50–50, 33–33–33, and 25–25–25–25% for the two-, three-, and four-species mixtures, respectively).

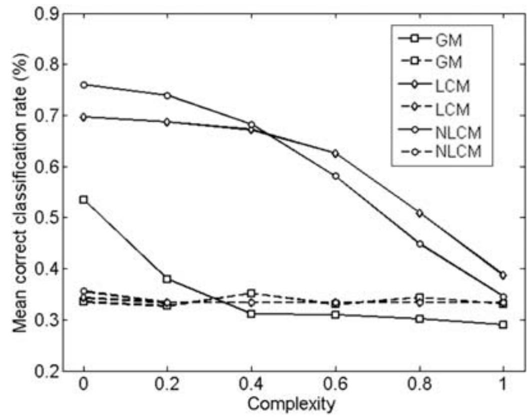

Figure 2. Comparison of classification models trained using species presence–absence data vs. species proportion data. Mean correct-classification rate on D2 vs. three-class mixtures (from unmixed, 10% for each of two classes and 80% for the third class, complexity 0; to highly mixed, 33% for the three species, complexity 1). The GM (square), the LCM (diamond), and the NLCM (circle) were trained using species-proportion data (solid line) and presence–absence data (dashed lies).

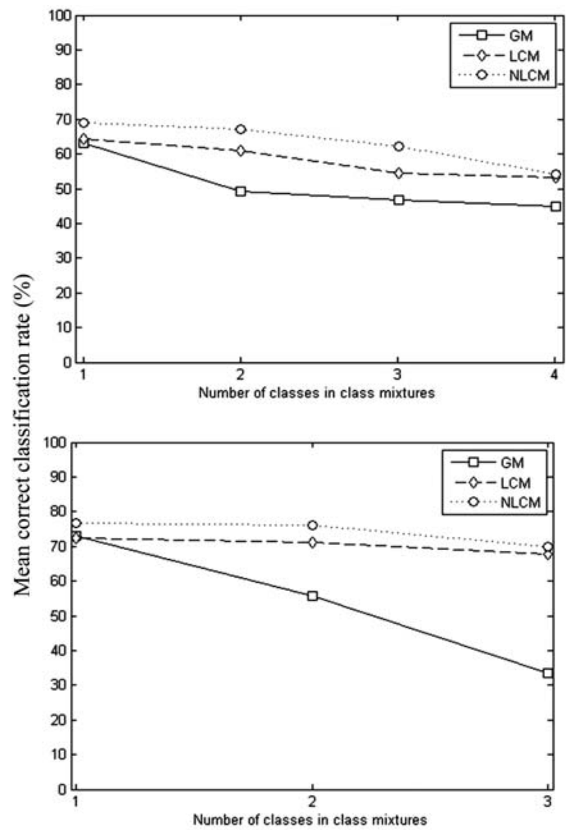

Figure 3. Classification performances for single-species to multispecies mixtures. Mean correct-classification rates for D1 (top) and D2 (bottom). Acronyms are defined in the caption of Figure 2.

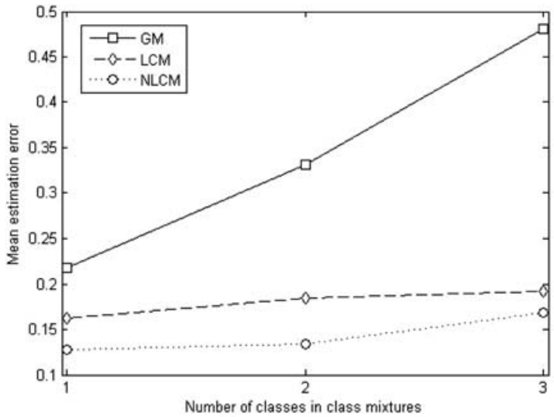

Figure 4. Estimations of class proportions. Mean estimation error as a function of the number of classes in the training mixture data for the three models for D2. Acronyms are defined in the caption of Figure 2.

Table 1. School classification for D1.

		SA	AN	HM	BW
SA	NLCM	60%	19%	18%	1%
	LCM	65%	17%	16%	0%
	GM	30%	48%	21%	0%
AN	NLCM	7%	77%	14%	0%
	LCM	12%	70%	13%	3%
	GM	2%	87%	8%	0%
HM	NLCM	9%	27%	59%	4%
	LCM	14%	31%	45%	7%
	GM	5%	65%	25%	3%
BW	NLCM	3%	2%	9%	85%
	LCM	5%	2%	2%	90%
	GM	1%	7%	17%	73%

Mean correct classification: 70% (NLCM), 68% (LCM), 52% (GM)

		SA	AN	HM	BW
SA	NLCM	48%	20%	27%	3%
	LCM	62%	18%	17%	1%
	GM	33%	39%	26%	0%
AN	NLCM	5%	67%	26%	0%
	LCM	15%	55%	26%	2%
	GM	8%	65%	25%	0%
HM	NLCM	9%	24%	60%	4%
	LCM	19%	28%	42%	9%
	GM	10%	53%	34%	0%
BW	NLCM	4%	2%	23%	70%
	LCM	5%	3%	12%	81%
	GM	1%	7%	21%	70%

Mean correct classification: 62% (NLCM), 60% (LCM), 51% (GM)

Classification rates are reported for the training data involving two- (top) and three-class (bottom) mixtures. Three models were considered: the GM, the LCM, and the NLCM. The following is an example of how the classification rates should be read row-wise: for class SA (sardine) and model NLCM, 60% of the samples were classified in class SA, 19% in class AN (anchovy), 18% in class HM (horse mackerel), and 1% in class BW (blue whiting).

Table 2. School classification for D2.

		Class I	Class II	Class III
Class I	NLCM	88%	7%	3%
	LCM	79%	12%	8%
	GM	62%	18%	19%
Class II	NLCM	6%	75%	18%
	LCM	8%	73%	18%
	GM	13%	45%	41%
Class III	NLCM	7%	24%	68%
	LCM	12%	25%	62%
	GM	22%	12%	64%

Mean correct classification: 77% (NLCM), 71% (LCM), 57% (GM)

		Class I	Class II	Class III
Class I	NLCM	83%	8%	7%
	LCM	84%	8%	6%
	GM	32%	34%	32%
Class II	NLCM	7%	66%	26%
	LCM	11%	65%	22%
	GM	33%	34%	32%
Class III	NLCM	8%	27%	63%
	LCM	14%	28%	57%
	GM	30%	35%	33%

Mean correct classification: 71% (NLCM), 69% (LCM), 33% (GM)

Confusion matrices are reported for the training data involving two- (top) and three-class (bottom) mixtures. Acronyms are defined in Table 1. Classes I, II, and III refer to sardine-, anchovy-, and horse mackerel-like schools, respectively.

Table 3. School classification for D2 using only school features at 38 kHz.

		Class I	Class II	Class III
Class I	NLCM	83%	8%	8%
	LCM	72%	10%	17%
	GM	37%	21%	41%
Class II	NLCM	6%	76%	16%
	LCM	8%	71%	20%
	GM	17%	45%	37%
Class III	NLCM	13%	23%	63%
	LCM	18%	26%	54%
	GM	25%	13%	60%

Mean correct classification: 74% (NLCM), 66% (LCM), 48% (GM)

		Class I	Class II	Class III
Class I	NLCM	70%	13%	15%
	LCM	69%	13%	17%
	GM	32%	34%	33%
Class II	NLCM	7%	66%	25%
	LCM	10%	64%	24%
	GM	32%	34%	33%
Class III	NLCM	13%	26%	60%
	LCM	20%	23%	55%
	GM	30%	35%	33%

Mean correct classification: 66% (NLCM), 63% (LCM), 33% (GM)

Confusion matrices are reported for the training data involving two- (top) and three-class (bottom) mixtures. Acronyms are defined in the caption of Table 1.

3. Using D2, school-classification rates were compared for one- to three-species echograms [Figures 3 and 4 (bottom) and Tables 2 and 3]. The training echograms were generated as in Experiment 2.

The SP values in Experiments 2 and 3 simulate the variability observed in trawl catches in multispecies environments. For example, in the Bay of Biscay, trawls commonly catch 80% anchovy and 20% sardine, or vice versa.

To evaluate the echogram-level procedure, 128 × 128 grids were generated, with grid points corresponding to simulated

Table 4. Estimation error for species proportions for the simulated three- (top) and four-region (bottom) examples; overall and class-by-class mean estimation error using the echogram-classification method (ECM) proposed by Petitgas *et al.*, (2003), and the proposed dissimilarity-based interpolation (DBI).

	Global	Class I	Class II	Class III
ECM	0.11	0.08	0.13	0.11
DBI	**0.09**	**0.07**	**0.11**	**0.09**
NLCM	0.17	0.15	0.14	0.20
NLCM2	0.14	0.16	0.14	0.11
GM	0.30	0.32	0.19	0.35
GM2	0.19	0.20	0.14	0.22
	Global	**Class I**	**Class II**	**Class III**
ECM	0.10	0.10	0.11	0.11
DBI	**0.09**	**0.09**	**0.10**	**0.09**
NLCM	0.21	0.21	0.14	0.25
NLCM2	0.19	0.22	0.10	0.23
GM	0.30	0.23	0.28	0.37
GM2	0.25	0.25	0.16	0.33

Comparison with school-based approaches is also reported. Acronyms are defined in the caption of Table 1. Best estimation values are emboldened.

echograms with target SP values (Table 4). Two more experiments were conducted:

4. using D2, three two-class regions were simulated (typically 20–80%), and
5. using D2, four regions were simulated where one was nearly monospecific and the other three included balanced two-class mixtures (nearly 50–50%).

In each case, smooth transitions of the SP values from one region to the other were simulated.

Two performance measures were considered: mean school-classification rates (i.e. the percentage of schools of each species correctly classified) and the error of the estimation of SP values.

Results

School classifications

Experiment 1 clearly shows that models trained from proportion-based data perform better than those trained from presence or absence data (Figure 1). For slightly to moderately mixed schools, approximately 30–40% correct classification was achieved for the NLCM and LCM. For the GM, proportion-based training only improves the classification performance at low complexities. Because all species were present in all echograms, the presence or absence training was unsupervised, and the classification rate was random.

Mean correct-classification rates are reported for Experiments 2 and 3 (Figure 2). For all models, classification performances decrease from the single-species case to the three- or four-species mixtures. NLCM and LCM were, however, more robust to increasing species mixtures, whereas correct classifications with GM declined more than 10% between one- and two-species cases. The variability in SP values of the simulated, multispecies mixtures resulted in classification rates greater than those reported in Experiment 1, for moderate mixtures. NLCM performed better than the two other models for both D1 and D2 always, with gains of up to 7% compared with LCM, and 30% compared with GM. The main difference became evident with the relatively weak classification performance of the GM compared with the conditional models. Species-by-species classification rates are reported for D1 and D2 in the two- and three-class mixture cases (Tables 1 and 2). They emphasize that classification performances are class-dependent. Note that classification results evaluated for D1 and D2 are similar. For D2, the multifrequency features (38 and 200 kHz) significantly improved the mean correct-classification rate for all models (Table 2 vs. Table 3). The main improvement was observed in the discrimination between the first and third classes. Note, the first class was horse mackerel-like, which was difficult to distinguish from sardine and anchovy. Similar conclusions can be drawn from the analysis of the estimation errors of SP values, as illustrated for D2 (Figure 4).

Species proportions

Visually, the interpolation-based method produced more consistent spatial estimates than the method of Petitgas *et al.* (2003). It also performed better than the latter method for overall and class-by-class, mean-square estimation errors of the proportions (Table 4).

The NLCM and GM were applied independently or in combination with the echogram-level method, using its estimated SP values. For both examples and all classes, the echogram-level method provided better estimates of the SP values. For the two school-based classifiers, NLCM performed better than the GM and the additional information from the estimated SP values resulted in small improvements in the estimations of species proportion and school classification. Regarding classification performance, this improvement was minor for NLCM (69 vs. 70% of mean correct classification), but more significant for GM (from 33 to 42%).

Discussion

School-based classifications

This paper proposes conditional and generative probabilistic models and their training procedures for classifying schools in a multispecies environment. It constitutes an original advance over earlier methods, which require a significant number of single-species trawl catches to train the models. In addition, the probabilistic models are more flexible and could be effective in preprocessing fishery-acoustic data.

The proposed models performed better than previously reported models tested with similar datasets (Scalabrin *et al.*, 1996). Using two-frequency features, the classification results for three-species mixtures of D2 were >70%. This indicates that useful classification performances could be expected in a multispecies environment.

Overall, the classification performance emphasized that the conditional models performed better than the generative ones. Unpublished complementary experiments by the authors indicated that the latter were also more sensitive to the choice of the school features, i.e. their classification performance decreased significantly when the number of correlated features was increased. In contrast, the discriminative models were only weakly affected by the presence of correlated features. Empirical studies using pattern-recognition schemes reached similar conclusions (Schölkopf and Alexander, 2002).

The NLCM was also a significant improvement over the LCM. This agreed with other comparisons between linear and non-linear classification models (Schölkopf and Alexander, 2002).

In addition, the greater correct-classification rates reported for Experiment 2 than for Experiment 1 emphasize the importance of the variability of SP values in the training dataset to reach good school-classification performances.

Echogram-level species proportions

An echogram-level interpolation method has been proposed to infer SP values from known proportions at trawl sites. This interpolation scheme was an improvement over the classification-based method proposed by Petitgas *et al*. (2003). The comparison of the school-level and echogram-level methods demonstrated that the latter achieved lower estimation uncertainty.

School classifications were also improved using the SP values from the echogram-level procedure in the training of the school-classification models. Coupling these two complementary methods proved promising and this will be investigated further. The computational costs of both methods were similar for the estimation of SP values. The offline-training step was, however, more complex for the school-classification models. Reported results were consistent with those obtained from operational applications. The echogram-level method could be preferred for estimations of SPs if no specific inference at the school level were required. The design of specific sampling strategies should also be of use to optimize trawl durations, species mixture in the trawl, and school-echogram representation.

Training data quality

The reported results can be regarded as the best performance that could be expected for an operational application to survey data. The dependence of classification performance on the quality of the acoustic data in trawled areas and their association with trawl catches should be assessed further. Differences were evident between the school- and echogram-level methods. From a statistical vantage point, the school-level method assumes that the dataset of schools at trawled sites is representative of the overall set of schools. In contrast, the echogram-level method assumes that echograms at trawled sites are representative of echograms along the survey track. Operationally, the latter assumption might be less easily satisfied.

Both methods consider trawl catches as representative of the observed acoustic data in the trawled areas. In practice, this assumption might not be entirely met, depending on the type of trawls used, e.g. pelagic vs. bottom trawls. Therefore, only those acoustic data corresponding to the actual trawl volume in the water column should be considered for training. Similarly, an estimate of the relative species catchability is required to relate trawl-catch analysis to SP values in the training echograms. In this study, catchability was considered equal for all species.

Acknowledgements

This study was undertaken with financial support from the DGE (Direction Générale des Entreprises), project "pôle Mer" ITIS and Region Bretagne.

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doi:10.1093/icesjms/fsp109