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Accuracy of Acoustic Methods in Fish Stock Assessment Surveys

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1. Introduction

Acoustic methods have been widely used in fisheries research for pelagic fish biomass estimation, lately including very sophisticated techniques, such as multi-frequency, wide band, multibeam, vertical and horizontal echosounding. Moreover, in the new era of ecosystem-based management, developments in acoustic technology could extend our knowledge from the stock to the ecosystem (Bertrand, 2003) and enhance our understanding of the ecosystem structure (Koslow, 2009). Until now, biologists utilised acoustic technology mainly for fish biomass estimation. Normally, acoustics are superior to other methods for pelagic fish stock assessment (Simmonds, 2003); acoustic surveys are therefore often used to tune the VPA or other classical biomass estimation methods. The main advantage of fisheries acoustics is its ability to estimate most measurements errors and provide a level of the total accuracy of the abundance, which only crudely can be asserted by the other methods. This error analysis and de-biasing approach is not easy to design and less easier to implement in a real situation. However, it is worth to investigate each error factor affecting the measurement, estimate its nature (random or systematic) or its magnitude and try to minimise its impact if possible. Finally, a procedure known as intrinsic error analysis takes into account all errors sources and estimates the total error, hence revealing the quality of the final results. Detail studies of error analysis are recently published for krill (Demer, 2004) and Norwegian spring-spawning herring assessment (Løland et al., 2007).

The chapter will review some of the most important sources of errors and their impact on acoustic biomass estimation, with emphasis on the assessment of pelagic species and the development of methods aiming at relevant de-biasing approaches. Simmonds & MacLennan (2005) reviewed this problem and provided some indicators of how much error might be expected in a typical acoustic survey, with optimum sampling design and proper instrument preparation. The expected error magnitudes are reproduced in Table 1 slightly modified. The errors are divided in two groups, those generated due to the instrumentation uncertainty and others caused by the living resource complexity of behaviour. Absolute biomass estimations expressed in weight per unit area have a higher uncertainty compared to the estimates of relative indices, namely acoustic integration values per unit area. According to Table 1, large systematic errors such as these generated by bubble attenuation, hydrographic conditions and vessel avoidance can underestimate the biomass up to 10% of its original value. However, if the same research vessel is used under similar speed, weather

conditions and instrumentation, particularly the same frequency and beam angle, it can be assumed that the relative biomass estimates are less affected by these error sources. In any case, the decision for using relative or absolute estimates should carefully be made, taking into account both the survey conditions, as well as the requirements of the stock assessment and its management.

| A. Errors affecting both relative and absolute biomass estimation | | | |
|----------------------------------------------------------------------------|---------------|-------------|--------------------------------------------------------------|
| SOURCE OF ERROR | Random | Bias | Comment |
| Instrument platform | | | |
| Instrument calibration | ± 2 to 5% | ± 2 to 5% | Worse at higher frequencies |
| Vessel motion | | 0 to 25% | Narrow beams are more biased |
| Bubble attenuation | | 0 to 90% | Keel mounted and deep towed systems are less sensitive |
| Hydrographic conditions | ± 2 to 5% | 0 to 25% | High frequencies and deep targets are more biased |
| Fish behaviour | | | |
| Target Strength | ± 5 to 25% | | Uncertainty in fish size and fish orientation |
| Species identification | ± 0 to 50% | | Depends on species and level of species mix |
| Random sampling | ± 5 to 20% | | Depends on spatial distribution and school size distribution |
| Migration | | 0 to 30% | Depends on timing between survey and fish movement |
| Vertical movements | ± 0 to 50% | | Depends on TS change due to pressure variations |
| Vessel avoidance | | 0 to 50% | Stronger in shallow areas and noisy vessels |
| B. Additional errors affecting only the absolute biomass estimation | | | |
| Source of error | | Bias | Comment |
| Instrument calibration | | ± 3 to 10% | Worse at higher frequency and narrow beam |
| Hydrographic conditions | | ±2 to 25% | High frequencies and deep targets are more biased |
| Target Strength | | 0 to 50% | Best for well investigated swimbladdered species. |

Table 1. Expected errors in well designed and properly calibrated acoustic surveys (modified from Simmonds & MacLennan, 2005)

The sampling error caused by the acoustic measurements being stochastic samples of the true mean density is affected by the survey design, the spatial structure of fish and the encountered intrinsic variability among samples. It is worth noticing, that depending on bathymetry, acoustic sampling volume and ping interval, the insonified water volume is often 10 000 – 20 000 smaller than the volume of interest in a typical survey, and therefore a high uncertainty should be expected due to this small sampling portion.

In this chapter, we focus on the three most important sources of errors which affect the assessment accuracy, namely: target strength (TS) estimation, species identification - biomass allocation per species and fish avoidance reactions to survey vessels.

2. Target strength estimation

The unbiased target strength (TS) estimation is a prerequisite for any approach of fish stock abundance monitoring. It is a key parameter that transforms backscattering into biomass. The TS of an individual fish depends on the sound frequency, as well as on some fish characteristics such as size, anatomy, physiology and swimming behaviour. It is suggested that environmental factors cause different morphological adaptations within species (Fässler et al., 2008) and consequentially backscattering properties. For that reason it is necessary to elaborate on multivariate relationships between TS and its possible regressors, concurrently to the biomass estimation surveys. Certain detailed investigations have been recently published on herring (Ona, 2003), anchovy (Zhao et al., 2008) and squid (Soule et al., 2010). Modern echosounders perform a direct compensation of the directivity pattern effect to determine beam angles and size of single targets. The method is based on some "single target detector" algorithms, which filter out multiple echoes from the total echo population. The performance of these algorithms is acceptable only in very low fish density conditions (Ehrenberg & Torkelson, 1996; Simmonds & MacLennan, 2005), contrary to the biological sampling efficiency, which is higher by well defined fish layers. The resulting bias in target strength estimation due to failure to reject multiple echoes can be very high, especially in the case of small pelagic fish species, where the signal to noise ratio is lower and the expected packing densities prevent the successful operation of the single target detectors (Soule et al., 1997). Fish biomass is mixed with plankton, particularly in the tropics, and thresholding is used for reducing plankton echoes. Unfortunately, thresholding biases the target strength distribution, because a high proportion of small targets are compensated. For relative large fishes ($L \sim 50$ cm) this bias is negligible, however for small fish, such as the small pelagic species ($10 \text{ cm} < L < 30 \text{ cm}$) the bias can be increased to a TS overestimation of 50% (Simmonds & MacLennan, 2005).

The *in situ* TS measurements of wild fish, despite their practical difficulties, are superior to other methods where fish is immobilised or confined within a case, since swimming behaviour affects considerably the fish body tilt angle and the backscattering echo. The goal of *in situ* measurements is to estimate an average swimming pattern, as this can be expressed in backscattering. Either implemented in software (Ona & Hansen, 1991; Schell et al., 2004) or hardware (Hedgepeth et al., 2002), single fish tracking algorithms isolate single fish echoes and provide TS point estimates as well as further information concerning the swimming pattern (Furusawa & Amakusu, 2010).

2.1 Target strength experiments

The acoustic data were recorded in Thermaikos Gulf during the "FISHCAL" research project, aiming at the TS estimation of the three most commercially important species, namely sardine (*Sardina pilchardus*), anchovy (*Engraulis encrasicolus*) and horse mackerel (*Trachurus trachurus*). A modified French pelagic trawl was employed for species identification and fish length measurements. The trawl was monitored by a FURUNO Net Data Recorder to increase catch performance.

The hydroacoustic measurements were carried out by use of a calibrated SIMRAD EK-500 echo-sounder (Foote & MacLennan, 1984; Bodholt et al., 1989), with mounted circular 38 and 120 kHz split beam transducers. The pulse duration was 1.0 and 0.5 ms respectively for the two frequencies. Data were collected using a -60 dB noise threshold, from standard EK-500 telegrams. Since the internal single-echo-detection (SED) algorithms are unable to reject all multiple targets within the sample (Sawada et al., 1993; Soule et al., 1995), some post processing is required, implementing tracking filters (Ona & Hansen, 1991; Handegard et al., 2005). The detection volume for tracking was calculated by applying the maximum angle (± 5 degrees) of the split beam angle detectors. However, in order to reduce the impact of the noise threshold, only beam corrections less than 1 dB were included in the final TS estimation statistics. Before tracking, all data were scrutinised and multiple targets were identified by plotting the TS [dB] measurements against the integration values s_A [$m^2 n.mi^{-2}$].

Echo tracking algorithms were developed (initially in standard C and later in R), which scrutinise the raw data and extract the echoes with the highest possibility to belong to the same fish. User defined threshold criteria are: instantaneous and average depth angle, horizontal angle, deviations of mean depth angle and mean horizontal angle. Finally, the following parameters are calculated:

- Fish identification code and number of echoes belonging to the same fish body
- Compensated and non-compensated TS values of each single echo
- Compensated less than 1 dB and their mean acoustic cross section $\langle \sigma \rangle$
- Variability of the sampled σ , within the same target
- Angles of the fish track in relation to the transducer position

The algorithm is applied off-line on the 3-dimensional information provided by the split beam concerning each encountered echo. For each echo, the fish position relative to the ship is represented in a 3 dimensional coordinate system by the vector P as:

$$R\cos(\phi)\sin(\theta), R\sin(\phi)\sin(\theta), R\cos(\theta) \quad (1)$$

where R is the range between transducer and fish, (ϕ) and (θ) define the target direction relative to the acoustic axis and the vessel speed vector respectively.

The mean Target Strength $\langle TS \rangle$ is usually expressed in a linear relation to the fish length:

$$\langle TS \rangle = a * \text{Log}_{10}(L_{cm}) + TS_0 \quad (2)$$

where TS_0 is the intercept of the regression and represents the TS of a hypothetical fish of length $L=1$ cm. The scope in the following experimental design was the identification and quantification of the parameters that affect the unbiased estimation of mean TS and finally the estimation of parameters defining the linear regression in (2).

Target echoes plotted according to their beam angles (a and b) show a uniformly spatial distribution (Fig. 1a), whilst the filtered by tracking echoes reveal a longitudinal distribution, due to the ship's movement (Fig. 1b).

2.2 Fish tracking results

Following the tracking procedure, echoes could be identified as belonging to the same fish, once, twice or more times inside the beam. By isolating targets which occurred more than 3 times inside the lobe, it is possible to study the variation of back-scattering energy per individual fish. Mostly, increasing the sample (n) of insonifications per fish, the statistics

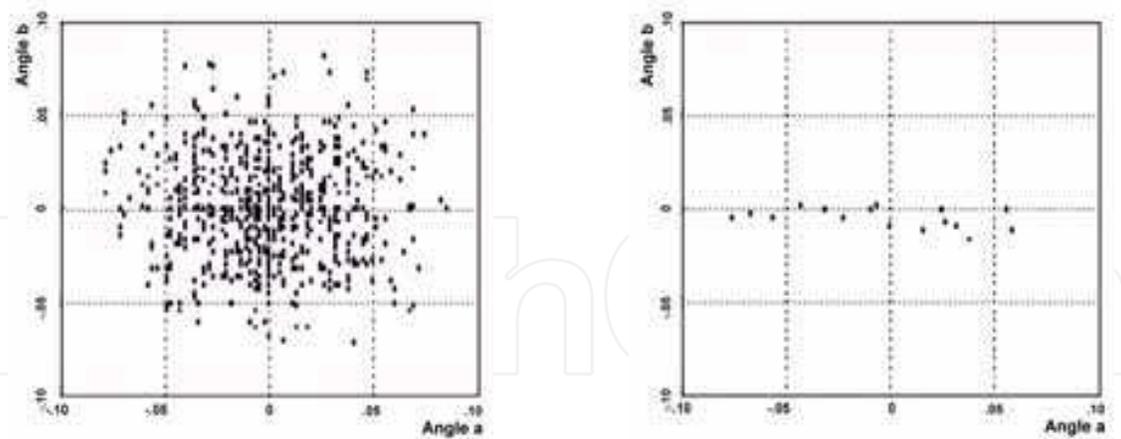


Fig. 1. Filtering echoes using tracking algorithms. 1a, left: The same dataset before filtering and 1b, right: After filtering by tracking, where each point on the angle scatterplot reveals that fish was encountered 6 times inside the beam.

remain relative stable (Fig. 2). Both mean and maximum values converge to their maximum values, where the mean difference between maximum and mean TS per fish stays stable around the 3 dB. Certain factors are responsible for the gradual change of TS values. There is a preference in the sampling procedure for bigger targets, due to their higher signal to noise ratio and increased sampling volume, especially in deeper waters. Furthermore, it is known that the fish has a specific angle which is responsible for the maximum back scattering energy and that this value is an upper limitation for the recorded TS maxima.

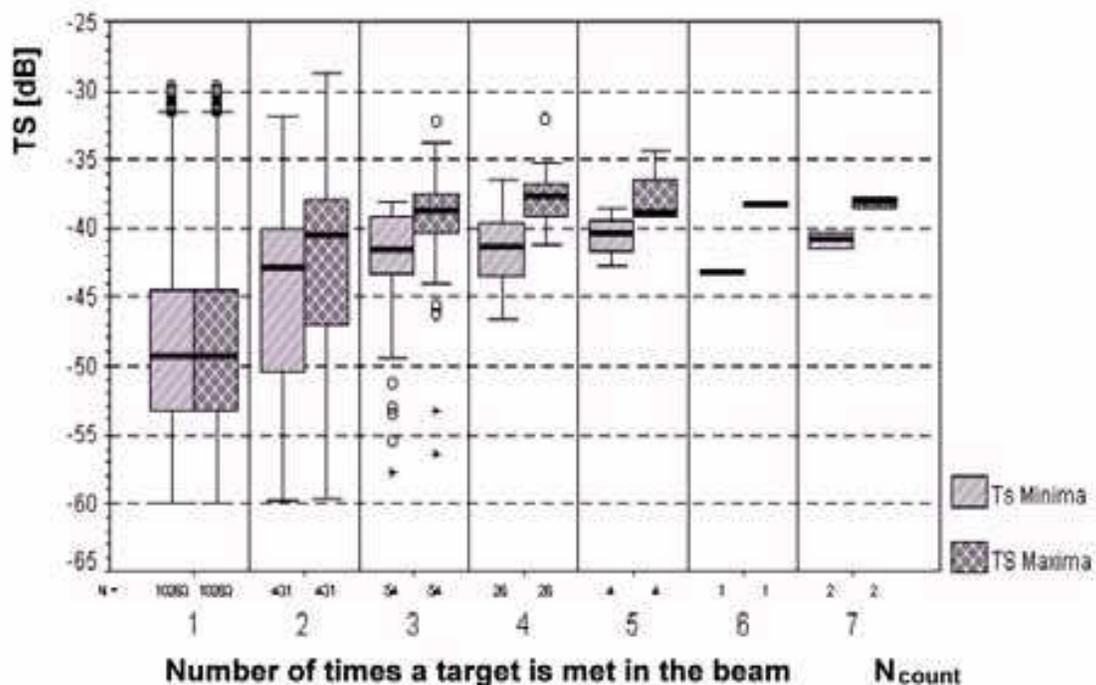


Fig. 2. Echoes encountered more times inside the beam belong to fish with higher backscattering cross sections, measured as average or as maximum observed value.

By increasing the echo samples per fish ($n > 3$) the possibility of including multiple echoes is minimised. Unfortunately, as mentioned above, the lower voltage echoes that belong to smaller targets have fewer chances to be detected in successive pings and therefore are underestimated by tracking. This is a limitation of the tracking procedure and we next describe a de-biasing technique based on a simulation approach.

Simulated fish tracking

In order to study the tracking-induced bias a simulated procedure was performed, using targets with TS obeying a normal distribution (mean = -39.0 dB and sd = 10.0 dB).

After fish tracking the mode of the observed echoes, corrected for the beam effect (on-axis) is increased by 2 dB (Fig. 3), whilst the calculated TS mean:

$$\hat{TS} = \log_{10} \langle \sigma_{bs} \rangle \quad (3)$$

is overestimated by 1.5 dB. The standard deviation in the logarithmic form was reduced to 8 dB, namely adjusted to the same average dispersion level observed in the *in-situ* data.

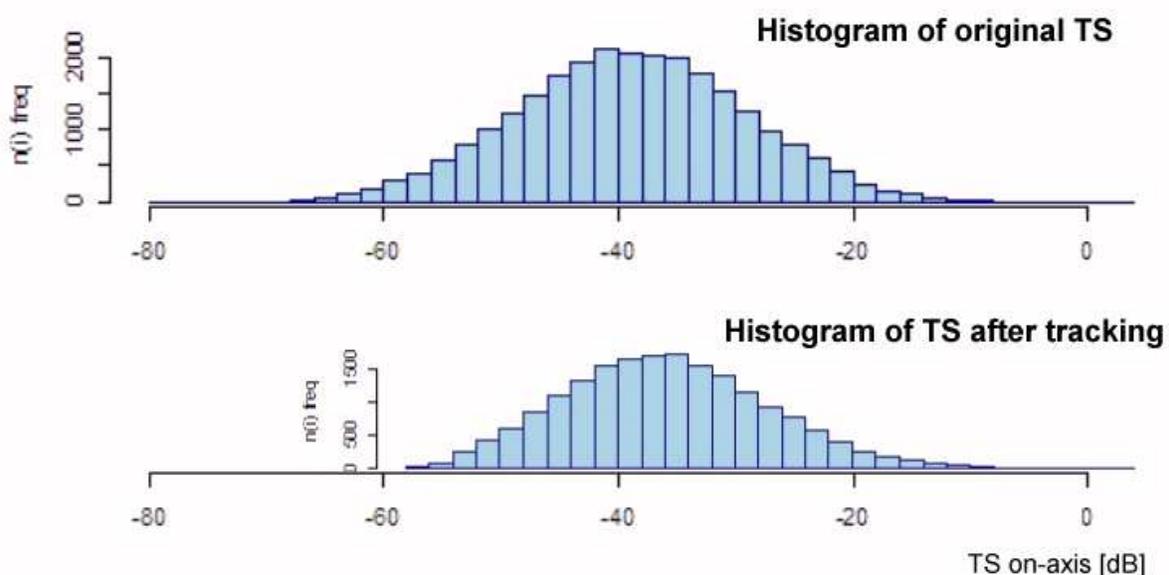


Fig. 3. Histograms of TS data: Original values before tracking (above) and “observed” values after fish tracking and beam angle correction (below).

Specifically, small pelagic species backscatter echoes with low signal-to-noise ratio (SNR). Experimental (Reynisson & Sigurdsson, 1996) as well as simulation studies (Ehrenberg & Torkelson, 1996; Kieser et al., 2005) predict that a decrease in SNR tends to increase the bias in TS estimates. Additionally to the mentioned loss of small fish near the beam border, the additive noise increases the average TS level and affects the single fish detectors of the split or dual beam techniques. The expected additional bias is about 0.2 to 0.5 dB, for a standard 7° beam-width transducer, with 38 kHz pulses on targets of -30 dB size (on-axis values), insonified at 150-200 m depth (Kieser et al., 2005). For smaller targets this bias can be higher. Therefore, all TS estimations based on tracking should be finally corrected for the total error by reducing their TS values by 1.0 - 2.0 dB.

It is recommended to quantify the working limits of the fish density in order to avoid overlapping echoes (Ona, 1999; Ona & Barange, 1999). The probability to encounter multiple

echoes inside the acoustic beam is expected to be 5%, assuming a fish Poisson distribution with mean number of targets about 0.10 individuals. This relationship between integrated values s_A and TS has been calculated for targets in 50 and 100 m depths (Fig. 4).

It can be seen that for a given average observed TS different maximum s_A limits are allowed, according to the accepted probability to have multiple echoes (2% and 5%).

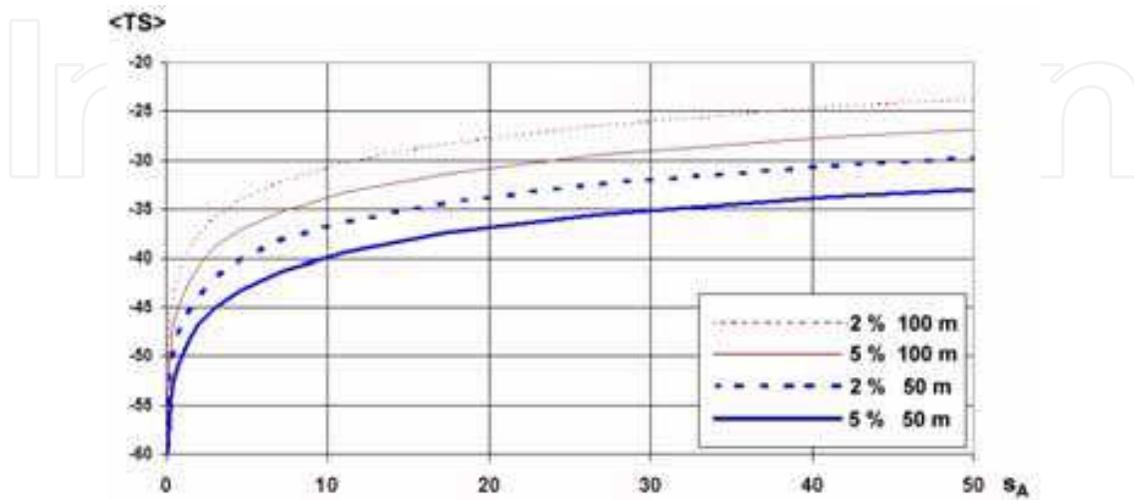


Fig. 4. Observed average TS [dB] vs. maximum allowable nautical area back scattering coefficient s_A [$m^2 \text{ nmi}^{-2}$]. Solid lines represent 5% and dashed lines 2% probability to have multiple echoes.

Further analysis including both frequencies of the isolated post-tracking single fish echoes brings out a significant relationship between the two frequencies (Fig. 5).

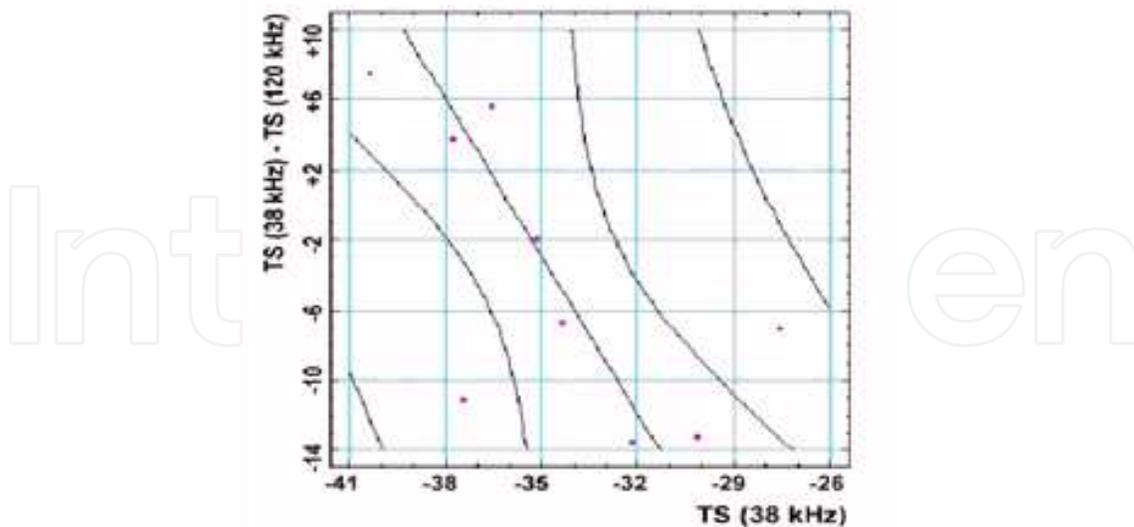


Fig. 5. Comparison of fish TS measured by two frequencies 38 and 120 kHz (detail in text).

The TS difference between 38 and 120 kHz expressed in dB is related to the echo level itself, which indicates different resonance and fish beam characteristics for different fish sizes (correlation coefficient $r=0.67$, $p<5\%$). Each point on the scatterplot represents data sets with

echo tracks encountered simultaneously by 38 and 120 kHz and regarding each time the same fish. The estimated correlation coefficients among different data sets varied between $r=0.38$ and $r=0.7$.

2.3 TS estimations relative to the fish body length

According to common practice, especially valid for the pelagic fish species, we forced the slope of the regression between the average TS and the body length L , in equation (2), to be 20 (Simmonds & MacLennan, 2005). The resulted intercepts TS_0 have been summarised by categories and are displayed in the box plots of the figure 6.

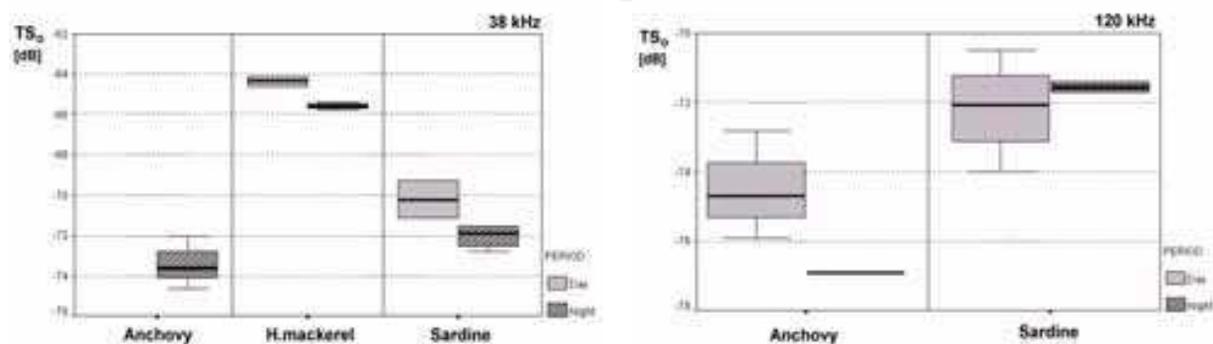


Fig. 6. Box plots of tracked echoes during *in-situ* measurements of free-swimming fish by 38 kHz (left) and 120 kHz (right) split beam transducers.

The box plots of tracked echoes (3-5 times per fish) display values not yet corrected for the bias mentioned in 2.1.1. According to these results significant TS differences exist among species, periods of the day and insonification frequency. Another important outcome of the study is that daytime acoustic data display systematically higher values compare to night time. In most cases the amount of data groups was sufficient to prove the significance of this hypothesis at the 5% level. Unfortunately anchovy was not always present, because the collected data very often showed a higher fish density and therefore were extremely biased.

2.4 Target strength conclusions

As is well known, the backscattering energy from the swimming fish is a dynamic quantity, highly dependent on fish behaviour, particularly the swim tilt angle (Huse & Ona, 1996). The different behaviour is also responsible for the measured systematic differences in estimated mean TS values between day and night. The validity of this finding was proved for all three target species. This phenomenon was well known from cage experiments (Simmonds & MacLennan, 2005), but for the *in-situ* measurements it is relative new (Axenrot et al., 2004) and should be taken into account during the fish stock assessment estimation.

Detailed TS estimations of sardine, anchovy and horse mackerel echoes are very rare and biomass estimations especially in Mediterranean Sea are based on a general equation established for Clupeoids (Simmonds & MacLennan, 2005) or on closely related species from other regions (Bonanno et al., 2005). Given that biomass estimation is carried out mainly applying 38 kHz, the final TS_0 estimations of different species are summarised in Table 2 for this frequency only.

| Intercepts (b_{20}) of target strength estimations relative to fish body length | | | |
|-----------------------------------------------------------------------------------------------------|----------------------------|------------|----------------------------|
| SPECIES | b_{20} | kHz | REFERENCES |
| Anchovy (<i>Engraulis encrasicolus</i>) | - 71.2 | 38 | ICES (1983) |
| Anchovy (<i>Engraulis capensis</i>) | - 76.1 | 38 | Barange et al. (1996) |
| Anchovy (<i>Engraulis japonicus</i>) | - 71.6 | 38 | Zhao et al. (2008) |
| Anchovy (<i>Engraulis encrasicolus</i>) | - 74.8 | 38 | This study (night) |
| Sardine (<i>Sardina pilchardus</i>) | - 72.6 | 38 | Ben Abdallah et al. (2000) |
| Sardine (<i>Sardina pilchardus</i>) | - 71.2 | 38 | ICES (1983) |
| Sardine (<i>Sardina pilchardus</i>) | - 70.4 | 38 | Patti et al. (2000) |
| Sardine (<i>Sardina pilchardus</i>) | - 74.0 | 38 | Hannachi et al. (2005) |
| Sardine (<i>Sardina pilchardus</i>) | - 72.5 | 38 | This study (day) |
| Sardine (<i>Sardina pilchardus</i>) | - 74.0 | 38 | This study (night) |
| H. mackerel (<i>Trachurus trachurus capensis</i>) | - 66.8 | 38 | Barange et al. (1996) |
| H. mackerel (<i>Trachurus trachurus</i>) | - 66.5 | 38 | This study (day) |
| H. mackerel (<i>Trachurus trachurus</i>) | - 67.0 | 38 | This study (night) |

Table 2. Comparisons of the estimated target strength values with available references for European anchovy, European pilchard and Atlantic horse mackerel or closely related species.

The b_{20} intercepts for anchovy were estimated only from night time data, since day time data were biased from high fish density. The estimated value in this study (-74.8) is lower than the ICES recommendation (-71.2), however it is very likely that the day intercepts are higher, like those observed in sardine echoes. The median of night-TS of sardine is similar to the recently measured average value by Hannachi et al. (2005), whilst the day estimation is in generally lower than the rest of the published values. Regarding horse mackerel, the results are consistent with the published data of the closely related sub-species (*Trachurus trachurus capensis*).

As demonstrated by the historical cage experiments of Edwards & Armstrong (1983), the TS of a fish with swimbladder is depth dependent, following Boyle's law. Consequently, comparisons between echoes from different depths should be carefully interpreted. Unfortunately, TS is affected by the cross-section of the fish swimbladder, which does not follow its volumetric change. Furthermore, it is not clear if the swimbladder compression alone is responsible for TS reduction or additional the fish swimming behaviour changes with depth. Recently, detailed studies on the compression mechanism of the swimbladder of herring (Ona, 2003) and anchovy (Zhao, 2008; Sawada et al., 2009) demonstrated the importance and complexity of the TS variability by increasing depth.

3. Species identification

Traditionally, in biomass estimation surveys, acoustic backscattering is allocated to different fish species by taking into account the species composition of trawl samples. Obviously, this procedure is time consuming, subjective and not testable for bias.

The basic idea for a more objective approach derived in the early 90s, with the development of specific software for automatic extraction of school parameters and by further testing the

hypothesis that school features can be used for school species identification (Scalabrin et al., 1992, 1996; Reid & Simmonds 1993; Georgakarakos & Paterakis 1993). This approach triggered the development of sophisticated expert systems for species identification, where the artificial neural networks (ANNs) provided a promising solution (Ramani & Patrick, 1992; Dunne, 2007). The first approach of fish school species identification applying ANNs was implemented in early 90s (Haralabous & Georgakarakos 1993, 1996). There were feed-forward neural networks (also called Multi-Layered Perceptrons, MLPs), using as species predictors morphometric, energetic and bathymetric school descriptors.

Meanwhile, modern systems were developed, utilising faster school scrutinisation algorithms (Reid et al., 2000, Fernandes et al., 2002), multi-frequency (Korneliussen & Ona, 2002, Korneliussen et al., 2009), multi-dimensional school descriptors (Paramo et al., 2007; Trygonis et al., 2009) and advanced artificial neural networks (Cabreira et al., 2009). In the following we describe an advanced species classification system based, among other tools, on Bayesian Neural Network techniques.

3.1 Data collection and pre-processing

Data were acquired in two different geographic areas, namely in Thermaikos Gulf (Northern Aegean Sea) and in North Sea (Shetland Island and Norway). Emphasis was given on cross-validating school echograms with trawl samples. Schools' images matched one by one the respective trawl samples were characterised with a species identification attribute (species id).

Greek data were obtained during three surveys (October 1996a and b, May 1997) carried out in Thermaikos Gulf, utilising a SIMRAD EK-500 echosounder with two mounted split-beam transducers (38 and 120 kHz). The surveys were mainly devoted to the selection of acoustic information related to the schools of the target species: sardine, anchovy and horse mackerel.

The second data set was obtained from two different surveys in the North Sea (Shetland Islands, July 1996) and Norway (November 1997), operating the same instrumentation and software. The school species identity has been supplied by the Marine Laboratory of Aberdeen and the Institute of Marine Research Bergen by means of trawling. Target species were herring (*Clupea harengus*), sprat (*Sprattus sprattus*), blue whiting (*Micromesistius poutassou*), Norwegian pout and 0-group pout (*Trisopterus esmarkii*).

3.1.1 Software development

The developed in-house software implemented in C the following three software modules: an echo data pre-processing system, as an interface to the standard Bergen Integration System (Korneliussen, 2004), a SCHOOL algorithm for school isolation and parameterisation and certain ANNs implementations, mostly based on the Bayesian approach. The interface module allows data extraction from the echograms, using windows that cover certain school traces of interest. The interface outputs the echogram volume backscattering values together with ping and depth information to the second software module (SCHOOL), which is responsible for school isolation, parameterisation and quantification of school descriptors. Finally, these school parameters compose the input data for the Artificial Neural Networks during training or application processes. The SCHOOL module is a set of algorithms written in standard C, that are responsible for detection of school aggregations inside a given echogram or window in an echogram.

| Abbreviation | School Descriptor | Abbreviation | School Descriptor | | |
|-------------------------|-------------------|----------------------------------|-------------------|------------------|---------------------------------------------------------------|
| Time & Space | | Bathymetric | | | |
| 1 | YEAR | Year | 21 | DMEAN | Mean school depth |
| 2 | DAY | Day of the year | 22 | DMIN | Minimum school depth |
| 3 | HOUR | Time | 23 | DMAX | Maximum school depth |
| 4 | LAT | Latitude | 24 | BOTT | Bottom depth |
| 5 | LON | Longitude | 25 | AMIN | Minimum altitude |
| Morphological | | 26 | AMAX | Maximum altitude | |
| 6 | N | Samples above threshold (N) | Energetic | | |
| 7 | H | Height (H) | 27 | EMEAN | Mean school energy ($m = E / N$) |
| 8 | L | Length (L) | 28 | EMAX | Max. energy sample |
| 9 | PERI | Perimeter (P) | 29 | EMIN | Min. energy sample |
| 10 | AREA | Cross-sectional area (A) | 30 | ESD | SD of energy sample |
| 11 | ELON | Elongation (L/H) | 31 | EVAR | Variance of energy sample (V) |
| 12 | CIRC | Circularity ($P^2/4\pi A$) | 32 | ECV | CV of energy sample |
| 13 | RECT | Rectangularity (LH/A) | 33 | E | Total school energy (E) |
| 14 | RMEAN | Mean radius | 34 | CROWD | Mean crowding of school ($m_c = m + (V/m - 1)(1 + V/Nm^2)$) |
| 15 | RMIN | Min. radius | 35 | PATCH | Patchiness of school (m_c / m) |
| 16 | RMAX | Max. radius | 36 | I | Index of dispersion (NV/ m) |
| 17 | RVAR | Variance of radius | 37 | K | Clumping coefficient ($m^2 / (V-m)$) |
| 18 | RSD | SD of radius | | | |
| 19 | RCV | CV of radius | | | |
| 20 | FRAD | Fractal ($2 \ln(P/4) / \ln A$) | | | |

Table 3. Data output of the SCHOOL module

The main routine of the algorithm “scrutinises” the values of the pixels and filters out all pixels with values lower than a basic threshold (default -60 dB). The filtered pixels are then tested for vertical and horizontal continuity, according to the minimum allowed vertical and horizontal gap between neighbourly pixels inside an isolated single school. Finally, a second threshold is applied filtering out low-density aggregations (such as plankton) with very low mean integration level. A procedure similar to the SCHOOL algorithm is used for bottom detection in combination to the nominal bottom depth provided by the EK-500.

3.1.2 The applied neural network simulators

Certain ANNs simulators have been tested in order to assess their performance. Most of the non-Bayesian ANN implementations were based on the commercial 32-bit neural network simulator “NeuroShell 2” (Ward Systems Group©). All Bayesian ANNs presented here are developed under the UNIX environment using the SFBM simulator (Neal, 2006).

General design of Neural Networks

The SCHOOL module generates a set of school descriptors (Table 3), which are used as a whole or as a subset in the neural network module. Three examples of descriptor patterns of sardine schools are displayed in Figure 7.

The input layer is always a subset (13-20) of the descriptors extracted from the “known” fish schools. The amount of the available “known” schools limits the number of the concurrently in use descriptors. Bayesian Neural networks are less sensitive to this limitation. Non-Bayesian ANNs have been developed using a complex hidden layer, containing 3 sublayers. Different activation functions were applied to the 3 sublayers in order to detect different features in a pattern processed. In addition to the classical sigmoid function, a Gaussian

function was used on the second sublayer in order to detect features in the mid-range of the data. In the third sublayer, a Gaussian complement was used for detecting features from the upper and lower extremes of the data set. In the output layer, each unit corresponds to a certain species, taking the value of 1 if the school belonged to this category and 0 otherwise. To measure the classification efficiency of the ANNs we compare the actual output of the network to the correct output over a number of testing trials. The most widely used method to obtain this test set is to reserve a separate representative subset of the available examples. We experimented with testing subsets ranging from 5% to 30% of the available data.

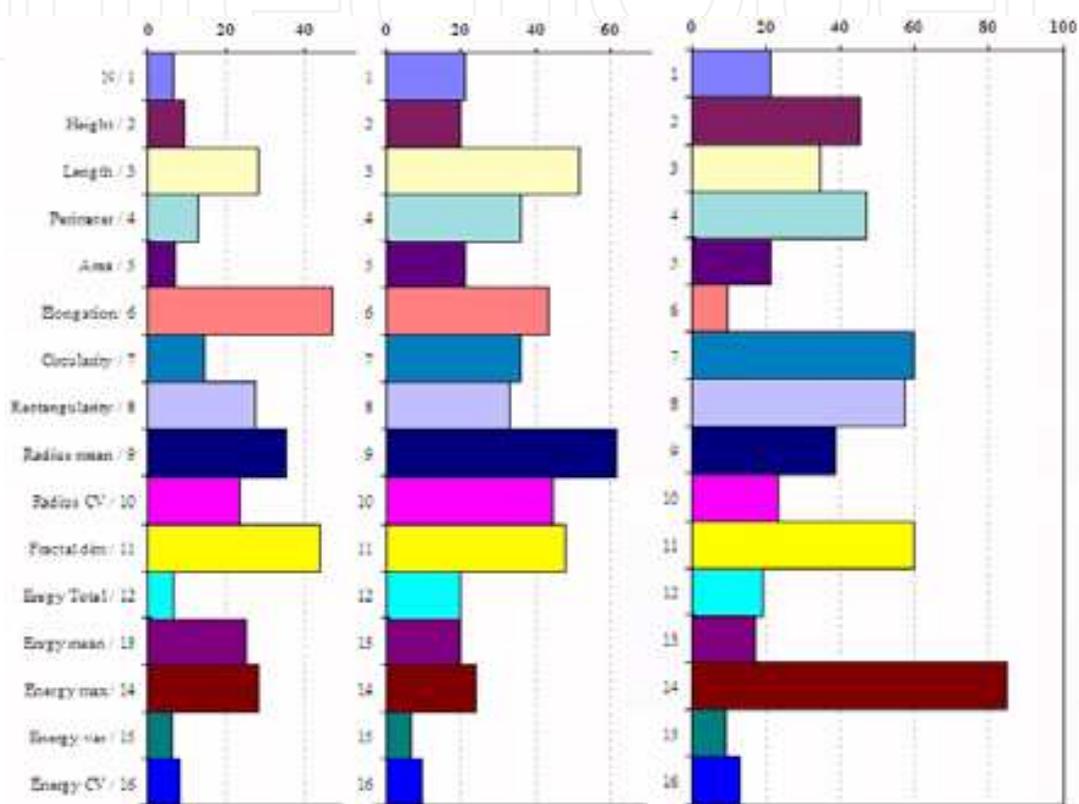


Fig. 7. Three example-patterns from sardine schools, in Thermaikos Gulf: each pattern is the vector of input values (16 descriptors) extracted using the SCHOOL module. Values are rescaled into a common range of 0-100.

For the evaluation of the accuracy of a trained ANN we calculated certain statistics, the most interesting of which is the R^2 : the coefficient of multiple determination. R^2 was not the ultimate measure of whether a net produced good results, especially for classification nets such as those used. For example, if the ANN generated output values of 0.5, 0.6 and 0.4 in the three outputs, the R^2 value would not be very high, but the classification would be correct if the second output was the answer. In addition, a confusion matrix was established counting the number of correct classifications.

3.2 Results

The target species were predicted applying ANNs and Discriminant Function Analysis (DFA) methods. The results of this comparative study are summarised in Tables 4 (Greek data) and 5 (Shetland data).

| COUNTS | | DFA predictions | | | | NN predictions | | |
|---------|------------------------|-----------------|---------------------|-----|----|---------------------|-----|----|
| Species | TRUE | AN | SA | HM | AN | SA | HM | |
| Train | Anchovy | 313 | 284 | 23 | 6 | 313 | 0 | 0 |
| | Sardine | 159 | 41 | 109 | 9 | 0 | 159 | 0 |
| | H. mackerel | 44 | 9 | 17 | 18 | 0 | 0 | 44 |
| | Total | 516 | 334 | 149 | 33 | 313 | 159 | 44 |
| | Total correctly | | 411 (79.65%) | | | 516 (100%) | | |
| Test | Anchovy | 170 | 144 | 19 | 7 | 165 | 4 | 1 |
| | Sardine | 93 | 22 | 66 | 5 | 3 | 89 | 1 |
| | H. mackerel | 25 | 11 | 8 | 6 | 2 | 0 | 23 |
| | Total | 288 | 177 | 93 | 18 | 170 | 93 | 25 |
| | Total correctly | | 216 (75.00%) | | | 277 (96.18%) | | |

Table 4. Classification results of 804 known-species “Greek” schools using both DFA and NN predictions. A total of 516 schools are used for training (~ 64%) and 288 for testing (~ 36%). Abbreviations used: AN=anchovy, SA=sardine, HM=horse mackerel.

| COUNTS | | DFA predictions | | | | | NN predictions | | | | |
|--------------|------------------------|---------------------|----|----|----|----|----------------------|----|----|-----|----|
| Species | TRUE | 0-P | NP | BW | HR | SP | 0-P | NP | BW | HR | SP |
| Train | | | | | | | | | | | |
| 0-P | 31 | 22 | 2 | 0 | 7 | 0 | 31 | 0 | 0 | 0 | 0 |
| NP | 83 | 1 | 65 | 3 | 12 | 2 | 0 | 83 | 0 | 0 | 0 |
| BW | 14 | 0 | 4 | 8 | 2 | 0 | 0 | 0 | 14 | 0 | 0 |
| HR | 111 | 6 | 10 | 0 | 95 | 0 | 0 | 0 | 0 | 111 | 0 |
| SP | 3 | 0 | 2 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 3 |
| Total | 242 | | | | | | | | | | |
| | Total correctly | 190 (78.51%) | | | | | 242 (100.00%) | | | | |
| Test | | | | | | | | | | | |
| 0-P | 4 | 3 | 0 | 0 | 1 | 0 | 3 | 0 | 0 | 1 | 0 |
| NP | 12 | 0 | 11 | 1 | 0 | 0 | 0 | 12 | 0 | 0 | 0 |
| BW | 3 | 0 | 0 | 2 | 1 | 0 | 0 | 0 | 3 | 0 | 0 |
| HR | 19 | 1 | 0 | 0 | 18 | 0 | 0 | 0 | 0 | 19 | 0 |
| SP | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Total | 38 | | | | | | | | | | |
| | Total correctly | 34 (89.47%) | | | | | 37 (97.37%) | | | | |

Table 5. Classification results of 280 known-species “Shetland Islands” schools using both DFA and NN predictions. A total of 242 schools are used for training and 38 for testing. Abbreviations used: 0-P= 0-group pout, NP= Norwegian pout, BW= blue whiting, HR= herring, SP=sprat.

In the Greek data set, the neural network was very adaptive to the data during the training procedure, providing a higher classification rate (100%) than the DFA (79.65%). The classification of horse mackerel schools by DFA was the worst (40.91%). Testing the two models (ANN vs. DFA), the ANN achieved scores between 92% (horse mackerel) and 97.06 % (anchovy), whilst the DFA varied between 24% (horse mackerel) and 84.71% (anchovy).

Both models provided lower prediction scores for the classification of horse mackerel. Note however that the total amount of schools of this species is relative low (69 schools).

In the Shetland data set, some species had very few examples to satisfy both training and testing requirements, as for example no data for testing sprat schools were available. During training, the neural network achieved very high classification (100%) in all species while the DFA varied from 85.59% (herring) to 57.14% (blue whiting). The score provided for sprat was not taken into account due to its limited presence in the data set. Testing the two models, the ANN achieved 100% scores for three species but only 75% for the 0-group pout, whilst the DFA varied between 94.74% (herring) and 66.67% (blue whiting). Both models provided lower scores (75%) for the 0-group pout, which could be explained by the limited amount of available data.

3.2.1 Prediction probability

The application of Bayesian ANNs also provided each prediction with the probability of the inference. This allowed a decision with different confidence limits on the probability threshold of accepting or not the network prediction. An example of box plots displaying the distribution of the school-species prediction probabilities is shown in Fig. 8. The median of the provided predictions varied from 0.975 (horse mackerel) to 1 (anchovy). In all species, the distribution was skewed to the high values (close to 1).

The evaluation of the discrimination power of each descriptor was achieved by means of two coefficients, namely the “contribution factors” and the distribution of the “sigma” values (Fig. 9). The first was specific for each species and represented the weights used by the ANN after a successful application. The weights were based on the neural implementation run during the training procedure as generated from a standard ANN.

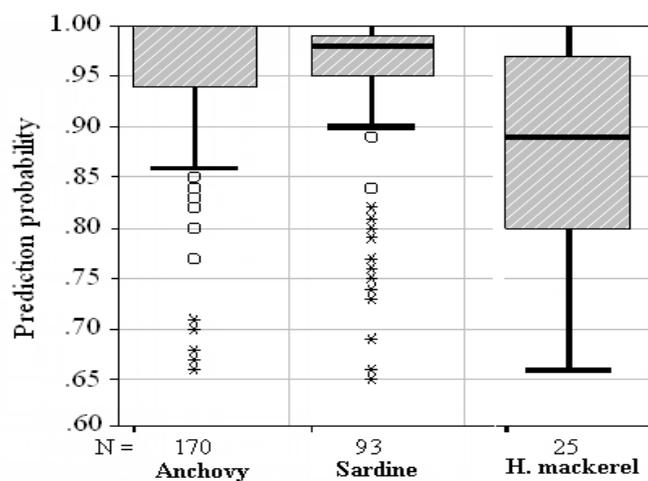


Fig. 8. Prediction probabilities given by the Bayesian NN for the “Greek” schools

The second coefficient was based on the automatic relevance determination (ARD) method and is complementary to the first one. The hybrid Markov Chain Monte Carlo (MCMC) simulation algorithm produced a sample of several network implementations, which showed the distribution of the variance of the synaptic weights (MacKay, 1992a, 1992b; Neal, 2006). It should be mentioned that, for ease of different trials comparison, the school descriptors were logarithmically transformed and standardised and that the relative

importance of input descriptors increased by higher sigma values. The results showed that the two data sets contained some common and highly discriminating descriptors: mean bottom depth, mean school depth, mean and variance of school energy. In particular, the Crowding and Index of dispersion in the case of the Greek data, as well as other depth descriptors for the Shetland data could be of importance. For both data sets, the bathymetric descriptors seemed to be more important than the energetic ones while the latter were more important than the morphometric descriptors.

3.2.2 The generalisation problem

Bayesian networks had an increased performance in recognising schools of the same species, but encountered in different survey areas. This is important, taking into account that schools have been insonified in different depths and their morphological and energetic descriptors were distorted, due to the increased beam effect in deeper waters. This generalisation performance of the Bayesian networks has been tested during the joint project ACOUSTICS (Ona et al., 1998), applying school data collected in two different environments, namely training the network with schools from Shetland Islands (UK) and predicting schools in Norway.

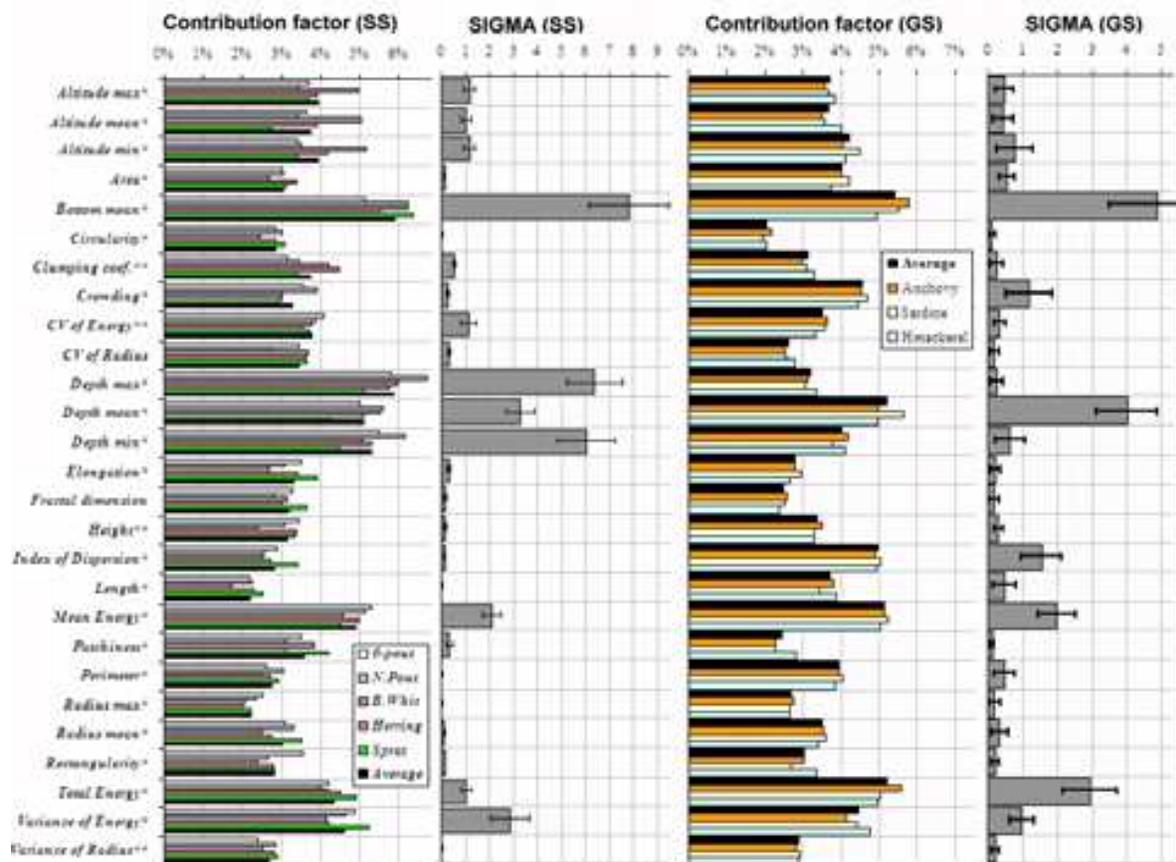


Fig. 9. Contribution factors of school descriptors extracted by the standard ANNs and sigma values extracted by the Bayesian ANNs, for the Greek (GS) and the Shetland Islands (SS) schools. The higher the contribution factor and the sigma value the higher the relevance of the descriptor. The error bars on sigma values represent the standard deviation of a distribution from 100 hybrid Markov-chain Monte-Carlo samples (* descriptor Ln transformed, ** Ln+1 transformed).

As example, the test output of a Bayesian Neural Network is summarised in Table 6a. The used network was trained and tested with data collected from the same area at Shetland in 1996. The overall correct classifications on the test set were above 97%. The performance was perfect (100%) for the classification of herring and Norwegian pout, i.e. the two species that had enough representatives in the training set (45.8% and 34.3% of cases respectively).

| Shetland | | | Predicted species | | | | | |
|--------------|-----------|---------------|-------------------|-----------|------------|-----------|-------------------------|--------------|
| True species | | | 0 Pout | N. Pout | B. whiting | Herring | Total correct predicted | |
| 0 Pout | 4 | 10.5% | 3 | 0 | 0 | 1 | 3 | 75% |
| N. Pout | 12 | 31.6% | 0 | 12 | 0 | 0 | 12 | 100% |
| B. whiting | 3 | 7.9% | 0 | 0 | 3 | 0 | 3 | 100% |
| Herring | 19 | 50.0% | 0 | 0 | 0 | 19 | 19 | 100% |
| TOTAL | 38 | 100.0% | 3 | 12 | 3 | 20 | 37 | 97.4% |

Table 6a. Summary results of the species prediction of 38 test schools (14%) out of 280 total schools from the Shetland 1996 survey, using a Bayesian Neural Network

In a second experimental step, this already trained and validated network with data collected from Shetland Islands was applied on the “different” school data set collected in Norway. Therefore, this test functioned as measure of the “generalisation power” of the Bayesian Network, namely to predict the unknown Norwegian herring schools. The resulted predictions of this network on the Norway data are given in Table 6b.

| Norway | | | Predicted species | | | | |
|--------------|------------|---------------|-------------------|------------|------------|-------------------------|--------------|
| True species | | | N. Pout | B. whiting | Herring | Total correct predicted | |
| B. whiting | 36 | 12.29% | 1 | 13 | 22 | 13 | 36.1% |
| Herring | 257 | 87.71% | 20 | 10 | 227 | 227 | 88.3% |
| TOTAL | 293 | 100.0% | 21 | 23 | 249 | 240 | 81.9% |

Table 6b. Summary results of the species predictions of 293 Norway schools using the Bayesian Neural Network that had been trained with 5 species of Shetland schools.

When a non-Bayesian ANN was used, the percent of correct predicted herring schools was about 60%. The high prediction rate (88.3%) of the Bayesian Neural Network concerning herring schools of another survey area (Norway) emphasises its good generalisation properties. One important difference between the collected school data from the two areas was the average school depth. Taking Norwegian schools only from depths similar to those from Shetlands, the prediction score of herring has been improved from 88.3% to 97.8%, indicating that deeper encountered schools can be hard recognised by the neural networks. These results suggested that if we want to mix data from schools insonified in different depth ranges, any attempt to reduce the beam effect on school parameters is a promising way to overcome this problem (Diner, 2001; Georgakarakos, 2005).

3.2.3 Species identification conclusions

The presented methodology demonstrated how school species identification is feasible by extracting specific descriptors from echograms, generated from single-beam and narrow-band transducers. The identification efficiency was related to the ability of non-linear

modelling; a fact that explains the higher predictive ability of the ANNs compared to the classic discrimination procedures (DFA).

The proper application of both methods required a dataset containing the details of schools of well-defined species composition, obtained by means of aimed trawling in the target area. The problem of selecting the appropriate size of the training and the testing data sets was more crucial for the classical (DFA) and the standard ANN analysis. The Bayesian neural networks appeared to be less sensitive, which theoretical considerations lead us to expect. However, predictions based on a small number of cases (for instance horse mackerel), independent of the applied methodology, carry the risk of emphasising non-homogeneous cases relative to the rest of the statistical population. This is expressed by the larger deviation between the medians of the probability distributions. Bayesian networks due to their probabilistic approach tend to “generalise” the sampled features of schools working on wider distributions than that empirically observed. This capability can also be used to confront the problem of applying a neural network to a different spatio-temporal domain.

4. Fish avoidance reaction to survey vessels

Acoustic fish stock assessment methods are based on the assumption that survey vessels do not affect the behaviour and distribution of fish, and that de-biasing techniques can be alternatively applied to correct the respective errors. This is emphasised and reviewed in the earlier literature by Olsen (1990), followed by a series of studies (Aglen, 1994; Misund, 1997; Mitson & Knudsen, 2003). After the investigations of Olsen (1971) however, several researchers have reported the avoidance reaction of fish due to vessel or fishing-gear induced noise (Ona & Godø, 1990; Gerlotto & Fréon, 1992), and noted its complex dependency on species, feeding behaviour, migration, visual and auditory stimuli, hydrographic conditions, or water surface and bottom boundary interactions (Fréon et al., 1993; Levenez et al., 1990; Misund, 1990).

This behavioural pattern is known in fisheries acoustics as “fish avoidance effect”, and involves an initial vertical fish movement towards the sea bottom, followed by a lateral displacement perpendicular to the approaching vessel’s course. Thorough experiments with split-beam sounder buoys (Handegard et al., 2003) and direct comparisons between conventional and low-noise vessels (Ona et al., 2007) revealed several aspects of this behaviour. The process alters fish target strength via compression of the swimbladder (Boyle’s law) and changes in tilt angle, reduces density in the acoustic beam compared to its undisturbed value, and further biases the acoustic observation through disposition, shape, and density distortion of fish schools near the surveying vessel. It is generally accepted that vertical echosounders are inherently prone to avoidance reaction bias due to their insonification geometry, and that vessel-induced noise is an important underlying factor, particularly at lower frequency noise bands (Vabø et al., 2002; Skaret et al., 2005). Following the ICES recommendations (Mitson, 1995), modern research vessels exhibit substantial reductions in noise levels compared to previous constructions (Mitson & Knudsen, 2003). Nonetheless, the question whether fish do or “do not avoid survey vessels” (Fernandes et al., 2000) can not yet be decisively addressed, nor its magnitude be quantitatively estimated under all possible sampling conditions.

In this context, multibeam sonars are powerful tools for studying fish school reactions to research vessels, fishing gears or predators, due to their large sampling volume and ability for long-range concurrent insonification of multiple schools. Diner & Masse (1987) used

sonar systems to record complex reactions of clupeoid schools relative to a research vessel, and Hafsteinsson & Misund (1995) reported species-specific differences: almost 20% of encountered North Sea herring schools exhibited some degree of reaction to the approaching vessel, but this behaviour was not observed in Barents Sea migrating capelin. Further scientific modification of commercial sonars provided quantitative measurements of fish school internal structure (Gerlotto et al., 2000), typology (Paramo et al., 2007) and spatial behaviour (Soria et al., 1996).

4.1 Multibeam experiments

The acoustic data were recorded during the AVITIS-98 survey in Greece (Thermaikos Gulf, April-May 1998) by utilising a 450 kHz RESON SEABAT 6012 multibeam sonar (60 beams over a 90° swathe). The transducer was mounted on a pole on the starboard side of the research vessel with the first beam of the sonar vertical and the 60th beam horizontal by 0° roll ship movements.

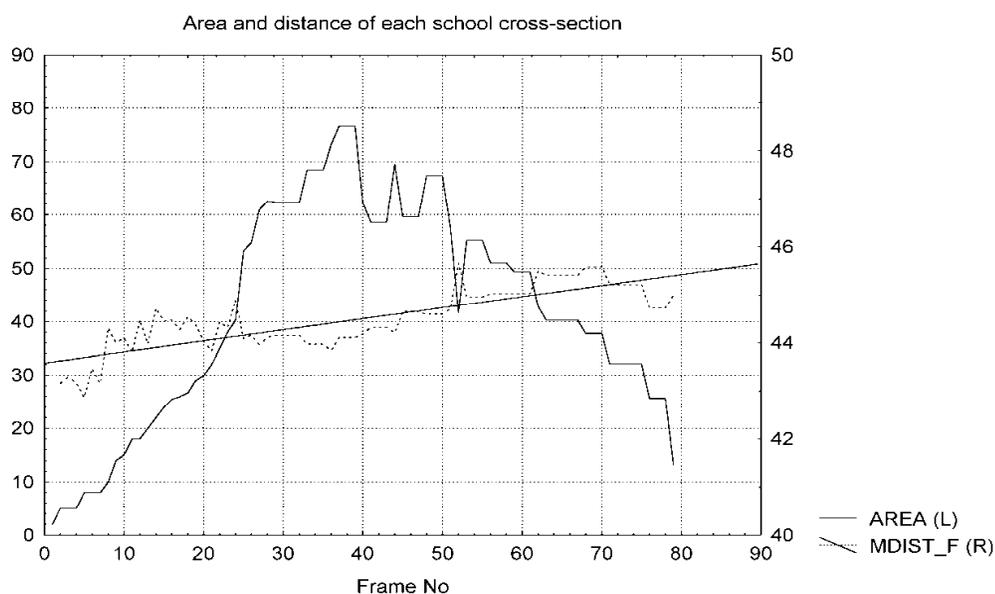


Fig. 10. Changes of mean school area (solid line, left axis) and school distance to the transducer (dotted line, right axis) as this school pass starboard side the vessel. Distance between frames about 30 cm. The straight line represents the slope of the increasing distance (see text for detail).

In this position the encountered schools were scanned in successive vertical 2D cross-sections and the acquired volume backscattering coefficients were recorded and analysed off-line. In-house software was used to estimate morphological and energetic 2D and 3D school descriptors. Most of the observed schools showed the earlier first edge (Fig.10 first frame) closer to the ship than their later and final edge (frame 80). This increasing distance indicated a mean school movement of 0.2 ms^{-1} perpendicular to the vessel. A similar increasing in depth is also observed. Using joint echosounder and sonar observations, Soria et al. (2003) formulated a behavioural model for sardine and anchovy Mediterranean schools, and argued that school length variations in echosounder data are initially related to the avoidance reaction in front of the research vessel, while environmental factors like the thermocline or halocline depth may also have a subsequent effect.

4.2 Fish avoidance conclusions

Recent technological developments such as high resolution sonar hardware with calibrated output (Trenkel et al., 2008) or operational software systems that can quantitatively process large amounts of multibeam raw data (Balabanian et al., 2007; Trygonis et al. 2009) promise further insights into the fish avoidance effect, and the provision of *in situ* measurements of pelagic fish aggregative dynamics. Such a case is illustrated in Fig. 11, where the pelagic aggregation associated to a drifting Fish Aggregating Device (dFAD) was observed *in situ* with a vessel-mounted long range multibeam SP90 sonar; the research vessel drifted alongside the dFAD at a relatively constant distance of 400 to 500 m. Acoustic data were processed using the *Multibeam Sonar Tracer system* (Trygonis et al., 2009), which can detect, measure, and track pelagic fish schools and the dFAD echotracers, subsequently transform fish school echotrace coordinates to the Cartesian system centred on the dFAD position per ping, and reveal the spatiotemporal distribution of the aggregation in its natural, undisturbed state.

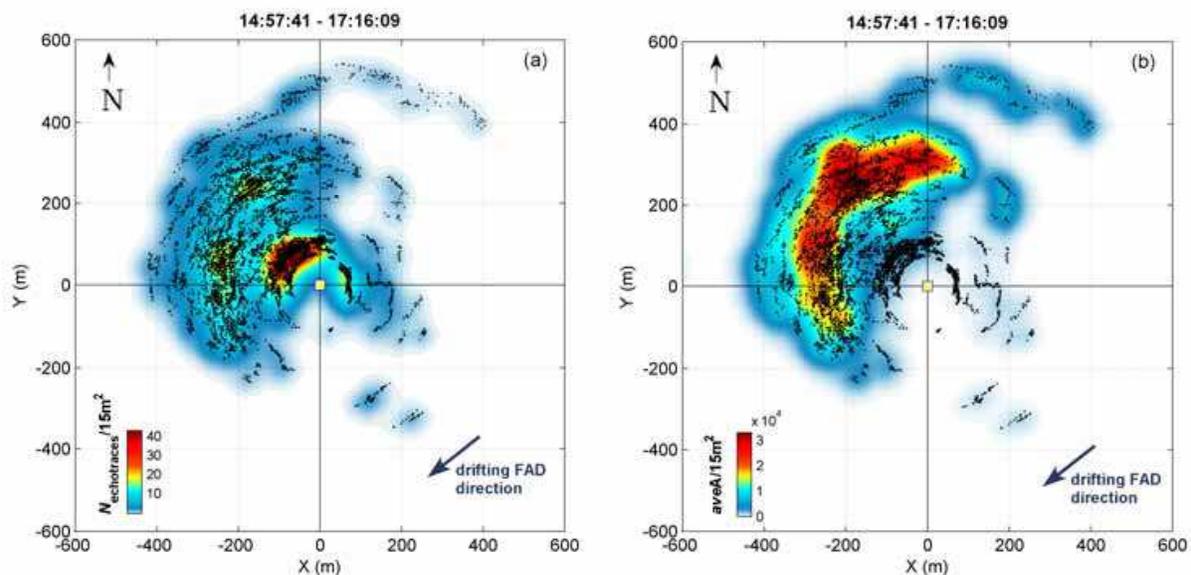


Fig. 11. Distribution of large pelagic echotracers around a dFAD in the Indian ocean, pooling all tracked acoustic observations within a sampling period of approx. two hours. Colour in Fig.11a denotes the number of tracked echotracers per 15m \times 15m bin ($N_{echotracers}/15m^2$), and Fig. 11b is coloured by the respective average area ($aveA/15m^2$); the drifting FAD resides at the centre of the Cartesian system.

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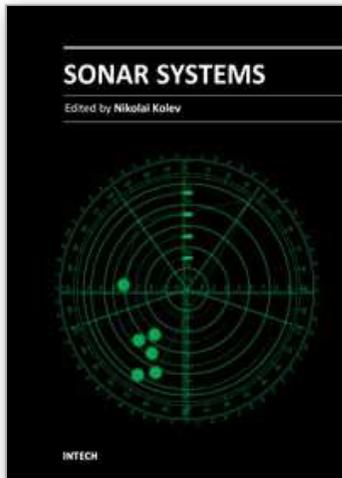
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The book is an edited collection of research articles covering the current state of sonar systems, the signal processing methods and their applications prepared by experts in the field. The first section is dedicated to the theory and applications of innovative synthetic aperture, interferometric, multistatic sonars and modeling and simulation. Special section in the book is dedicated to sonar signal processing methods covering: passive sonar array beamforming, direction of arrival estimation, signal detection and classification using DEMON and LOFAR principles, adaptive matched field signal processing. The image processing techniques include: image denoising, detection and classification of artificial mine like objects and application of hidden Markov model and artificial neural networks for signal classification. The biology applications include the analysis of biosonar capabilities and underwater sound influence on human hearing. The marine science applications include fish species target strength modeling, identification and discrimination from bottom scattering and pelagic biomass neural network estimation methods. Marine geology has place in the book with geomorphological parameters estimation from side scan sonar images. The book will be interesting not only for specialists in the area but also for readers as a guide in sonar systems principles of operation, signal processing methods and marine applications.

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