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Acoustic identification of small pelagic fish species in Chile using support vector machines and neural networks

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ABSTRACT

Hydroacoustic techniques are a valuable tool for the stock assessments of many fish species. Nonetheless, such techniques are limited by problems of species identification. Several methods and techniques have been used in addressing the problem of acoustic identification species. In this paper, schools of anchovy, common sardine, and jack mackerel were classified using support vector machines (SVMs) and two types of supervised artificial neural networks (multilayer perceptron, MLP; and probabilistic neural networks, PNNs) during acoustic surveys in south-central Chile. Classification was done using a set of descriptors for the schools extracted from the acoustic records. The problem was approached through two multi-class SVMs classifiers: one-species-against-one (1-vs-1) and one-species-against-the-Rest (1-vs-R). Multi-class classifications showed that the MLP neural network and SVM approach performed better than the PNN. The classification rates averaged 79.4% with PNN and 89.5% with MLP and SVM.

1. Introduction

Hydroacoustic techniques are a valuable tool for stock assessments and behavioural studies of many fish species, offering advantages related to their high sampling capacity in the water column and in the sense of navigation. Nevertheless, these methods are limited in terms of direct species identification, which can be done either by trawl sampling or by scrutinizing the echograms, applying expert criteria, and considering additional information such as shoal distribution and behaviour patterns (Horne, 2000; Simmonds and MacLennan, 2005). Because the second alternative is time-consuming and depends on the experience of the operator, it incorporates some level of uncertain or ambiguity. Incorrect species classification can limit the usefulness of acoustic abundance estimates. The objective identification of species directly from acoustic data may, therefore, make an important contribution to the accuracy of acoustic abundance estimates (Lawson et al., 2001).

Horne (2000) and Fernandes et al. (2006) offer an excellent review of the progress made in the development of acoustic methods and techniques for automatic species identification. Recently, new studies and statistical techniques have been used for fish-species identification. Demer et al. (2009) used a statistical-spectral method for echo classification and Fernandes (2009) used classification-trees for species identification of fish-school echotraces. Korneliussen et al. (2009) combined acoustic data with information on the morphological properties of schools and the geographical distribution of fish. Buelens et al. (2009) applied kernel methods to classify fish schools in single beam and multibeam acoustic data. Fablet et al. (2009) used a probabilistic model introduced in Bishop and Ulusoy (2005). In almost all these articles, the authors used multifrequency data.

Several studies have used school descriptors extracted from acoustic data to classify species. The descriptors are generally divided into four categories (Scalabrin, 1991; Scalabrin and Massé, 1993; Reid, 1999): morphological (e.g., geometry of the school), bathymetric (e.g., position of the school in the water column), energetic (e.g., properties of the backscattered signal), and positional (e.g., distance of the school offshore).

Different statistical methods such as principal-component analysis (PCA), discriminant function analysis (DFA) and, recently, classification-trees (Scalabrin et al., 1996; Lawson et al., 2001; Fernandes, 2009) have been used to classify species based on acoustic-school descriptors. Some of these techniques have been compared with heuristic methods like artificial neural networks (ANNs). Haralabous and Georgakarakos (1996) used DFAs and ANNs to classify schools of anchovy (*Engraulis encrasicolus*), sardine (*Sardina pilchardus*), and horse mackerel (*Trachurus trachurus*) in the Thermaikos Gulf, basing their classification on morphological, bathymetric, and energetic descriptors of the schools. Also,

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Simmonds et al. (1996) compared the results of species classifications using DFA and ANN for cod (*Gadus morhua*), haddock (*Melanogrammus aeglefinus*), saithe (*Pollachius virens*), mackerel (*Scomber scombrus*), and horse mackerel (*T. trachurus*), keeping the five species under controlled experimental conditions in cages and measuring the acoustic responses on eight different frequency bands (from 27 to 54 kHz). Cabreira et al. (2009) evaluated different ANN configurations for fish identification in the southwest Atlantic Ocean using acoustic-school descriptors.

Comparisons of these statistical and heuristic methods have generally shown the latter to perform better (Haralabous and Georgakarakos, 1996; Simmonds et al., 1996). Therefore, in this study, two heuristic techniques (artificial neural networks and support vector machine) were selected as automatic methods for classifying small pelagic fish species.

Support vector machine (SVM) is a relatively new technique type of network developed as a tool for recognizing patterns or discriminating between two groups (Vapnik, 1995). Since preliminary studies indicate that SVM may be more effective than ANN at discriminating a single species against a background of N other species (Morris et al., 2001), we compared the results of SVM-based classification methods with two types of ANNs (multilayer perceptrons, MLP; and probabilistic neural networks, PNNs). The discrimination study was done using descriptors of morphology, bathymetry, energy, and positional for schools of anchovy (*Engraulis ringens*), common sardine (*Strangomera bentincki*), and jack mackerel (*Trachurus murphyi*) in southern-central Chile.

2. Materials and methods

2.1. Data collection and descriptors

School data were obtained from 11 acoustic assessment surveys performed with the R/V Abate Molina, a stern trawler of 43.6 m total length, in northern and southern-central Chile (18°25′S–43°50′S) between 1991 and 2006. The data were collected using a scientific echosounder (SIMRAD EK-500) with a split-beam transducer mounted on the hull (ES38 38 kHz) with a nominal −3 dB beam width of 7°, calibrated according to standard procedures (Foote et al., 1987). The ping rate of the echosounder in the surveys was 1 s^{-1}, the pulse duration was 1 ms and a minimum threshold of −65 dB. An Engel pelagic trawl with a 14-m vertical opening and 14-mm mesh size in the codend was used to identify the species in the acoustic survey. The flotation line of this net was adapted for fishing near the surface.

We used 12 descriptors for each school detected. The descriptors were divided into four categories: morphological, bathymetric, energetic and positional (Table 1). The parameters of the fish schools were determined automatically by the algorithm SHAPES programmed into the software Echoview and described in Barange (1994), Coetzee (2000), and Lawson et al. (2001). Each aggregation was manually marked in a region on the image of the echogram, and each case was individually analyzed. The parameters used were minimum candidate height = 1 m, minimum candidate length = 1 m, maximum vertical linking distance = 1 m, and maximum horizontal linking distance = 15 m.

Only the schools detected during the survey and present along the trawl haul route were considered. Fig. 1 presents some typical echotraces of the shoals of the species studied; it also shows the "mark" of mote, a small pelagic fish (maximum length 11 cm) that is normally distributed very close to the coast. We selected information from those hauls in which ≥90% of the catch was of a same species. The final number of schools used in the analysis was limited to those in the study area most frequently shared by all three species, thereby allowing us to work with a more homogenous sample in terms of environmental conditions. Moreover, only summer and daytime observations were considered. Thus, the database for the experiments was reduced to two surveys performed in 2006 between 25°50′S and 41°00′S and 70°30′W and 73°00′W. The total database in these two surveys contains 15,205 isolated schools and 1944 monospecific schools of the species studied validated by the trawl. A subset of 990 schools was selected for pattern recognition analysis in the study area: 134 were jack mackerel, 442 common sardine, and 414 anchovy. A total of 762 schools were used for calibration and 228 for validation.

Table 1
List of acoustic descriptors, computations, and units of the acoustic schools.

Descriptor	Computations	Units
Morphological		
Mean height (H)	–	m
Length (L)	–	m
Perimeter (P)	–	m
Area (A)	–	m^2
Elongation (Elon)	Elon = L/H	–
Fractal dimension (Fdim)	Fdim = 2 ln(0.25P)/ln A	–
Bathymetrical		
Bottom depth (D)	–	m
Mean school depth (Dm)	–	m
School altitude index (Arel)	Arel = 100(D-Dm)/D	–
Energetic		
Acoustic energy (Sa)	–	m^2/mn^2
Acoustic density (MVBS)	–	dB
Positional		
School-shore distance	–	mn

2.2. Artificial neural network models: MLP and PNN

Artificial neural networks (ANNs) are mathematical models inspired by the neural architecture of the human brain. The most widely studied and used structures are multilayer perceptrons (MLPs) (Rumelhart et al., 1986). These models 'learn' in an iterative way in which the data set are introduced to the neural network the necessary times until to reach a determined error level (one iteration where all the data set are introduced to the MLP is named epoch). These supervised ANNs allow the analysis of complex data sets and its non-linear partition in two or more groups. A detailed description of MLPs performance can be found in Tsoukalas and Uhrig (1997), Gutiérrez-Estrada et al. (2000, 2007), Czerwinski et al. (2007), and Pulido-Calvo and Portela (2007).

A typical three- or four-layer MLP has one input layer, one or two hidden layers and one output layer. The processing elements in each layer are called nodes or neurons. In this work the input data to the MLP are the school descriptors and the output corresponding to the classification results. The neurons are connected through a set of connections called weights, which is analogous to synapse strength in biological neural nets. There are many MLP calibration or learning methods. In this work the standard backpropagation algorithm was applied and solved using STATISTICA® Neural Network software package from StatSoft (2005).

Probabilistic neural networks (PNNs) are a type of ANNs (Specht, 1990). The neural network architecture for PNN contains a sequence of layers: input layer (features of school), pattern layer (schools for calibration samples), summation layer (density function value by species) and output layer (results of classification). PNN provides a general solution for classify fish schools based on Bayes's technique of classification. The idea is that, given a sample pattern, we can make a decision as to the most likely species that sample is taken from. PNNs use a probability density function as transfer function. The probability density function is estimated by using multi-dimensional kernels in the pattern layer. In this work, a Gaussian kernel is used as activation function following Rutkowski

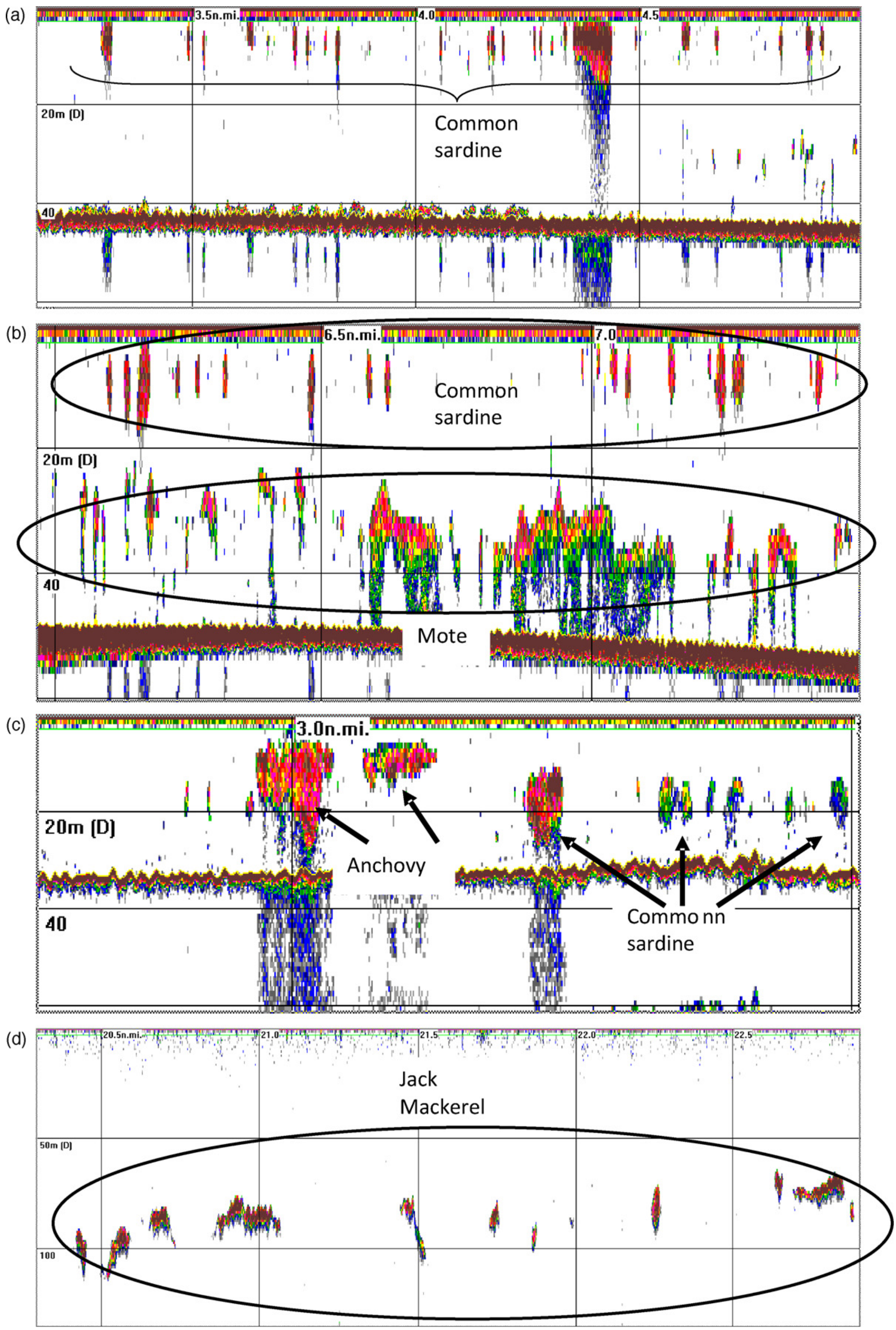

Fig. 1. Typical echotraces of common sardine (a–c), anchovy (c); mote (*Normanichthys crockeri* Clark, 1937) (b), and jack mackerel (d) in the central-south area of Chile.

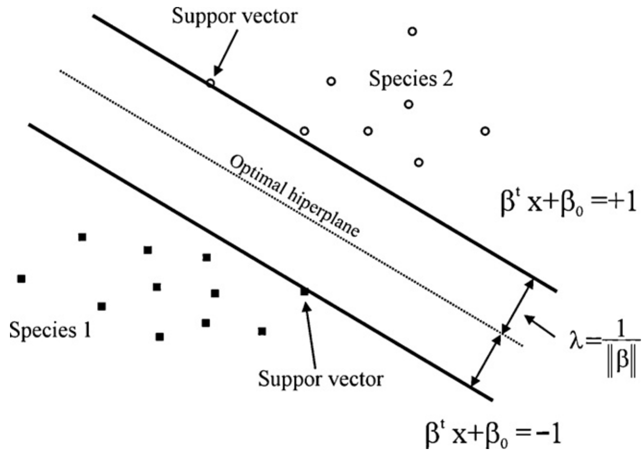

Fig. 2. Optimal hyperplane on support vector classifiers.

(2004), which is controlled for the standard deviation, the width of the activation function. Thus, a PNN essentially constructs an estimate of the probability density function of each species (class) by adding together Gaussian curves located at each point in the calibration set. There is no training with PNN in the sense of MLP since the set of weights are determined from the calibration data.

2.3. Support vector machines: SVM

Support vector machines is a statistical classification method proposed by Vapnik (1995), belongs to the family of linear classifiers since it seeks separation hyperplanes in the space of characteristics. At an algorithmic level, the learning of SVM is modeled as a quadratic optimization problem with linear constraints and whose size depends on the dimension of the space of the characteristics.

In this work, we have a set of fish school belonging to three different species, anchovy, jack mackerel and common sardine, and they are represented as a set of pairs of data, $\{(x_1, y_1), (x_2, y_2), \ldots, (x_n, y_n)\}$, in which $x_i \in R^d$ represents the vector of characteristics, for instance, the dimension d is 12 because we are considering 12 descriptors of the fish school (see Table 1) and each fish school is represented by the vector x_i. On the other hand, $y_i \in \{-1,+1\}$ is the variable that allows us to identify each fish school or, in our case, discern between one species and another. A hyperplane or linear function of separation of the data or simply, the classification function of data can be written as $D(x) = \beta^t x + \beta_0$ and therefore, all the possible separation hyperplanes that satisfy all constraints used to define the separation of the fish school can be represented compactly using the inequalities $y_i[\beta^t x_i + \beta_0] \geq 1$ for all fish schools and for appropriate coefficients, and then, the parameters $\beta \in R^d$ and $\beta_0 \in R$ will be the variables of the optimization problem. The main idea is to find the minimum distance from the separation hyperplane to the nearest data (see Fig. 2, taken from Hastie et al., 2001). We will consider that a separation hyperplane is optimal if the margin (λ) is at its maximum size. Intuitively, larger margins correspond to better generalizations. Therefore, the problem of finding the optimal hyperplane is equivalent to finding $\beta \in R^d$, which maximizes the margin. In general, the quadratic optimization problem with linear constraints is expressed as:

$$\begin{aligned} &\min \frac{1}{2}||\beta||^2 \\ &y_i\left[\beta^t x_i + \beta_0\right] \geq 1, \qquad i = 1, 2, \ldots, n \end{aligned} \tag{1}$$

with respect to $\beta \in R^d$ and $\beta_0 \in R$, i.e., the solution is a vector in R^{d+1}. The data points where the constraints are active are called support vectors, i.e., are the fish schools that define the size of the margin.

In order to find a classifier function using the support vector machine, we must first determine what type of kernel function is going to be used, as this should reflect *a priori* knowledge of the problem. If it seems that the data might not be linearly separable, for example if we have two different species like anchovy and common sardine, that the position of the schools in the water column (bathymetric descriptors) is very similar, the kernel functions developed for non-vectorial structures should be used (e.g., polynomial, Gaussian, sigmoidal, or inverse multiquadratic kernels). However, for classification, Gaussian kernels are widely recommended in the literature (Scholkopf and Smola, 2002), since only the γ parameter of the kernel must be estimated and also, it is more stable. The C is another parameter, independently of the kernel that has to be estimated, that represents a balance between the size of the margin and the training error. In this work the SVM models were calibrated using SVM-light software, developed by Joachims (2001).

2.4. Data processing: calibration and testing samples

A total of 990 schools were used for these experiments: 134 jack mackerel, 442 common sardine, and 414 anchovy. The sample was not balanced due to the smaller number of mackerel schools. Previously to the calibration of any model (MLP, PNN or SVM), the data set was divided in two subsets: the first one namely calibration subset, grouped the 77% of the total data: 107 jack mackerel, 339 common sardine, and 316 anchovy schools, and the second one namely testing subset, with the remaining data (23% of the total data: 27 jack mackerel, 103 common sardine, and 98 anchovy schools). This second subset, which is unused during the models calibrations, was thus prepared solely for the verification or validation of models classification capacity. In the case of MLP, into the first subset (calibration) the 20% data (randomly selected) were used to avoid the MLP overcalibration (Tsoukalas and Uhrig, 1997). Each descriptor was standardized to a mean equal to zero and a standard deviation equal to one. This procedure is aimed to avoid the masking of features of interest (Ochoa-Rivera et al., 2007; Makkeasorn et al., 2008).

In order to solve the tendency of MLPs to get stuck in local minima, 30 neural networks were calibrated for each neural configuration (Iyer and Rhinehart, 1999). The best MLP was then selected as the one with the lowest error in the validation phase. MLPs with one and two hidden layers were proved. The number of neurons in each hidden layer oscillated between 5 and 20. Therefore, a total of 300 neural networks were calibrated and validated.

There is no training with a PNN in the sense of back-propagation network since all the PNN network parameters (units and weights) are determined directly from the calibration data. In this work, smoothing factors (σ) between 0.1 and 0.3 were used. The value of the variance controls the wide of the activation function (Gaussian curve).

For the SVM method, two parameters must be estimated: C representing the balance between the size of the margin and the calibration error, and γ representing the parameter of the Gaussian kernel. There is not single procedure for estimating these two parameters. This study is an attempt to explore all the combinations of parameters in the interval [100, 500] with a subdivision of 50 (in the case of parameter C) and in the interval [0.05, 0.5] with a subdivision of 0.05 (for parameter γ). Each exploration consisted of 100 experiments performed with the same set of parameters (C, γ) and the average classification error was calculated for the testing data. In each of the 100 iterations, what changed was the data set used for calibration and testing, i.e., 77% of the data were chosen at random for calibration and the remaining 23% were used for testing and calculating the classification errors. Once the best parameters were found (C, γ), a finer separation was done around these, with subdivisions of 0.01 for γ and 1 for C. The same calibration and testing sample used with the MLP and PNN was used with the best pair of parameters (C, γ).

The procedure proposed in this work for estimating the set of parameters (C, γ) aims to establish a search criterion that will provide a better generalization of the learning machine, including all of the schools through the use of replicates. The estimated parameters that were finally applied to the calibration sample (used for both ANN and SVM) provided a deterministic solution to the SVM problem. This differs from ANN, in which case the solution depends on the weight of the neurons in the initial phase and the number of replicates.

2.5. Data processing: multi-class SVM

Support vector machines (SVMs) were originally designed for binary classification. However, they can be used for multi-class problems. In general, two strategies are used to approach the multi-class SVM problem (Hsu and Lin, 2002). In the first, a series of binary classifications are solved distinguishing between two approaches: one-species-against-one (1-vs-1) and one-species-against-the-Rest (1-vs-R). The second strategy directly considers all the data in a single optimization formulation, obtaining a problem that is far more difficult to solve numerically (Weston and Watkins, 1998). Herein, we used the first approach to classify multi-class SVM, applying both criterions 1-vs-1 and 1-vs-R. In the case of 1-vs-1, $k(k-1)/2$ classifier functions have to be created between two species, where k represents the number of species to classify, in our case $k = 3$, so we created three classifier functions, and a voting strategy is used to decide to which species the observation corresponds. Votes are obtained depending on the evaluation of each classifier function, in each fish school's vector of descriptors used for testing. Eventually, we can have some fish school unclassified if all three species have identical votes. With 1-vs-R binary classification, the classifiers are defined by labeling the species to be identified +1 and the remaining species −1. The classification corresponds to the species whose classifier functions, evaluated in the fish school's vector of descriptors used for testing, was greatest.

2.6. Sensitivity analysis

The sensitivity analysis was carried out by replacing each variable (descriptor) by missing values and assessing the effect of this on the output error. Following this, the new error calculated was compared with the original error to obtain a ratio value (ratio = error of the model with a variable with missing values/error of the model with all variables). In this way, for a given variable x, a ratio with a value equal to or very close to 1 indicates that this variable has a very low weight in the general structure of the model (Hunter et al., 2000).

3. Results

Table 2 shows the parameters (C, γ) estimated to solve the problem of classifying with SVM based on the proposed experimental procedure with 100 iterations. This table also presents the comparative performance of the artificial neural networks (PNN and MLP) and SVM using the Gaussian kernel with two approaches (1-vs-1 and 1-vs-R). The classification rate was lowest for the jack mackerel schools, although a single exception was obtained with MLP jack mackerel versus common sardine (J-vs-S). In this case, jack mackerel presented the highest percentage of correctly classified cases (96.3%). When comparing the classification percentages of the schools by species for each method (ANNs and SVM) obtained with the two partition approaches, the partition one species versus other species (1-vs-1) presented slightly higher classification rates than the partition one species versus the rest (1-vs-R).

Tables 3–5 show the confusion matrices for the PNN, MLP and SVM classification using a multi-class approach, including the percentages of grouped cases correctly classified. According to the multi-class classifications, MLP and SVM performed better than PNN. Although we cannot conclude from these results that one of the three classifiers was definitively better than the others, we were able to determine that PNN was the least effective. The average classification rates were 79.4% with PNN and approximately 89.5% with MLP and SVM. The multi-class classification results of SVM 1-vs-1 and SVM 1-vs-R only differed for the anchovy schools, in which the 1-vs-R partition was 1.9% better than the 1-vs-1 partition. At the multi-class classification level, therefore, no type of partition was more effective than another. However, the misclassification rates were different between the methods.

The difference between PNN and MLP was more important for anchovy and common sardine, while for jack mackerel both models provided a similar classification level. On the other hand, the comparison between the confusion matrices for MLP and SVM indicated that both methods behaved similarly, although SVM 1-vs-1 incorrectly classified three schools of jack mackerel as common sardine whereas MLP grouped all the errors in a single species (anchovy). Moreover, SVM 1-vs-1 reported three unclassified cases of common sardine.

The best multi-class performance was obtained from 1-vs-R: 85.2% of the jack mackerel were correctly classified by the SVM, 90.8% of the anchovy were correctly classified by SVM and MLP, and 90.3% of the common sardines were correctly classified by MLP.

The sensitivity analysis showed that in all cases the most important descriptors were the bathymetrical; the school altitude index and the mean school depth. Between the morphological descriptors, the mean height and fractal dimension were the variables with higher weights. In comparison with these descriptors, the energetic descriptors (acoustic energy and acoustic density) showed lower ratios. The relative relationships between individual ratios of each descriptor were similar for SVM, PNN and MLP (Table 6).

Table 2
Classification rates (%) using ANN and SVM according to the type of binary partition one-versus-one (1-vs-1) and one-versus-all (1-vs-R): anchovy (A), jack mackerel (J), common sardine (S), other (R). Estimation of parameters C and γ according was included in the last column.

Type of partition	ANNs		SVM	
	Probabilistic neural networks (PNNs) (%)	Multilayer perceptron (MLP) (%)	Gaussian Kernel (%)	Parameters (C, γ)
1-vs-1				
J-vs-A	70.4–98.0	85.2–92.9	85.2–96.9	(100, 0.45)
J-vs-S	74.1–100.0	96.3–93.3	85.2–99.0	(400, 0.05)
S-vs-A	92.2–87.8	96.1–92.9	90.3–88.8	(150, 0.45)
1-vs-R				
A-vs-R	78.6–79.2	90.8–86.9	86.7–88.5	(150, 0.14)
J-vs-R	74.1–99.5	81.5–99.0	81.5–99.5	(110, 0.12)
S-vs-R	80.6–81.6	90.3–84.8	90.3–94.4	(117, 0.15)

Table 3
Confusion matrix for the multi-class PNN classification. Percentages successful recognition rates by species and average classification rate was included in the last column.

Species	Jack mackerel	Anchovy	Common sardine	Unclassifier	Total cases	Classification rate
One species versus other species						
Jack mackerel	20	4	3	–	27	74.1%
Anchovy	25	73	0	–	98	74.5%
Common sardine	0	21	82	–	103	79.6%
					228	76.8%
One specie versus the rest						
Jack mackerel	20	7	0	–	27	74.1%
Anchovy	0	77	21	–	98	78.6%
Common sardine	0	19	84	–	103	81.6%
					228	79.4%

Table 4
Confusion matrix for the multi-class MLP classification. Percentages successful recognition rates by species and average classification rate was included in the last column.

Species	Jack mackerel	Anchovy	Common sardine	Unclassifier	Total cases	Classification rate
One species versus other species						
Jack mackerel	23	4	0	–	27	85.2%
Anchovy	3	88	7	–	98	89.8%
Common sardine	0	10	93	–	103	90.3%
					228	89.5%
One specie versus the rest						
Jack mackerel	22	5	0	–	27	81.5%
Anchovy	0	89	9	–	98	90.8%
Common sardine	0	10	93	–	103	90.3%
					228	89.5%

Table 5
Confusion matrix for the multi-class SVM classification. Percentages successful recognition rates by species and average classification rate was included in the last column.

Species	Jack mackerel	Anchovy	Common sardine	Unclassifier	Total	Classification rate
One species versus other species						
Jack mackerel	23	1	3	0	27	85.2%
Anchovy	1	87	10	0	98	88.8%
Common sardine	0	8	92	3	103	88.8%
Average rate					228	88.6%
One specie versus the rest						
Jack mackerel	23	4	0	–	27	85.2%
Anchovy	0	89	9	–	98	90.8%
Common sardine	0	11	92	–	103	89.3%

Table 6
Ratio values between the classification errors when one descriptor at time is removed and the classification error with all descriptors included.

Descriptor	SVM	PNN	MLP
Morphological			
Mean height (*H*)	1.21	1.11	1.21
Length (*L*)	1.17	1.02	1.00
Perimeter (*P*)	1.04	1.02	1.00
Area (*A*)	1.04	1.01	1.01
Elongation (Elon)	1.17	1.04	1.01
Fractal dimension (Fdim)	1.17	1.12	1.14
Bathymetrical			
Bottom depth (*D*)	1.38	1.08	1.42
Mean school depth (Dm)	1.55	1.33	3.64
School altitude index (Arel)	2.42	1.53	5.36
Energetic			
Acoustic energy (Sa)	1.00	1.00	1.04
Acoustic density (MVBS)	1.17	1.22	1.04
Positional			
School-shore distance	1.46	1.02	1.16

4. Discussion

This paper explored the capacity of probabilistic neural networks (PNNs), multilayer perceptron neural networks (MLPs), and support vector machines (SVMs) to identify small pelagic fish schools from two hydroacoustic surveys. Previous studies have already applied PNN and MLP models to fish school classification (Haralabous and Georgakarakos, 1996; Simmonds et al., 1996; Skander-Hannachi et al., 2004; Cabreira et al., 2009), but to the best of the writers' knowledge, the literature contains no studies in which an SVM approach was applied with this objective. Globally, the results indicated that MLP and SVM classify fish schools much better than PNN, unlike the results obtained by others authors such as Skander-Hannachi et al. (2004).

The classification rate for jack mackerel schools (85.2%) was lower than for anchovy and common sardine schools, regardless of the method used. This worse performance could be due to the imbalance in the calibration data (107 jack mackerel, 339 common sardine, and 316 anchovy's schools). Some authors have reported greater error rates for less-represented classes in other classification problems (Barnard and Botha, 1993; Al-Haddad et al., 2000; Gutiérrez-Estrada and Pulido-Calvo, 2006). Richard and Lippmann (1991) suggested that corrected classifiers should be obtained. However, Morris et al. (2001) indicated that further investigations are required for biological classification applications.

Many studies report different classification rates for species identification. However, there are no records of similar studies in the South Pacific. Haralabous and Georgakarakos (1996) used an ANN to classify 96% of the sardine, mackerel, and anchovy schools in Thermaikos Gulf. Furthermore, Simmonds et al. (1996) obtained classification rates of 95% using an ANN with an experimental design (measuring caged aggregations) that considered eight frequency bands and five species. Lawson et al. (2001) reported that 88.3% of the species of pelagic fish schooling off South Africa could be identified. Cabreira et al. (2009) reported different configurations of ANNs for fish identification using acoustic-school descriptors for the southwest Atlantic Ocean and the classification rates up to 96%, depending on the species, type of network, and number of school descriptors utilized. Fernandes (2009) considered a new statistical method based on classification-trees and reported an average classification rate of 90% (corrected) for mackerel and herring. Korneliussen et al. (2009) reported classification rates of 85% for herring and capelin using a method that combined multifrequency, geographical, and morphological data. However, these studies differed in several aspects (e.g., size of calibration samples, species classified, number and type of descriptors, geographic areas, classification methods), all of which impacted the final classification rates.

ANN and SVM represent some of the most advanced pattern recognition platforms today. In general SVM works very well in practice and it has proven to be very useful and even more effective than neural networks in the field of species identification in ecology and in other biological applications (Morris et al., 2001; Bermejo, 2007). SVM has few tunable parameters (C and γ) and its training often involves convex quadratic optimization. The solutions are global and unique, thereby avoiding the convergence to local minima exhibited by other statistical systems, such as neural networks. SVM differs from ANN, in which the solution depends on the weight of the neurons in the initial phase and the number of replicates. As with ANN, no statistical assumption is required with SVM. On the other hand, the principal criticism of the classical methods (PCA, FDA) is that the statistical assumption could be violated. Species identification based on multifrequency acoustic data is another approach to resolving the classification problem, but is limited when trying to distinguish between species with similar acoustics properties (Korneliussen et al. (2009)). The combination of multifrequency analysis with information about the morphology and geographical distribution of fish species, that reported Korneliussen et al. (2009), is an interesting approach for fish species classification; in this case SVM or MLP could be a useful method of classification between species unclassified with multifrequency. Recently, Fernandes (2009) considered a statistical method based on classification-tree. This method and SVM have been used to analyze ecological data and both appear to be alternatives for classifying fish species that should be evaluated and considered.

When fish schools have similar acoustic properties that hinder species identification, other complementary information, such as habitat use could become more relevant for distinguishing between species. Anchovy and common sardine have similar acoustic properties and biological characteristics; both species co-habit the same ecological area with only a few differences between them. The most notable of these is the slightly more coastal distribution of the common sardine with vertical migrations to the sea bed during some periods of the day. Jack mackerel, on the other hand, is found farther offshore. Only jack mackerel have different acoustic properties from those of anchovy and common sardine. The acoustic density of this species is also an important factor in its determination. In this sense, a multifrequency approach would be the most effective for distinguishing jack mackerel from anchovy and common sardine.

In the future, a remote classification work is expected to be conducted using ANN and SVM, jointly incorporating data on the school descriptors and on multifrequency. The results obtained with SVMs show this method to be a promising tool for remote species classification. We suggest that this relatively new technique should continue to be explored in hydroacoustics.

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References

Al-Haddad, L., Morris, C.W., Boddy, L., 2000. Training radial basis function neural networks: effects of training set size and imbalanced training sets. J. Microbiol. Methods 43, 33–44.
Barange, M., 1994. Acoustic identification, classification and structure of biological patchiness on the edge of the Agulhas Bank and its relation to frontal features. S. Afr. J. Marine Sci. 14, 333–347.
Barnard, E., Botha, E.C., 1993. Back propagation uses prior information efficiently. IEEE Trans. Neural Netw. 4, 794–802.
Bermejo, S., 2007. Fish age classification based on length, weight, sex and otolith morphological features. Fish. Res. 84, 270–274.
Buelens, B., Pauly, T., Williams, R., Sale, A., 2009. Kernel methods for the detection and classification of fish schools in single beam and multibeam acoustic data. ICES J. Marine Sci. 66, 1130–1135.
Bishop, C. M., and Ulusoy, I., 2005. Object recognition via local patch labelling. Deterministic and Statistical Methods in Machine Learning, LNCS, 3635, pp. 1-21.
Cabreira, A.G., Tripode, M., Madirolas, A., 2009. Artificial neural networks for fish-species identification. ICES J. Marine Sci. 66, 1119–1129.
Coetzee, J., 2000. Use of a shoal analysis and patch estimation system (SHAPES) to characterize sardine schools. Aquat. Living Resour. 13, 1–10.
Czerwinski, I.A., Gutiérrez-Estrada, J.C., Hernando-Casal, J.A., 2007. Short-term forecasting of halibut CPUE: linear and non-linear univariate approaches. Fish. Res. 86, 120–128.
Demer, D.A., Cutter, G.R., Renfree, J.S., Butler, J.L., 2009. A statistical-spectral method for echo classification. ICES J. Marine Sci. 66, 1081–1090.
Fablet, R., Lefort, R., Karoui, I., Berger, L., Massé, J., Scalabrin, C., Boucher, J.-M., 2009. Classifying fish schools and estimating their species proportions in fishery-acoustic surveys. ICES J. Marine Sci. 66, 1136–1142.
Fernandes, P.G., Kornielussen, R.J., Lebourges-Dhaussy, A., Masse, J., Iglesias, M., Diner, N., Ona, E., et al., 2006. The SIMFAMI Project: Species Identification Methods from Acoustic Multifrequency Information. Final Report to the EC, Q5RS-2001-02054.
Fernandes, P.G., 2009. Classification trees for species identification of fish-school echotraces. ICES J. Marine Sci. 66, 1073–1080.
Foote, K., Knudsen, H., Vestnes, G., MacLennan, D., Simmonds, J., 1987. Calibration of acoustics instruments for fish density estimation: a practical guide. ICES Cop. Res. Rep. 144, 57.
Gutiérrez-Estrada, J.C., Pulido-Calvo, I., 2006. Autoescam 1.0: Sistema integrado para la estimación automática de edades en especies piscícolas. In: XIII Congreso de la Asociación Española de Limnología/V Congreso Ibérico de Limnología, Barcelona, Spain, p. 134.
Gutiérrez-Estrada, J.C., Pulido-Calvo, I., Prenda, J., 2000. Gonadosomatic index estimates of an introduced pumpkinseed (*Lepomis gibbosus*) population in a Mediterranean stream, using computational neural networks. Aquat. Sci. 62, 350–363.
Gutiérrez-Estrada, J.C., Silva, C., Yáñez, E., Rodríguez, N., Pulido-Calvo, I., 2007. Monthly catch forecasting of anchovy Engraulis ringens in the north area of Chile: non-linear univariate approach. Fish. Res. 86, 188–200.
Haralabous, J., Georgakarakos, S., 1996. Artificial neural networks as a tool for species identification of fish schools. ICES J. Marine Sci. 53, 173–180.
Hastie, T., Tibshirirani, R., Friedman, J., 2001. The Elements of Statistical Learning. Springer, 533 pp.
Horne, J.K., 2000. Acoustic approaches to remote species identification: a review. Fish. Oceanogr. 94, 356–371.
Hsu, C.W., Lin, C.J., 2002. A comparison of methods for multi-class support vector machines. IEEE Trans. Neural Netw. 13, 415–425.
Hunter, A., Kennedy, L., Henry, J., Ferguson, I., 2000. Application of neural networks and sensibility analysis to improved prediction of trauma survival. Comput. Methods Prog. Biomed. 62, 11–19.
Iyer, M., Rhinehart, R., 1999. A method to determine the required number of neural network training repetitions. IEEE Trans. Neural Netw. 10 (2), 427–432.
Joachims, T., 2001. Learning to classify text using support vector machines. In: Methods, Theory and Algorithms. Kluwer Academic Publishers, 205 pp.
Korneliussen, R.J., Heggelund, Y., Eliassen, I.K., Johansen, G.O., 2009. Acoustic species identification of schooling fish. ICES J. Marine Sci. 66, 1111–1118.
Lawson, G., Barange, L., Freon, M.P., 2001. Species identification of pelagic fish schools on the South African continental shelf using acoustic descriptors and ancillary information. ICES J. Marine Sci. 58, 275–287.
Makkeasorn, A., Chang, N.B., Zhou, X., 2008. Short-term streamflow forecasting with global climate change implications—a comparative study between genetic programming and neural network models. J. Hydrol. 352, 336–354.

Morris, C.W., Autret, A., Boddy, I., 2001. Support vector machines for identifying organism—a comparison with strongly partitioned radial basis function networks. Ecol. Model. 146, 57–67.

Ochoa-Rivera, J.C., Andreu, J., García-Bartual, R., 2007. Influence of inflows modelling on management simulation of water resources system. J. Water Resour. Plann. Manage. 133 (2), 106–115.

Pulido-Calvo, I., Portela, M.M., 2007. Application of neural approaches to one-step daily flow forecasting in Portuguese watersheds. J. Hydrol. 332, 1–15.

Reid, D.G., 1999. Report on Echo Trace Classification. A Comprehensive Review of the State-of-the-art and Directions for Future Research. ICES Cooperative Research Report, 238, 107 pp.

Richard, M.D., Lippmann, R.P., 1991. Neural network classifiers estimate Bayesian a posterior probabilities. Neural Comp. 3, 461–483.

Rumelhart, D., Hinton, G., Williams, R., 1986. In: Rumelhart, D.E., McClelland, J.L. (Eds.), Learning Internal Representations by Error Propagation in Parallel Distributed Processing: Explorations in the Microstructureof Cognition. The MIT Press, Cambridge, MA, pp. 318–362.

Rutkowski, L., 2004. Adaptive probabilistic neural networks for pattern classification in time-varying environment. IEEE Trans. Neural Netw. 15, 811–827.

Scalabrin, C., Diner, N., Weill, A., Hillion, A., Mouchot, C., 1996. Narrowband acoustic identification of monospecific fish shoals. ICES J. Marine Sci. 53, 181–188.

Scalabrin, C., 1991. Recherche dune méthodologie pour la classification et identification automatiques des detections acoustics des bancs de poissons. Rapp. IFREMER, DITI/NPA 91.23.

Scalabrin, C., Massé, J., 1993. Acoustic detection of the spatial and temporal distribution of fish shoals in the Bay of Biscay. Aquat. Living Resour. 6, 269–283.

Scholkopf, B., Smola, A., 2002. Learning with Kernels. The MIT Press, Cambridge, MA/London, England, 626 pp.

Simmonds, E.J., MacLennan, D.N., 2005. Fisheries Acoustics: Theory and Practice, 2nd ed. Fish and Aquatic Resources Series 10. Blackwell Science, Oxford.

Simmonds, E.J., Armstrong, F., Copland, P.J., 1996. Species identification using wideband backscatter with neural network and discriminant analysis. ICES J. Marine Sci. 53, 189–195.

Skander-Hannachi, M., Abdallah, L.B., Marrakchi, O., 2004. Use of neural networks in the acoustic identification of small pelagic fish species off the Tunisian coast. Japan-Tunisia Workshop on Computer Systems and Information Technology, July 2004.

Specht, D.F., 1990. Probabilistic neural networks. Neural Netw. 3, 109–118.

Tsoukalas, L.H., Uhrig, R.E., 1997. Fuzzy and Neural Approaches in Engineering. Wiley Interscience, New York.

Vapnik, V.N., 1995. The Nature of Statistical Learning Theory. Springer, New York.

Weston, J., Watkins, C., 1998. Multi-class support vector machines. In: Verleysen, M. (Ed.), Proceeding of ESANN99, Brussels, 1999. D. Facto Press, 1999. Available online at http://citeseer.ist.psu.edu/8884.html.