Acoustic identification of small-pelagic fish species: target strength analysis and school descriptor classification

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Abstract

The acoustic identification of small-pelagic fish species is part of the INSTM ongoing project on the assessment of small-pelagic-fish species in Tunisian waters. The aim of this project is to develop a method for determining the species of fish detected by the EK–500 echosounder directly from their acoustic signature, instead of indirectly by experimental trawling.

Two principal subjects have been studied: target-strength analysis; and school descriptors as an indicator of fish species. Target-strength analysis empirically determines the constant *c* for each species in Foote's equation, which is then used for biomass estimation. Encouraging results have been obtained for the sardine (*Sardina pilchardus*), and work is continuing on other species. Fish-school descriptors (bathymetric, morphological etc.) are extracted from echograms and used for training artificial neural networks, which are then used as species classifiers. Two types of neural networks have been tested and three species have been successfully identified using probabilistic neural networks: the sardine (*Sardina pilchardus)*, the anchovy (*Engraulis encrasicolus)*, and the horse mackerel (*Trachurus trachurus)*. Results indicated that probabilistic neural networks are better for the acoustic identification of fish schools than feed-forward neural networks.

1. Introduction

Sonar techniques, especially echosounders, have been used since the beginning of the twentieth century for the detection of fish at sea by professional fishermen and by fishery oceanographers. It has been noted since the 1950s that the acoustic signature of fish can carry information on their species. In particular, the physical backscattering properties of small pelagic fish, such as their target strength or spectral response, are related to their species (Scalabrin, 1996; Simmonds *et al.*, 1996; Zakharia *et al.*, 1996). Moreover, small pelagic fish, known for their aggregation into schools, especially during the daytime, can be identified from the acoustic properties of these schools (Coetzee, 2000; Haralabous and Georgakarakos, 1996; Scalabrin, 1996). The technique of echo-integration, first developed by Dragesund and Ossien in 1965, makes possible an estimate of the biomass represented by schools of small pelagic fish (Masse, 1996). Since 1998, annual acoustic and experimental fishing surveys have been carried out during the summer for the study of the small-pelagic-fish stocks along the Tunisian coast. Small-pelagic fish-stock estimates can be improved by a better knowledge of the species composition of the biomass through acoustic identification of the detected schools. While many current acoustic identification studies are interested in wide-band and multi-beam echosounding technology, we chose to use a narrow-band echosounder. This is of special interest because most commercial trawlers in Tunisia use narrow-band echosounders operating at 38 kHz, and we hope that these results can eventually be used by professional fishermen for more selective fishing. Two main themes are explored by our research group:

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target strength (TS) analysis; and the use of school descriptors for species identification. Our objective with TS analysis is to determine the value of the specific constant *c* in Foote's equation (Maclennan and Simmonds, 1995) for the species of interest: $TS = 20\log(L_t) + c$

The parameter *c* is then used in echointegration formulae for biomass assessment. Data from three surveys were used. Currently, we have obtained results for sardine (*Sardina pilchardus*), since this species was the predominant species in most trawls, but work is progressing on other species. School descriptors as a function of species has been discussed by several authors (Cotzee, 2000; Haralabous and Georgakarakos, 1996; Scalabrin, 1996). Neural networks have been proposed as an alternative tool to parametric statistical methods for the identification of small pelagic species (Haralabous and Georgakarakos, 1996; Simmonds *et al.*, 1996; Zakharia *et al.*, 1996). Data from three acoustic surveys were used for the extraction of school decriptors. The data from 120 schools of sardine (*Sardina pilchardus*), anchovy (*Engraulis encrasicolus*) and horse mackerel (*Trachurus trachurus*) were used to train two types of neural networks, and data from 137 schools were used to test these networks.

2. Methods and data collection

2.1 General methodology

A detailed methodology for acoustic identification based on *in situ* data can be found in Scalabrin (1996). This is the approach that we used and it can be summarized in the following four steps:

- Acoustic survey at sea and digital recording of data from the echosounder
- Establishing experimental information by fish trawls
- Selection of the fish schools for which the species is known
- Choice and application of pattern recognition and classification methods

2.2 Data collection at sea

The data used in this study were collected by the R.V. "Hannibal" during the hydroacoustic surveys of the INSTM along the Tunisian coast, between July 2000 and August 2002. During each survey, the prospected areas were covered by a network of parallel transects adapted to the topography (MacLennan and Simmonds, 1995). Prospecting and trawling were both carried out during the daytime, while schools were closer to the seafloor. A SIMRAD EK–500 echosounder with a split-beam transducer operating at 38 kHz with a 7º×6.9º beam width and 100-ms pulse duration was used during these surveys. Calibration of the echosounder was done *in situ* at a depth of 25 m, using a copper sphere with a known TS value (-33.6 dB) and specialized software. Both the copper sphere and the software were provided by SIMRAD. Movies+ software, developed by the Institut français de recherche et d'exploitation de la mer (IFREMER) was used with the built-in EK–500 echointegrator for the analysis of the acquired data. Experimental fishing was carried out using a mid-water trawl, with a vertical opening of about 6 to 7 m. Trawls were made whenever a significant amount of small-pelagic-fish schools were observed with the echosounder. The speed of the vessel was about 3 to 4 knots during trawling. A netsonde sonar, attached to the mouth of the trawl, was used to monitor the catch in real time. The catch was then sorted by species and the length–frequency composition was determined for each species.

2.3 TS analysis

Of the 128 hauls made during our surveys, sardine was present in 55 of them. We limited ourselves only to hauls in which sardine represented more than 70% of the catch. Therefore, only 18 hauls were retained for TS analysis.

For each haul we established the size–frequency distribution (Table 1) and we sought the tables of the corresponding TS, as illustrated in the example below for haul no. 21 of the OASIS 6 survey (2002) (Fig. 1 and Table 2). The water column was divided into ten layers. Depending on the duration of the haul and the position of the schools in the water column, one or several TS values were attributed to the same size–frequency distribution.

Table 1. Distribution of sardine size frequencies for haul no.21, OASIS 6, 2002. The length mode (15.5 cm) is in bold.

Lt (cm)	9.0	9.5	10.0	10.5	11.0	11.5	12.0	12.5	13.0	13.5	14.0	14.5	15.0	**15.5**	16.0	16.5	17.0	17.5	18.0
%	0.4				0.4				1.8	0.7		1.1	11.9	**33.9**	26.4	14.1	4.3	1.1	0.4

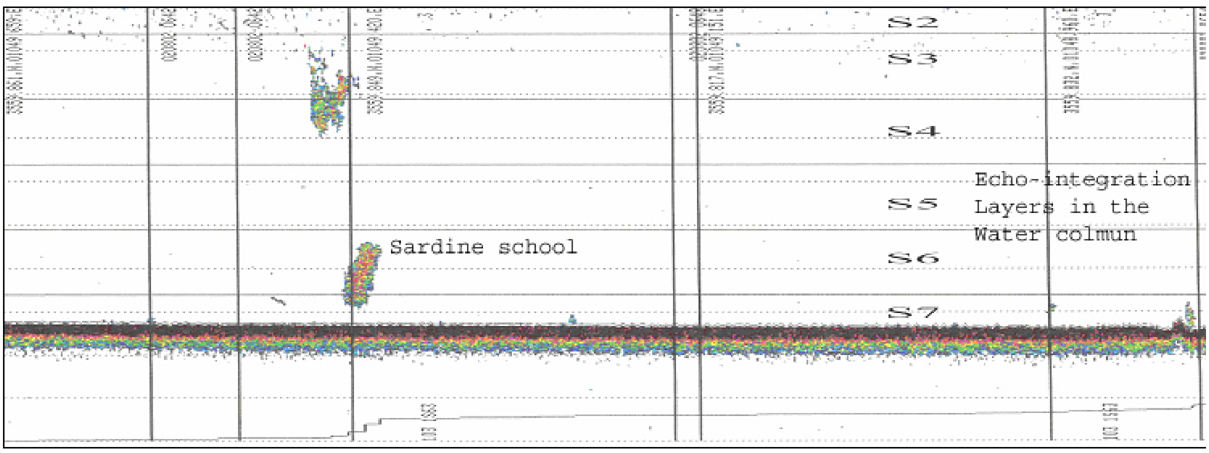

Figure 1: Sample of the echogram during haul no21 of OASIS 6, 2002.

Table 2. Count of the TS for each layer in haul no.21 of OASIS 6, 2002. The circle indicates the TS mode for layer S6 where the sardine school is present.

TS-max = -24.0 dB TS-step = 1.5 dB -60 -57 -54 -51 -48 -45 -42 -39 -36 -33 -30 -27 -24

1290.0 1	1 Sur.	2.0	702.0	658	8	7	14	22	26	12	6	2	1	0	0	0	0	0	1	0	1	0	0	0	0	0	0	0
02/08/02 38	3 Sur.	9.0	24.0	23	17	22	22	4	4	4	0	0	9	0	0	0	0	4	4	0	9	0	0	0	0	0	0	0
06.55.09 kHz	4 Sur.	24.0	39.0	152	16	12	22	31	14	3	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	5 Sur.	39.0	54.0	259	5	6	13	19	38	13	4	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	6 Sur.	54.0	69.0	172	4	4	8	20	24	22	11	4	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	7 Sur.	69.0	84.0	52	2	4	6	17	15	4	12	0	4	0	6	2	4	4	6	4	4	0	4	2	0	0	2	0

From the two distributions presented in Table 2 and in Figure 2, we took only the modes and thus obtained the modal lengths according to the TS (Table 3). The catch in some hauls was bimodal. Data from those hauls were not used in the final result.

Table 3. Length and corresponding TS modes.

Mode (cm)	10.0	11.0	11.0	11.0	11.0	11.0	12.0	13.0
Ts (dB)	-53.50	-53.40	-53.25	-51.90	-54.75	-53.57	-52.50	-52.50
Mode (cm)	14.0	14.0	15.0	15.5	16.0	16.0	17.5	
Ts (dB)	-49.50	-50.25	-51.75	-49.50	-51.75	-50.00	-48	

2.4 School descriptor extraction and classification

2.4.1 Descriptor extraction

Movies+ uses the digital output of the EK–500 to display echograms on a PC and record them for later use. Algorithms included in the software make it possible to recognize individual schools of fish on the echograms and to extract a set of school descriptors (Diner *et al.*, 2001). These descriptors can be used to identify the species of each school (Haralabous and Georgakarakos, 1996; Scalabrin, 1996) (Fig. 2, Table 4).

About 50,000 schools have been detected during these surveys. For the training of the chosen classifier, only those schools whose species identity has been established by experimental trawling can be used. If the catch was monospecific (i.e. 95% of the fish in the net belonged to one species), then all the schools detected during the trawling are considered to belong to that species (Scalabrin, 1996). This reduced the number of usable schools to less than 2,000, most of which were schools of sardines, anchovies and horse mackerel. It was considered preferable to use the same number of training examples for each species, so that the classifier would not be biased and would learn to recognize one species better than the others. The amount of usable data was thus reduced even more, since the number of horse mackerel schools detected was considerably less than the number of sardine and anchovy schools. Finally, only 120 schools were used for the training, 40 from each species; and 137 schools were used for testing the classifiers, comprising 59 sardine schools, 51 anchovy schools and 29 horse mackerel schools.

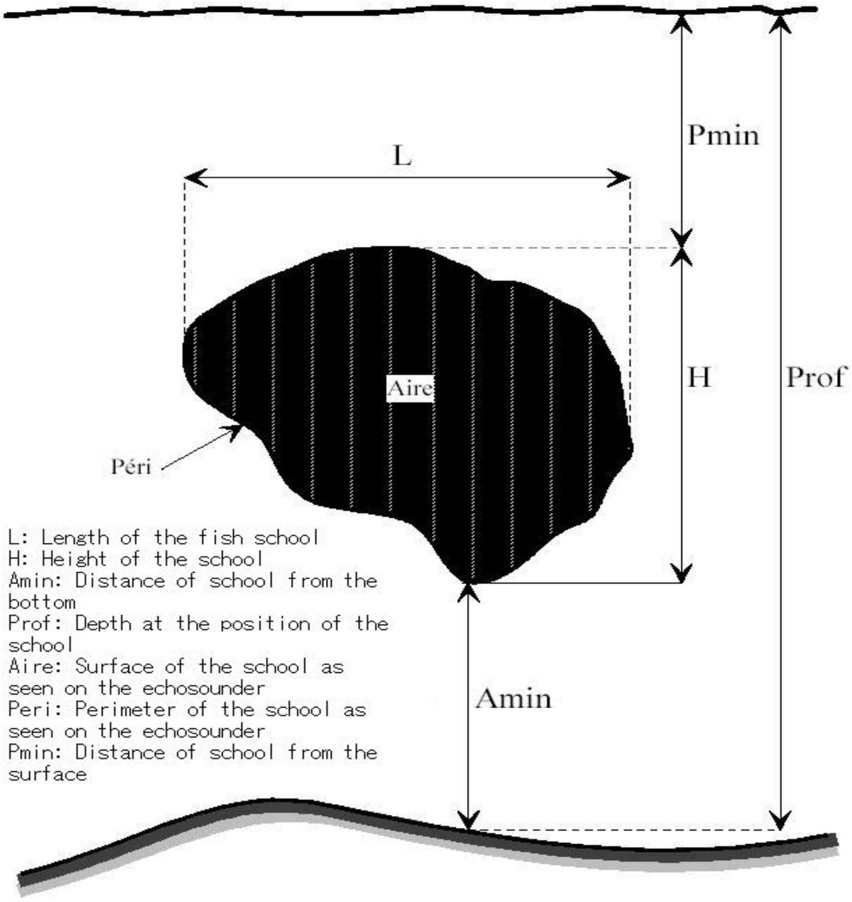

Figure 2. Some of the school descriptors used in this study (Diner *et al.*, 2001)

Table 4: School descriptors used in this study

Descriptors	***Units***
E: mean energy backscattered by the school per unit of surface	mV^2/m^2
S_v: total reverberation index of the school	dB
Vmoy: Mean amplitude of samples (pings) backscattered by the school	mV
Coefficient of variation of the amplitude of the samples	%
Prof: Bottom depth	m
Amin: minimum altitude	m
Pmin: minimum depth	m
Lmax: maximum length	m
Hmax: maximum height	m
Elon: Elongation = Hmax/Lmax	%
Peri: Perimeter	m
A: Area	m^2
Dfrt: Fractal dimension = 2ln(P/4)/lnA	
Arel: Relative altitude = [Amin + (Hmax/2)]/ Prof	%

2.4.2 Classification using neural networks

Artificial neural networks are a programming method based on a mathematical approximation of the functioning of human brain cells. A neural network (ANN) can be seen as a set of interconnected nodes implementing a mapping function from an input space (in this case the school descriptors) to one of several output categories or classes (in our case, a species of fish) (Fig. 3). The network is initialized with random values (or almost), then it is trained by successive examples of the problem to be solved, until it converges to the desired mapping. ANN have started to replace traditional statistical techniques in many modeling and classification problems, although some studies have criticized them for being a black-box method that does not provide any information on the models they approximate. A good overview of ANN, as well as their use in ecology and marine sciences, can be found in Recknagel (2003).

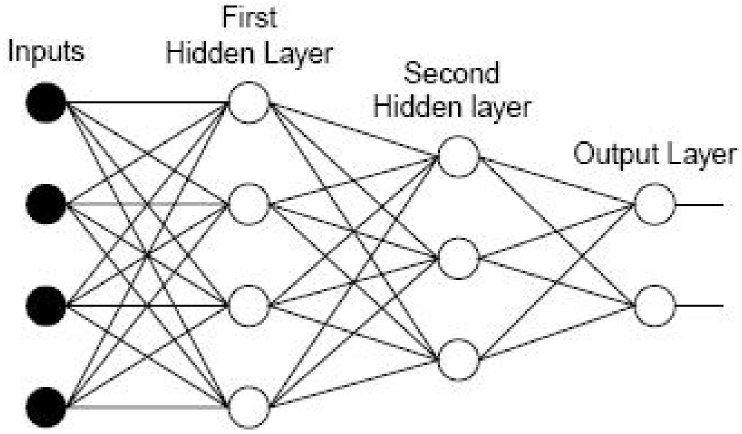

Figure 3. A standard feed-forward ANN

Two types of neural networks were used in this study: multi-layer perceptrons (MLP) and probabilistic neural networks (PNN). MLPs are trained by incrementally reducing the error between the real and the desired output for successive training examples. Several algorithms can be used for this purpose, the most common method being the gradient descent algorithm, in which the network weights are adjusted according to the following rule:

$$w_{i+1} = w_i - \eta \frac{\partial MSE}{\partial w_i}$$

where w_i is the network at the ith increment, η is the learning rate, and MSE is the mean-square error between the desired output and the real output.

For this study we chose a variant of this rule, in which the weight adjustment is in accordance with:

$$w_{i+1} = w_i - \eta(i) \frac{\partial MSE}{\partial w_i} - mc\left|w_i - w_{i-1}\right|$$

Using a variable learning rate $\eta(i)$ increases the learning speed, and adding a momentum term $mc|w_i - w_{i-1}|$ improves the chances of avoiding local minima.

PNNs (Specht, 1990; Ganchev *et al*., 2002; Grman *et al*., 2001) are a type of ANN in which the training examples are used to estimate each class's probability distribution, and then the Bayes decision rule is used to determine the most likely class given the input vector. The Bayes decision rule can be formulated as:

$$x \subset Class_i \text{ if } P(Class_i/x) > P(Class_j/x) \text{ for all } j \neq i.$$

The posterior probability $P(Class_i/x)$ is given by:

$$P(Class_i/x) = P(x/Class_i)P(Class_i)$$

The prior probability $P(x/Class_i)$ is estimated using the Parzen window technique (Specht, 1990). Matlab software was used for the design and simulation of the ANN.

3 Results

3.1 Results of TS analysis

The values that we used in the study are represented in Table 5.

Table 5. Modal length and mean TS.

Modal length (cm)	10.0	11.0	12.0	13.0	14.0	15.0	15.5	16.0	17.5
TS mean	-53.5	-53.4	-52.5	-52.5	-49.9	-51.8	-49.5	-50.9	-48.0

A linear correlation is established between TS and log(L) (Fig. 4) and we obtained:
$TS=20.568\log(L_t)-74.617$ with $R^2=0.77$

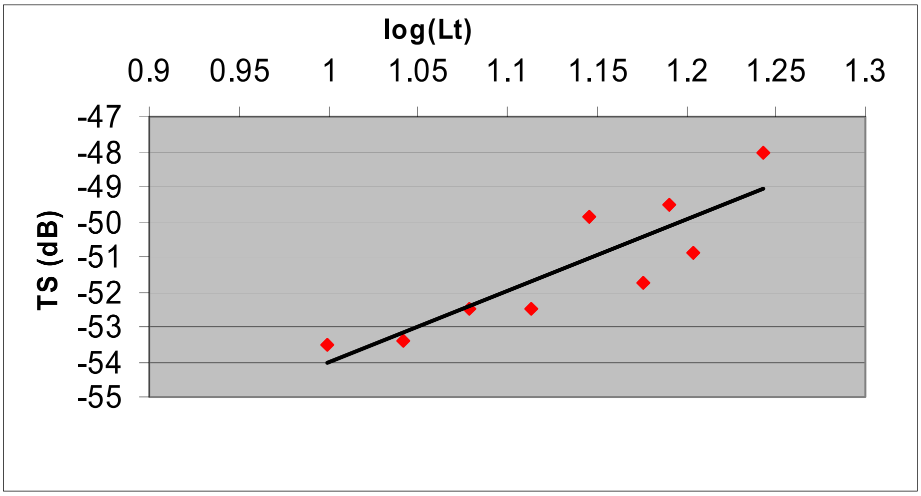

Figure 4. Graph of $TS=f(\log L_t)$.

If we consider that

$TS=20\log(L_t)+c$

then $20\log(L_t)+c=20.568\log(L_t)–74.617$.

Therefore,

$c=0.568\log(L_t)–74.617$

Thus for each length L_t, we have a value of c (Table 6).

Table 6. Values of L_t and c; c=f(L_t)

L_t(cm)	10.00	10.50	11.00	11.50	12.00	12.50	13.00	13.50
c	-74.05	-74.04	-74.03	-74.01	-74.00	-73.99	-73.98	-73.97
L_t(cm)	14.00	14.50	15.00	15.50	16.00	16.50	17.00	17.50
c	-73.97	-73.96	-73.95	-73.94	-73.93	-73.93	-73.92	-73.91

For sardines with a total length (L_t) between 10 and 17.5 cm, C_{mean} = –73.97 and the Foote equation becomes:

$TS=20\log(L_t)–73.97$

3.2 Discussion of TS analysis

Several relations for sardine TS are in use in other countries, as indicated below (Table 7)

Table 7. Various TS in use for the sardine.

Author	**TS for 38 kHz**
Spain (Ben Abdallah *et al.*, 2000)	$20\log(L_t)–72.6$
ICES (3) (Diner and Marchand, 1995)	$20\log(L_t)–71.2$
Italy (10) (Patti *et al.*, 2000)	$20\log(L_t)–70.44$

The obtained value of *c*, compared with those in use elsewhere, is relatively low. Indeed, the TS factor depends on several aspects, such as the physiological state of the fish, its behaviour and the time of day (Ona, 1999). In our case, all the measurements were carried out during the day and in the summer, which reduced the variations due to diel and seasonal factors. Moreover, during the day, the sardines gather in schools close to the bottom, consequently their swim bladders will have a lower volume, which may partly explain the difference between the obtained value and that recommended by ICES.

3.3 Results of classification using ANN

Several different configurations of MLP were designed and trained, and we finally settled on a three-layer network with 21 input neurons, 17 hidden neurons and 3 output neurons. For the PNN, the design was pretty straightforward; the only factor that we had to choose was the spread factor, which could be chosen manually. The rest of the network parameters (number of neurons, layers, etc.) are a function only of the training set and the training algorithm. The results are in Tables 8 and 9.

Table 8. Confusion matrix: classification rates using MLPs.

Real species	*Predicted species*			
	Anchovy	*Horse mackerel*	*Sardine*	*Unassigned*
Anchovy	100%	0%	0%	0%
Horse mackerel	0%	93%	3.5%	3.5%
Sardine	1.8%	0%	58%	40.2%

Table 9. Confusion matrix: classification rates using PNNs.

Real species	*Predicted species*		
	Anchovy	*Horse mackerel*	*Sardine*
Anchovy	100%	0%	0%
Horse mackerel	0%	96.5%	3.5%
Sardine	7%	2%	91%

3.4 Discussion of ANN classification

Tables 8 and 9 show that PNNs perform better than MLPs in fish-school classification. It has already been shown by Ganchev *et al.* (2002) and Grman *et al.* (2001) that PNNs are better than MLPs in other typical classification problems, such as voice recognition or fault recognition, especially when the training set is relatively small (as in our case). Moreover, it may be that PNNs are more robust than MLPs and are thus more suitable for dealing with the noise inherent in the training examples of fish schools.

4. Conclusion

A new relationship between TS and total length has been found for the sardine (*Sardina pilchardus*) off the Tunisian coast for the size range 9–18 cm and for the acoustic frequency of 38 kHz:

$$TS = 20\log(Lt) - 73.97$$

The obtained result must be regarded as provisional, because it does not cover all the sardine size-classes. Moreover, this relation can vary with the physiological state of the animal (stage of sexual maturity and fat content). However, this relation can be used under the same conditions in which it was established, but it is necessary to update it continuously, because any change not taken into account can affect the biomass estimation. For the school classification using ANN, the training data have also to be constantly updated. This will lead to better classification results for the three studied species, and the addition of other species to the training set. The results of future surveys are necessary before any definitive classification method can be achieved.

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