Artificial neural networks for fish-species identification

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Acoustic fish detection is a valuable tool for the continuous monitoring of fish schools. However, changes in species composition or mixed multispecies situations still complicate the analysis of acoustic data. Validation of echo recordings is usually accomplished by trawling, but only at point locations. However, species proportions and size distributions in the catch can be biased because of gear selectivity and fish avoidance. In this paper, techniques involving training and testing of artificial neural networks (ANNs) are applied for the automatic recognition and classification of digital echo recordings of schools in the Southwest Atlantic. Energetic, morphometric, and bathymetric school descriptors were extracted from the echo-recordings as the input for the ANNs. Several pelagic and demersal fish species known to aggregate into schools were considered, including anchovy, rough scad, longtail hoki, sprat, and blue whiting. Different types of ANNs were tested. Best performances were obtained by levelling the input data (number of schools) per species. Correct classification rates up to 96% were obtained, depending on the species, type of network, and the number of school descriptors utilized. Some of these species inhabit areas geographically distant from each other. Hence, the contribution of the school position as a descriptor was investigated. By deleting the geographical location of the schools from the ANN input data, the average performance decreased to some extent but was still satisfactory, proving the networks were able usually to recognize fish species based only on the intrinsic characteristics of the school. The results have encouraged further testing of this method as a useful tool for scrutinizing echograms.

Keywords: acoustics, artificial neural network, fish schools, species identification.

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Introduction

Acoustic instruments have been used for the underwater detection of organisms since the first third of the 20th century, providing the means for continuous monitoring of fish schools. An important issue in most acoustic surveys for mapping and assessment of aquatic organisms is the assignation of the backscattered energy to the different species present in the water column, or the so-called "echogram-scrutinizing" process. In certain cases, this becomes a real limitation for the application of the method, especially in multispecies environments characterized by continuous changes in the species composition of the schools. Identification of the fish species in the observed schools can only be done in the main at trawl stations, but other than these point observations the assignation of the backscattered energy to different species becomes increasingly uncertain.

Recent investigations aimed to characterize fish species using school descriptors obtained from the acoustic-backscattered signals. These descriptors may be different types: energetic (associated with the properties of the backscattered signal), morphological (related to the geometry of the school), and bathymetric (describing the depth of the school in the water column; Scalabrin and Massé, 1993; Scalabrin *et al.*, 1996; Zakharia *et al.*, 1996; Coetzee, 2000; Reid *et al.*, 2000).

Several methods are available for automatic species recognition and classification using acoustic-school descriptors. Multivariate analyses, such us discriminant function analysis and principal component analysis, are the most common statistical techniques used. An alternative to these statistical methods is to use an artificial neural network (ANN). An ANN is a mathematical model analogous to the human brain. It is a system comprising many basic elements (neurons), arranged in highly interconnected layers. The system has several inputs and outputs and can be trained ("the learning process") to react to the input stimulus in a desired way. To verify the efficiency of an ANN, a portion of the same dataset may subsequently be used to test the patterns learned during the training phase.

There are different types of ANN, according to their internal architecture: self-organizing mapping (SOM); back-propagation algorithms applied in feed-forward (FF or also called multilayer perceptrons) neural networks; radial basis network (RBN); learning vector quantification; and neocognitron, among others.

ANNs are used in many applications such as voice recognition (Ganchev *et al.*, 2002; Alotaibi, 2005), analysis and recognition of images and shapes (Paschalis *et al.*, 2004), weather forecasting (Mandal and Prabaharan, 2006), genetics (Izadifar and Jahromi, 2007), medicine (Frize *et al.*, 2001; Lisboa, 2002; Lisboa and Taktak, 2006), astronomy (Maneva *et al.*, 2003), and robotics (Balakrishnan *et al.*, 2000).

Ramani and Patrick (1992), Haralabous and Georgakarakos (1996), Simmonds *et al.* (1996), and Lawson *et al.* (2001) have applied ANNs for fish-species identification under different conditions, i.e. fish captive in tanks and in the wild and using different input signals to train the ANNs for fish-species classification. Haralabous and Georgakarakos (1996) used the same approach as that employed here: school descriptors as the input for the ANNs.

In the present study, we also tested the ANNs with school data, but from a much larger database that contains school information from the whole Argentine Sea. Fish species belonging to different environments are considered as items for classification with the ANNs. They are distributed over an area of $>$1 000 000 km^2, between latitudes 35°S and 56°S and from the coastal zone to the continental slope.

Several of the most important commercial species were selected for study: Argentine anchovy (*Engraulis anchoita*), rough scad (*Trachurus lathami*), sprat (*Sprattus fuegensis*), longtail hoki (*Macruronus magellanicus*), and blue whiting (*Micromesistius australis*). All of these species form schools during daytime. They are all important targets for the fishing industry.

Our study evaluates different configurations of ANNs for fish-species identification using acoustic-school descriptors obtained with calibrated echosounders deployed in the Southwest Atlantic Ocean.

Material and methods

Data collection

A fish-school database of $>$6400 records (one record per school) was built using information obtained from several acoustic surveys done over the Argentine continental shelf between 1995 and 2007 (Figure 1). The vessels involved were the RVs "Capitán Oca Balda" and "Dr Eduardo L. Holmberg", both operated by the National Institute of Fishery Research and Development (INIDEP). A commercial fishing vessel, the FV "San Arawa II" operated by Pesquera Sanford de Argentina S.A., was also employed for the data collection.

Simrad EK-500 echosounders were used on board the research vessels for data acquisition. A Simrad ES-60 echosounder was used on the commercial vessel. All the echosounders had 38 kHz split-beam transducers (ES-38B) with a circular beam width of 7° at half-power points. The transmitted pulse duration was 1 ms and a wide bandwidth was used. All the echosounders were calibrated with standard targets following Foote (1987). The Bergen Echo Integrator (Foote, *et al.*, 1991) was employed for data acquisition on the research vessels. On the commercial fishing vessel, the raw data files were logged directly by the ES-60 echosounder.

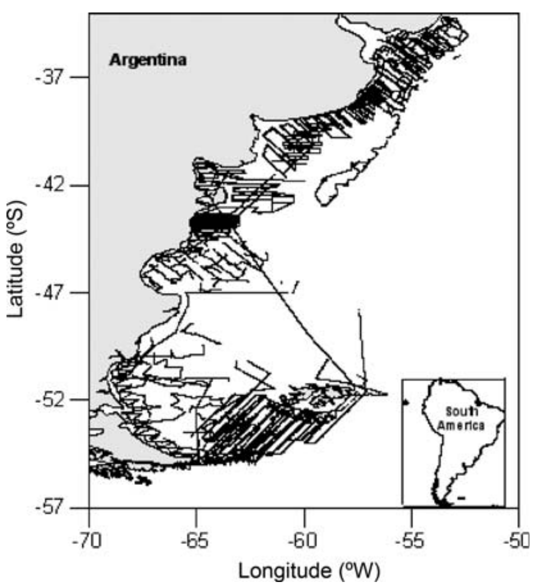

Figure 1. Hydroacoustic surveys done for fish-stock assessment by INIDEP between 1995 and 2007.

The present analysis is based only on acoustic data recorded at trawl stations. Because the fish schools disperse at night into scattered layers, only data obtained during daylight were considered.

Biological information was obtained from the trawl catches. Only those trawls where $>$95% of the catch comprised the same species were considered. All catches $<$100 kg were excluded from the analysis.

Acoustic data processing

School-data analysis was done using EchoView (v.4.10.67; SonarData, 2005). The fish-school boundaries were determined using the algorithm provided in the *school* program module. The school recognition algorithm is described in Lawson *et al.* (2001). Because of the very different school sizes among the considered species, the algorithm parameters were set accordingly.

In all, 30 school parameters or "descriptors" were extracted from each detected school. These descriptors were grouped into three main categories: energetic, bathymetric, and morphological (Table 1, Figure 2). All morphological measurements were corrected for beam width effects (Diner, 2001). The analysis was done on the echogram data with $20 \log R$ time-varied gain applied. The S_v threshold used was -70 dB always. Additionally, the temporal and geographical details of each school were recorded.

Data extracted from each school were organized and stored as records in a relational database (Ingres, 2007). Software code was developed at INIDEP for database queries. Fish schools with an estimated length $<$1 m or intersecting less than four consecutive pings were excluded from this analysis.

The resulting fish-school database contains $>$6400 records, one record per school, from a total of six analysed species/stocks. There are 4100 records of Argentine anchovy (*E. anchoita*), which are divided between two stocks: 2999 and 1101 for the northern and southern stocks respectively; 168 records of rough scad (*T. lathami*), 279 of sprat (*S. fuegensis*), 1768 of longtail hoki (*M. magellanicus*), and 124 of blue whiting (*M. australis*). The variable number of records per species is as a result of their relative abundances as well as the different number of surveys targeting the considered species during the data-collection period (1995–2007). Echo-recordings characteristic of the analysed species are illustrated in Figure 3.

Artificial neural networks

ANNs are mathematical models based on biological neural networks. Schemes of generic ANNs are outlined in Figure 4. The model is an interconnected group of artificial neurons that process information in parallel. Usually, an ANN is an adaptive system that changes its structure based on external or internal information that flows through the network during the learning phase. In more practical terms, neural networks are non-linear, statistical, data-modelling tools used for modelling complex relationships between inputs and outputs, or to find patterns in data. In our case, the inputs are the school descriptors. The patterns contained in the input data are presented to the network, which has to categorize them according to the predefined classes; in our case, the six species or fish stocks. After training,

Table 1. The main school descriptors used for training and testing the ANNs.

School descriptor	Symbol	Computations	Units
Energetic			
Volume-backscattering strength*	S_v	–	dB
Maximum volume-backscattering strength*	$S_{v\max}$	–	dB
Vertical roughness	VR	–	dB
Horizontal roughness	HR	–	dB
Skewness	Skew	Equations (7.7) and (7.8) of Zar (1984)	–
Kurtosis	Kur	Equations (7.13) and (7.15) of Zar (1984)	–
Morphometric			
Length*	L_c	$L_c = [L - 2\,D\tan(f/2)]$	m
Height*	H_c	$H_c = H - ct/2$	m
Perimeter*	P_c	$P_c = P - 2[(L - L_c) + (H - H_c)]$	m
Area*	A_c	$A_c = A\,(L_cH_c)/(LH)$	m^2
Volume*	V_c	$V_c = L_c(H_c/2)^2$	m^3
Fractal dimension	FD	$FD = 2\ln(P_c/4)/\ln(A_c)$	–
Elongation	EL	$EL = L_c/H_c$	–
Image compactness	IC	$IC = P^2/(4\pi A_c)$	–
Rectangularity	Rec	$Rec = (LH)/A$	–
Circularity	Cir	$Cir = P^2/(\pi A)$	–
Bathymetric			
School depth	Z_c	–	m
Bottom depth	Z_f	–	m
Altitude index 1	Alt 1	$Alt\ 1 = (Z_c + H_c/2)/Z_f$	
Altitude index 2	Alt 2	$Alt\ 2 = Z_f - (Z_c + H_c/2)$	m

*Selected energetic and morphometric descriptors used as input for Trial 3.

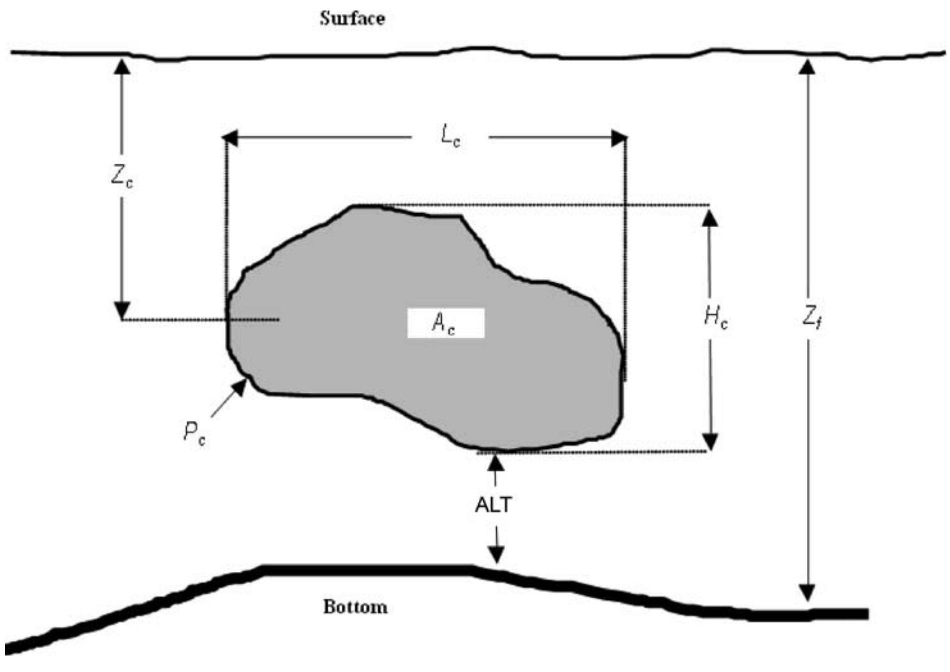

Figure 2. Examples of the school descriptors utilized for the study.

the network should be able to detect and correctly classify even complex patterns.

The internal process of an ANN can be summarized as follows. Each input signal passes through a gain or weight, called the synaptic weight or strength connection whose role is similar to the synaptic function of the biological neuron. The weights can be positive (excitatory) or negative (inhibitory). The node summation accumulates all the entered signals multiplied by the weighted input and passes to the output through a threshold or transfer function (TF; Figure 5). Typical TFs are polynomial (linear, quadratic, cubic, etc.), hyperbolic (tan, sigmoid), kernel (Gaussian), and wavelet.

Training and testing an ANN

When the system of neurons detects an object (e.g. a fish school), some of the sensors are activated and send signals to the hidden neurons. This is achieved by the so-called activation function. Neurons that fire with the input signal increase the degree of connection to themselves. If the same object is presented repeatedly, the interconnection of neurons is reinforced,

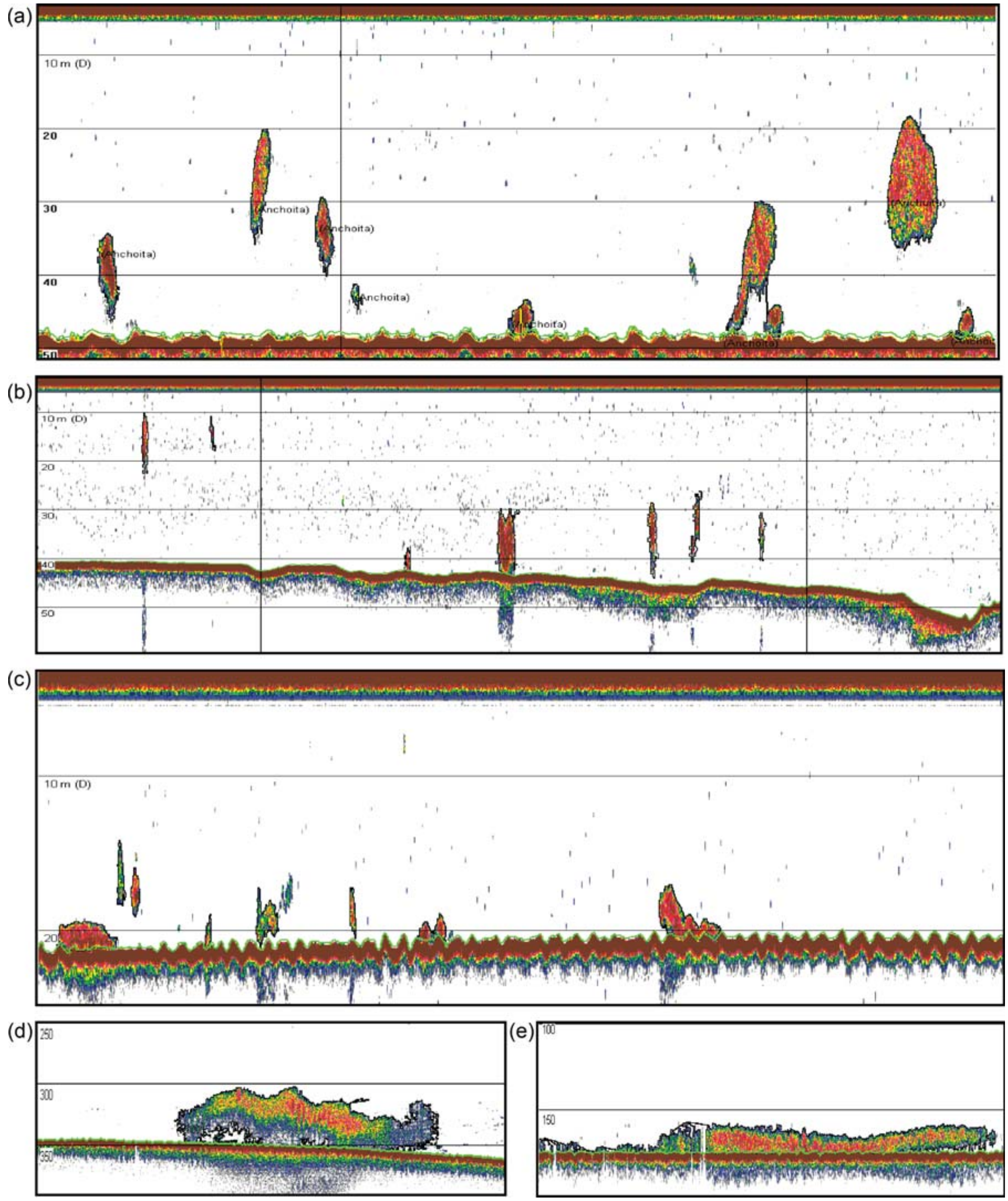

Figure 3. Typical echo-recordings: (a) anchovy, (b) sprat, (c) rough scad, (d) longtail hoki, and (e) blue whiting.

and so is the knowledge of the subject. This is known as the weight of the connection. Later, if the network is presented with a different school of the same species, the encountered union of neurons will be weak initially, so the network must be trained to recognize the object in this new presentation. After some training sessions, the neural system is able to recognize the object, e.g. a school of a certain species, in all its forms (Figure 6).

Most of the classifiers perform better if the input data are pre-processed (normalized). This can be done by applying different criteria; in our case, normalization was done by scaling the ranges of variables to the interval 0–1. Table 2 presents an example with two of the school descriptors considered in this study: the mean volume-backscattering strength (S_v) and the school height (H_c). To measure the classification accuracy of the network, we must compare its actual output with the correct output over a number of trials. This is the testing phase and requires additional, randomly selected examples from the same set of verified data, but excluding any used during the training phase. In practice, the ground-truth dataset is partitioned at random into two parts; one is used for training and the remainder is used for testing the ANN.

In our study, different fractional partitions of the whole dataset were tried for training and testing the ANNs: 50:50, 60:40, and 70:30%. The best performance was achieved with a partition of 70:30% for training vs. testing.

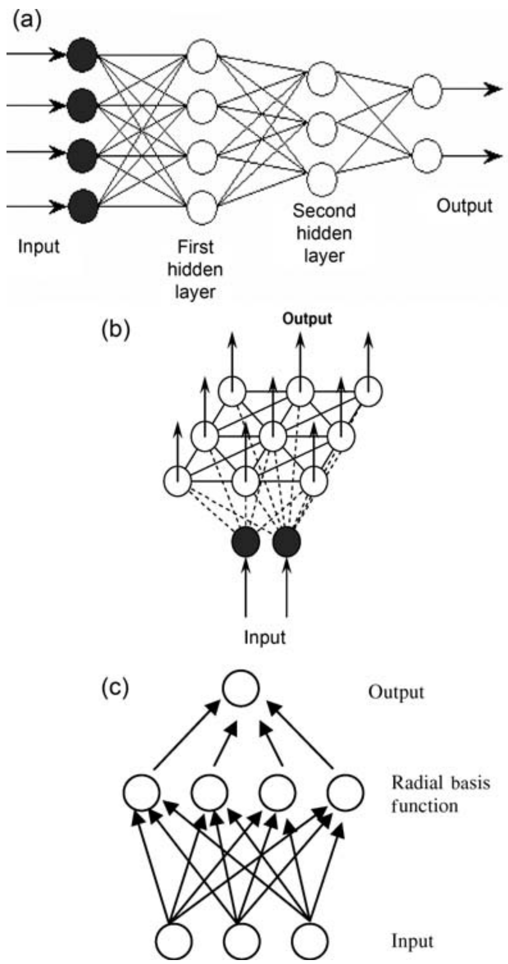

Figure 4. General schemes of the ANN structures: (a) multilayer network, (b) SOM, and (c) RBN.

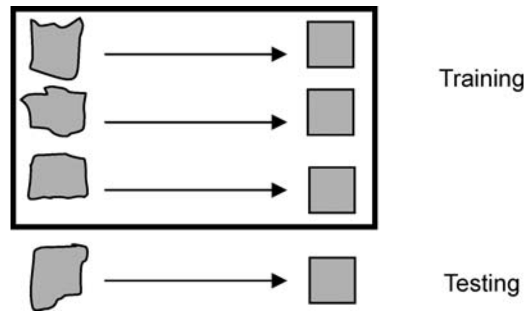

Figure 6. Classification process illustrating the training and testing phases.

Table 2. Statistics from data preprocessing for two school descriptors, the mean volume-backscattering strength S_v, and the school height H_c.

Parameter	S_v (dB)	S_v (0, 1)	H_c (m)	H_c (0, 1)
Mean	−48.1	0.55	7.72	0.06
Min.	−70	0	0.25	0
Max.	−23.9	1	121	1
s.d.	8.18	0.15	7.36	0.61

In the final column, H_c is normalized to the interval 0–1.

Types and architectures of the ANNs utilized for this study

Three different types of ANN were considered for this study: SOM, FF using back-propagation algorithm, and RBN.

A SOM is a type of ANN that is trained with unsupervised learning to produce a two-dimensional representation of the input data using the training samples, commonly called a map. Like most ANNs, SOMs work in two modes: training and mapping. Training builds the map using input examples. It is a competitive process (Kohonen, 2001).

An FF network with a back-propagation algorithm is a type of supervised learning network, which employs a cycle-spread adaptation of two phases. Once a pattern has been fed to the input of the network as a stimulus, it spreads from the first layer through the upper layers of the network to generate an output. This is compared with the desired output, and an error signal is calculated for each output. In our case, networks of three layers (input–hidden–output) were tested. In this type of architecture (multilayer), there

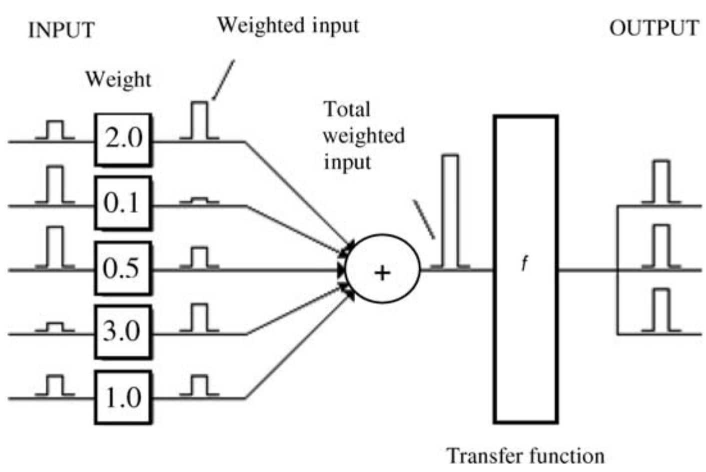

Figure 5. Neural-network process from input data (left) to output of results (right).

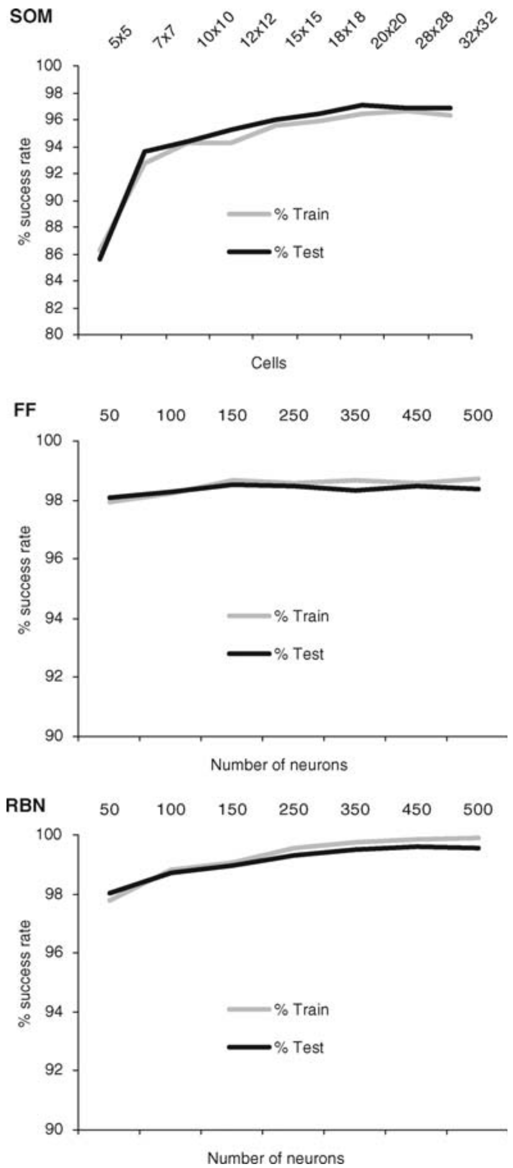

Figure 7. Relationship between the success rate and the number of neurons/cells for each neural network.

is a risk of convergence on a local minimum of the transfer function rather than on the absolute minimum. Then, the ANN will stay on the local minimum and the training process will end. This can happen when the simple back-propagation algorithm is used. To avoid this, a so-called resilient back-propagation algorithm, which implements sigmoid functions, was employed for the FF-ANN.

Radial basis function networks typically have three layers: the input, hidden, and output layers. This type of network iteratively creates one neuron at a time. Neurons are added to the network until the mean-square-error (MSE) falls below a threshold or a maximum number of neurons has been achieved (Blanzieri, 2003).

To determine the optimal number of neurons for every architecture, the relationship between the successful rate and the number of neurons/cells was studied. Figure 7 shows this relationship for the different configurations considered. We finally established our networks with 450 neurons for RBN and FF and an array of 20 columns and 20 rows for SOM.

The number of epochs (i.e. a finite set of input patterns presented sequentially) for training and testing the ANNs was set at 2000 in every case. As an example, Figure 8 shows the relationship between the number of epochs and the obtained MSE for an FF of 450 neurons. From Figures 7 and 8, it is evident that fewer neurons as well as fewer epochs could be employed with little loss of performance. However, the speed of modern PCs allows easy application of the employed architectures.

Accuracy of the ANNs

To measure the accuracy of the ANNs for classifying the school data into fish species or stocks, we computed for each species/stock within each trial global the per-species percentages of successful identifications. Five repetitions were done for every trial and for every ANN, as recommended by Maravelias *et al.* (2003).

The trials

The entire set of school descriptors contains both the acoustic description of the school (backscattering strength and geometry) and concurrent information describing the spatial and temporal location of the school. We designed the trials to investigate the contribution of these two main categories of school data. Hence, the proposed trials were as follows.

(i) All available school descriptors, including temporal and geographical, are used as inputs.

(ii) All energetic, morphometric, and bathymetric descriptors are used as inputs.

(iii) Only selected energetic and morphometric descriptors are used as input (Table 2).

Additionally, to evaluate the individual contribution of each school descriptor, a one-by-one analysis (one descriptor at a time is removed in successive runs) was done for the SOM type of ANN (Figure 9).

The amount of information contained in the survey database was very different from species to species and was rather small in some cases. This is not unusual for such a database, given the different sizes of the stocks and the different effort applied in surveying them. To study the possible effects of training ANNs with such asymmetric input data, we did the three described trials under two different scenarios, named Experiments I (using a full school dataset considered as input) and II (using a school dataset levelled per species as input).

Results

In each proposed scenario (full and reduced datasets), three different trials were done. Each trial was run on the three types of ANNs (FF, RBN, and SOM). In each trial, the input vector contained the same six species/stocks considered. All percentages of the global success rate (one percentage for each ANN and each trial) are summarized and presented in Table 3. The percentages of success rates per species are evaluated in the form of confusion matrices (one matrix per ANN and per trial). From a total of 18 matrices (three trials with three different ANNs under two different scenarios), seven confusion matrices were chosen to exemplify the most relevant results.

Experiment I: full dataset

When testing the ANNs with all the available school descriptors as the input (Trial 1), the best resulting performance was obtained

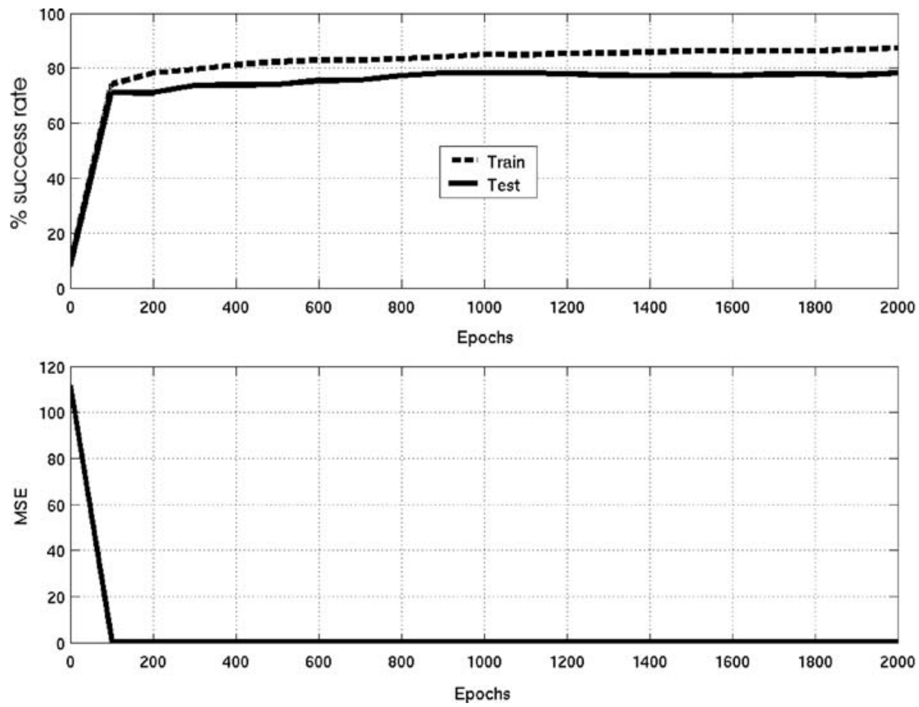

Figure 8. Relationship between the number of epochs and the obtained MSE; example for an FF with 450 neurons.

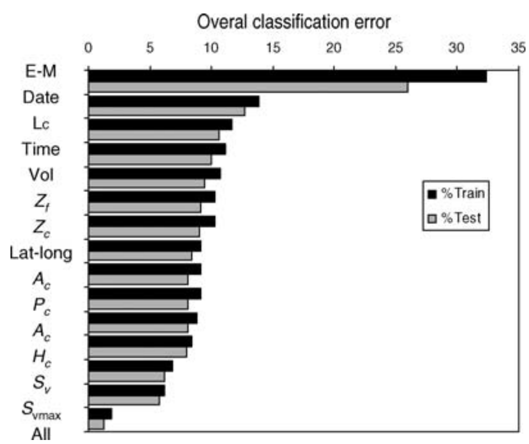

Figure 9. Overall classification error for the SOM when particular descriptors are removed one by one. Descriptor labels are on the left (E-M, all energetic and morphometric descriptors are removed; All, all available descriptors are used).

(Table 3). Taking into account that most of the considered species inhabit non-overlapping areas and that surveys targeting a particular species are always done in the same season, it is expected that a good proportion of the successful species identification will be provided by the geographical and temporal input rather than by the school characteristics themselves.

For that reason, a second trial was done considering all energetic, morphometric, and bathymetric descriptors, but intentionally excluding the geographic position, time, and date. As expected, the overall performance decreased to some extent (Table 3) but is still satisfactory for classification purposes. The confusion matrix of this trial is presented in Table 4.

The third trial comprised only selected energetic and morphometric descriptors as the input for the ANNs and resulted in a further decrease of the overall performance (Table 3). The corresponding confusion matrix is presented in Table 5.

The average performance obtained for Trials 2 and 3 may be considered as satisfactory for the simultaneous identification of six different species/stocks. However, as can be seen in the confusion matrices presented in Tables 4 and 5, most of the

Table 3. Summary of the ANN performance in each conducted trial.

			Total performance (%)							Total performance (%)			
	Trial	**ANN**	**Average**	**Minimum**	**Maximum**	**s.d.**		**Trial**	**ANN**	**Average**	**Minimum**	**Maximum**	**s.d.**
Full dataset	1	FF	97.99	97.05	98.50	0.56	With data levelling	1	FF	98.28	96.46	98.99	1.05
		SOM	96.63	96.32	96.93	0.23			SOM	97.77	97.47	98.48	0.45
		RBN	98.67	97.05	99.58	1.01			RBN	98.89	97.47	100.00	1.15
	2	FF	84.10	83.27	84.98	0.61		2	FF	74.18	72.95	75.68	1.22
		SOM	82.01	81.05	83.32	0.82			SOM	81.67	80.45	85.00	1.67
		RBN	84.43	83.64	84.88	0.51			RBN	69.05	67.73	70.27	1.16
	3	FF	67.88	66.81	69.54	1.12		3	FF	51.97	48.75	55.10	2.27
		SOM	68.73	67.74	69.60	0.78			SOM	69.69	68.93	71.00	0.92
		RBN	66.41	65.87	67.68	0.77			RBN	45.80	43.31	48.07	1.72

Table 4. Confusion matrices of the three ANNs for Trial 2.

		Recognized category (%)							
SOM	**Species**	**Bonaerensis anchovy**	**Sprat**	**Rough scad**	**Hoki**	**Blue whiting**	**Patagonian anchovy**	**Unrecognized**	**Number of cases**
True category (%)	**Bonaerensis anchovy**	**90.2**	0.6	1.5	0.9	0	6.8	0.1	886
	Sprat	45.5	**23.4**	0	5.2	0	26.0	0	77
	Rough scad	49.0	0	**51**	0	0	0	0	51
	Hoki	3.1	0.7	0.2	**93.5**	0.5	2.0	0	556
	Blue whiting	0	0	0	55.6	**44.4**	0	0	36
	Patagonian anchovy	25.5	2.5	1.5	3.7	0	**66.8**	0	325
								Total	1 931

		Recognized category (%)							
FF		**Bonaerensis anchovy**	**Sprat**	**Rough scad**	**Hoki**	**Blue whiting**	**Patagonian anchovy**	**Unrecognized**	**Number of cases**
True category (%)	**Bonaerensis anchovy**	**93.3**	0	0.7	0.9	0.1	5.1	0	923
	Sprat	41.8	**35.4**	0	6.3	1.3	15.2	0	79
	Rough scad	63.5	0	**36.5**	0	0	0	0	52
	Hoki	2.3	0.2	0.2	**92.7**	0.8	3.9	0	533
	Blue whiting	0	2.6	0	23.7	**73.7**	0	0	38
	Patagonian anchovy	27.1	1.6	0	2.3	0	**69.0**	0	306
								Total	1 931

		Recognized category							
RBN		**Bonaerensis anchovy**	**Sprat**	**Rough scad**	**Hoki**	**Blue whiting**	**Patagonian anchovy**	**Unrecognized**	**Number of cases**
True category	**Bonaerensis anchovy**	**93.8**	0.1	0.8	1.1	0	4.2	0	886
	Sprat	41.6	**36.4**	0	6.5	0	15.6	0	77
	Rough scad	52.9	0	**37.3**	5.9	0	3.9	0	51
	Hoki	3.1	1.1	0	**92.6**	1.6	1.6	0	556
	Blue whiting	0	2.8	0	47.2	**50**	0	0	36
	Patagonian anchovy	26.2	0.9	0	2.8	0	**70.2**	0	325
								Total	1 931

Emboldened numbers represent the percentage of successful recognitions.

Table 5. Confusion matrices of the three ANNs for Trial 3.

SOM	Species	Recognized category (%) Bonaerensis anchovy	Sprat	Rough scad	Hoki	Blue whiting	Patagonian anchovy	Unrecognized	Number of cases
True category (%)	**Bonaerensis anchovy**	**86.8**	0.6	0.1	6.0	0	6.5	0	904
	Sprat	63.5	**16.5**	0	4.7	0	15.3	0	85
	Rough scad	69.4	0	**6.1**	16.3	0	8.2	0	49
	Hoki	17.3	0	0.2	**76.8**	0.6	4.9	0.2	513
	Blue whiting	40.6	0	0	25.0	**25**	9.4	0	32
	Patagonian anchovy	50.3	2.3	0.6	15.8	0	**31**	0	348
								Total	1 931

FF		Recognized category (%) Bonaerensis anchovy	Sprat	Rough scad	Hoki	Blue whiting	Patagonian anchovy	Unrecognized	Number of cases
True category (%)	**Bonaerensis anchovy**	**90.2**	0	0.1	6.1	0	3.6	0	892
	Sprat	70.1	**5.2**	0	10.4	0	14.3	0	77
	Rough scad	53.3	0	**11.1**	28.9	0	6.7	0	45
	Hoki	16.4	0.2	0	**81.8**	0.5	1.1	0	548
	Blue whiting	45.9	2.7	0	29.7	**21.6**	0	0	37
	Patagonian anchovy	70.5	0.6	0.6	15.1	0	**13.3**	0	332
								Total	1 931

RBN		Recognized category Bonaerensis anchovy	Sprat	Rough scad	Hoki	Blue whiting	Patagonian anchovy	Unrecognized	Number of cases
True category (%)	**Bonaerensis anchovy**	**87.9**	1.1	0.1	6.6	0.3	3.9	0	904
	Sprat	56.5	**14.5**	0	17.4	0	11.6	0	69
	Rough scad	65.1	0	**9.3**	23.3	0	2.3	0	43
	Hoki	15.5	0.5	0.4	**80.5**	0.9	2.2	0	554
	Blue whiting	37.8	2.2	0	42.2	**11.1**	6.7	0	45
	Patagonian anchovy	62.0	1.6	0	21.2	0.3	**14.9**	0	316
								Total	1 931

Emboldened numbers represent the percentage of successful recognitions.

Table 6. Confusion matrix of the SOM for Trial 3 with similar numbers of observations per species.

SOM	Species	Recognized category (%)							Number of cases
		Bonaerensis anchovy	Sprat	Rough scad	Hoki	Blue whiting	Patagonian anchovy	Unrecognized	
True category (%)	Bonaerensis anchovy	**67.3**	8.9	5.9	4	2	10.9	1	101
	Sprat	11.1	**66.7**	3.3	5.6	4.4	8.9	0	90
	Rough scad	11.9	2.4	**64.3**	7.1	4.8	9.5	0	42
	Hoki	6.5	3.3	2.2	**78.3**	3.3	5.4	1.1	92
	Blue whiting	9.1	9.1	2.3	9.1	**65.9**	4.5	0	44
	Patagonian anchovy	8.5	9.9	4.2	5.6	7	**64.8**	0	71
								Total	440

Emboldened numbers represent the percentage of successful recognition.

contribution to the overall performance comes from the successful identification of only two items (Bonaerensis anchovy stock and longtail hoki), with a high level of confusion in the remaining four items. Another conclusion from these trials is that most of the failures in identifying a given species result from false identifications of other species more frequently found in the input dataset, i.e. those having more records in the database and thus were more familiar to the ANNs during the training phase. In our case, this is the Bonaerensis anchovy stock.

Experiment II: dataset levelled per species

To analyse the effect of the asymmetrical input data per species, a second experiment, namely "data levelling", was considered. The input dataset used for Trials 1–3 in Experiment I was adjusted with fewer records of the three most frequent species/stocks to have similar numbers of observations per species. This was achieved by randomly subsampling the original (larger) dataset on anchovy (Bonaerensis and Patagonian stocks) and longtail hoki. After the data reduction, the probability density functions of the corresponding descriptors remained comparable with their original forms.

The resulting overall performances in species recognition are summarized in Table 3 for the three ANNs considered. Comparing the overall performances of the ANNs in both experiments (full input dataset vs. levelled), a similar decrease was observed from Trials 1 to 3. However, in the levelled input-data experiment, better results were achieved using SOM than with FF and RBN. The confusion matrices obtained after levelling the input data per species, displayed not only a good overall performance for SOM but also the best internal consistency (best confusion matrix) with similar success rates in identifying the six items considered. The confusion matrix for Trial 3 using the SOM is illustrated in Table 6.

Discussion and conclusions

Similar to results presented in earlier studies (Ramani and Patrick, 1992; Haralabous and Georgakarakos, 1996; Simmonds *et al.*, 1996; Lawson *et al.*, 2001), the ANNs we used in our study to classify fish species from echo-recording data performed satisfactorily. However, most of the cited studies only considered the use of an FF neural network and employed small fish-school databases, usually emanating from the same environmental area.

We tested the methodology by using three different types of ANN on a database containing information from >6000 fish schools, grouped into six different items (species/stocks). The geographic scale of the experiment comprised a total area of >1 000 000 km^2. Fish-school data were obtained from different surveys and observational platforms (research and fishing vessels), over a period of >7 consecutive years.

The effect of the number and type of school descriptors employed was empirically studied in three different trials. This selection of trials made it possible to determine whether the information contained in the acoustic descriptors of the schools was sufficient for their classification into species, even if they belonged to different ecosystems, as was the case for the six fish species in our study. This was investigated in Trial 3. In addition, a one-by-one analysis of the individual contribution of each descriptor was made for one of the employed ANNs (the SOM).

The effect of very asymmetrical input data (number of schools per species) was studied by repeating the trials on a species-levelled, subsampled database. By comparing results from Experiments I and II, we found that even when the overall performance is satisfactory, whenever the classification fails there is a clear tendency of the ANNs to fail towards the most frequent item (fish species) present in the database, i.e. the one they have learned most about.

Three configurations of ANNs were tested for the three proposed trials (different sets of school descriptors) and under two scenarios (asymmetrical and levelled input data per species). A very different response, and the best performance obtained, corresponded to the SOM neural network, when the quantity of the input data is levelled per species. Further work should address the issue of levelling to establish whether this "overtraining" behaviour is a characteristic of the particular architecture of the SOM.

The increasing use of ships-of-opportunity in marine research allows very large amounts of data to be collected to train ANNs. In our study, the ANNs were tested as an aid for echogram scrutiny and partitioning echo-records between species. However, taking advantage of the fast performance of the ANNs and the speed of modern PCs, further research should explore the application of ANN methodology for automated biomass estimation from acoustic-survey data and for real-time school classification at sea, with the aim of developing a useful tool for both scientific and commercial use.

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