Report on Echo Trace Classification

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1 Introduction

This report has been prepared as a result of discussions held within the Fisheries Acoustics Science and Technology (WGFAST) Working Group of ICES. Following discussions in Woods Hole, United States in April 1996 it was agreed to set up a study group to review the state-of-the-art in Echo Trace Classification (ETC). The Study Group was tasked to produce a report including:

i) methods for classifying echo traces,
ii) comparison of the performance of these methods,
iii) the effect of fish behaviour on the precision of classification,
iv) the scope for integrating existing research programmes.

The Study Group first met in Hamburg, Germany in April 1997 and tasks and responsibilities defined. It met again in La Coruña, Spain in April 1998 to review progress to date and finalise the structure of the report. A final editorial meeting was held in St Johns, Canada in April 1999, where the final format was agreed.

Reports on the progress of the report were presented at WGFAST in 1997, 1998 and 1999. Reports were also made to the Fisheries Technology Committee of ICES at the Statutory Meetings in Baltimore, USA in September 1997, Lisbon, Portugal in September 1998 and in Stockholm, Sweden in September 1999.

Acoustic surveys are generally carried out to provide estimates of stock abundance for major commercial species. They are also used to provide distribution maps and information on the age and maturity structure of the stock. In general these analyses are carried out using acoustic data integrated over a number of short spatial or temporal spans - the EDSU (Elementary Distance Sampling Unit). However, there is a great deal of information available at smaller scales within and between EDSUs. Most importantly, it is often possible to see objects on the echogram which can be identified as fish or fish schools, swarms of plankton etc. Together these can be termed "Echo Traces" (definitions of the other terms are provided in Section 2). A number of methodologies now exist to extract these echo traces, mostly based on image processing techniques applied to the echograms. These methodologies are capable of producing databases of echo traces with associated positional, morphometric, energetic, environmental and biological descriptors. This report reviews methodologies for processing and analysing these databases. Although most echo trace data will be available from surveys using vertical single frequency echosounders it is also possible to gather such information using multiple frequencies or wide-band systems. Another approach, which can reveal important information for Echo Trace Classification (ETC) is the use of sonars, which can give a more complete description of the object. Both these topics are reviewed in this report and their future potential appraised.

The aim of this report is to review the state-of-the-art in Echo Trace Classification (ETC). It provides an overview of the major questions in this field and a comprehensive review of the technologies and analysis tools to investigate these. This is currently a fast developing field both in terms of the technologies available and the analysis tools. As such, this report must be seen as representing a "snap-shot" of the subject area. All major areas of development have been considered, however, it is anticipated that new developments will appear regularly. The main value of this report is to provide a framework for both new workers in the field and for those wishing to enhance existing work. To this end, in a number of areas of the report we present anticipated and promising future directions of research.

1.1 Acknowledgements

We would like to thank François Gerlotto in his capacity as Chair of the Fisheries Acoustics Science and Technology Working Group and all the members of the Working Group for their useful comments and helpful discussion during the preparation of this report. We would also like to thank all the other people who provided helpful comments and advice, particularly the partners in the EU funded research project CLUSTER1.

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1 The EU CLUSTER project was a project on - "Aggregation patterns of commercial pelagic fish species under different stock situations and their impact on exploitation and assessment". It was jointly funded by the European Union under the FAIR programme (FAIR CT-96-1799) and the Institut de Resereche pour le Development - ORSTOM/IRD (France), the Institut Francais de Recherche pour l'Exploitation de la Mer - IFREMER (France), Fisheries Research Services - Marine Laboratory, Aberdeen - FRS-MLA (UK), the Instituto Espanol de Oceanografia - IEO (Spain), and the Institute of Marine Biology, Crete - IMBC (Greece).
The standard use of fisheries acoustics is to estimate fish or plankton abundance in the context of a stock assessment survey. It is also used to map the abundance distribution of these resources. However, it is generally agreed that there is a great deal more information available from the acoustic data collected during such surveys than a simple integration of target species biomass. This report describes the state-of-the-art in the extraction of such information. This can be defined as Echo Trace Classification (ETC).

The study of Echo Trace Classification (ETC) is the characterisation of objects or features seen in an echogram and relating these together to understand more about the behaviour and biology of the organisms involved.

Before considering the tools and approaches to carrying out Echo Trace Classification (ETC) studies it is important to consider two major questions:

- What is Echo Trace Classification (ETC)?
- Why should we want to use Echo Trace Classification (ETC)?

These questions will be considered in this overview chapter of the report. This then leads to a second set of questions:

- How do we collect data for Echo Trace Classification (ETC)?
- How do we analyse Echo Trace Classification (ETC) data?
- What is the future for Echo Trace Classification (ETC)?

These questions will be considered in more detail in the main body of the report.

2.1 What is Echo Trace Classification (ETC)?

A casual examination of an echogram output from any echo-sounder or sonar will reveal immediately a number of obvious features. There will usually be a seabed, apparent as a strong, horizontally continuous echo, usually near the bottom of the picture; there will be a trigger pulse at the top of the picture, often close to the surface; and between these features there will be a variety of other, more or less discrete, features. These features are normally considered as being the acoustic energy reflected from one or many biological objects in the water column. These are the "echo traces" to be classified.

Sometimes these features can be interpreted as single objects e.g. the "inverted V" or "thumbnail" of a single fish. More often, they will represent aggregations of fish or planktonic organisms. A feature which can be considered to be from a single organism or an aggregation of organisms can be termed an "echo trace". Echo traces can be produced on the echogram from other, inanimate, sources e.g. submerged objects, oceanographic discontinuities, entrained air bubbles or even false bottom echoes. However, for the purposes of this report we will only be considering echo traces from biological, living entities.

Echo Trace Classification (ETC) is the process whereby we extract these features or "objects" from the echogram and describe each individual object with a set of descriptors. Normally these descriptors would fall into five broad categories:

- **Positional** - The position of the object in time and space, e.g. longitude, latitude, depth, time of day and season etc;
- **Morphometric** - The shape of the object as seen on the echogram e.g. height, width, area, perimeter length, circularity etc;
- **Energetic** - The acoustic energy in the object e.g. total, mean or maximum energy, spatial variability in energy or other more detailed descriptors such as echo-phase statistics or frequency dependence;
- **Environmental** - Parameters describing the immediate environment of the school, e.g. temperature, salinity, seabed substrate and topography etc;
- **Biological** - The taxonomy of the objects and associated variables e.g. length, weight, age etc;

Section 3 provides a suggested standard protocol for the collection of these descriptors. We have chosen a set of primary descriptors within each of the five categories above, and described the methods for extraction of these descriptors. The descriptors are also divided into those available at the individual echo trace level (e.g. morphometric and energetic descriptors), those available at the level of the EDSU - Elementary Distance Sampling Unit\(^2\) (e.g. topography and substrate), and those available at a wider spatial scale (e.g. hydrographic or meteorological data). The descriptors chosen are primary in the sense that they cannot be derived from other descriptors and are relatively simple to extract from an echogram. This "standard" set is offered as a guide or starting point for users, and to provide a standard by which workers can compare results. They are not intended as a constraint on innovation, and we would encourage all workers in this field to develop their own descriptors as appropriate.

\(^2\) The EDSU or Elementary Distance Sampling Unit is the length of cruise track along which the acoustic measurements are averaged to give one sample (MacLennan and Simmonds, 1992). It is defined in terms of distance travelled (e.g. one nautical mile). Determination of EDSU length depends on the spatial structure of the fish or plankton in the area and on the objectives of the survey. Note EDSU is equivalent to ESDU which is no longer used.
Once we have each object and its associated descriptors we can then construct classifications of these objects as appropriate. One of the most commonly adopted approaches is to attempt to classify objects to species based on the descriptors. However, we can also study the aggregation of these objects, or the relationships between these objects and their surroundings i.e. with depth, time of day, hydrography and so on.

2.2 What is a school?

Throughout the text so far we have explicitly restricted the discussion to the classification of "echo traces", objects or features. In reality, in most cases these objects will either be traces from individual objects i.e. fish or plankton or from aggregations of individual objects i.e. schools of fish or swarms of plankton. Situations where individual objects can be seen are relatively rare and so are considered only briefly in this report. Thus the normal situation is where objects on the echogram represent aggregations of organisms not individuals. Henceforth, we will use the term "school" to describe such an aggregation, of fish or plankton.

The use of the term "school" raises the question of "what is a school?" This question was raised regularly throughout the preparation of this report, and is raised wherever aggregation patterns of marine biota are discussed. The exact biological definition of a school is beyond the scope of this report. The schools are as seen on acoustic survey equipment. A school as seen on an echo sounder or sonar can take many forms. The most obvious is the single, strong, discrete echo trace. This is readily identifiable as a school. However, there are then a wide range of other types of echo trace, e.g. layers, looser aggregations ("clouds") etc. After considerable debate in the Study Group and other fora it was agreed that no specific definition of a school could, or should, be produced. Effectively, a school is a phenomenon defined by the scientist in a particular biological situation and which is appropriate for that situation.

A second, related, issue is the relationship between the school as seen on the echo-sounder or sonar and the real school which produced that echo trace. Echo-sounders and sonars do not produce perfect reproductions of the real school. The instrument produces a beam which has a number of important characteristics. It has a sampling volume defined by the depth sampling interval and the width of the beam (beam pattern). It has an echo-energy detection threshold. And it has a sampling (transmission or ping) interval. A school can be detected anywhere in the sampling volume, if it is above the detection threshold. Whether it is detected on multiple pings depends on the school size and density AND the ping interval and beam pattern. Therefore the image of the school seen on the echogram can be considered as a version of the "true" image masked or filtered by the physical characteristics of the acoustic equipment. The image of the school on the echo-sounder is thus a distorted image. To some extent it is possible to correct, or to compensate for, these distortions. Section 4 of this report describes methods for correcting the main morphometric and energetic descriptors for observed schools with reference to the physical characteristics of the instrumentation. It also details the situations where schools should be considered as too small to allow any accurate description.

All this in turn affects what the observer considers to be a school. For instance, consider the detection threshold. More, probably larger "schools" with a lower threshold will be seen. Thus the scientist who wishes to work in Echo Trace Classification (ETC) should be careful to use good quality scientific instrumentation and equipment settings which allow the best representation of the type of schools they expect to encounter.

2.3 Why should we want to use Echo Trace Classification (ETC)?

As stated above, there is a great deal more information available from the data collected during acoustic surveys than a simple integration of target species biomass. Echo Trace Classification (ETC) allows the construction of a survey database containing information on all the schools seen during the survey. As detailed above, this will include data on the schools morphometry, acoustic energy characteristics, spatio-temporal location, environment and biology. From this the scientist can then study much wider aspects of the biology and behaviour of the fish or plankton in situ. Within the context of a survey situation it is then possible to study the variation in school pattern over the course of the day, for instance. Do we see more, or larger, or shallower schools in the middle of the day than at dawn or dusk? With this information, it may then be possible to design the survey more appropriately in the context of the fish behaviour. Variation in the aggregation patterns e.g. fewer, larger schools, or a tendency for schools to aggregate in clusters may affect the "catchability" of a stock for an acoustic survey.

Perhaps the most important application of Echo Trace Classification (ETC) is the possibility of identifying echo traces to species. At present most scientists analysing acoustic surveys have to rely on trawl data to assign echo traces (schools) to species. Trawls are selective and the samples collected are generally subject to a high level of variability. Relatively few trawls are possible in the context of an acoustic survey, and it is not always possible to be sure that the trawl is actually sampling what is seen by the echo sounder. It would be very useful to be able have an objective technique for assigning traces to species based on the suite of descriptors listed above, and described in Section 3. The use of Echo Trace Classification (ETC) for this purpose is beyond the scope of this report, but it remains one of the most important potential applications for the technique.

In broader terms, it should be possible to develop a more accurate view of how, when and where fish or plankton aggregate and how this varies in relation to external parameters, e.g. environmental or hydrographic variables. It should also be possible to determine how aggregation varies in relation to the biology of the stock e.g. age structure or stock state. Do younger fish aggregate differently to older fish? Does the aggregation pattern change when the stock is depleted? In general Echo Trace Classification (ETC) should allow the scientist to ask more wide ranging questions about the biology and
behaviour of fish and plankton in the field using data acquired with acoustic instruments.

2.4 Two-dimensional image of a three-dimensional object?

Most data for Echo Trace Classification (ETC) will be gathered using the standard, vertical beam scientific echo-sounder, and most of the discussion above has concentrated on this. It is fundamentally important to understand that the standard echogram provides a two-dimensional (2-D) view of scatterer aggregations which actually occupy three-dimensions (3-D) in space and change over time. Essentially, the echo-sounder takes a slice, at an unknown point, across the school. Thus, the echo-sounder measurements only provide 2-D spatial observations of a 3-D variable and may only approximate reality by generalisation (e.g. mean values). If the vessel passes over the edge of a school only, it will appear as a much smaller school on the echogram than it actually is in reality. Given that we do not know the "true" dimensions of a school, then even the corrected values are only an approximation to reality. For example, it is only when the dimensions of the school sizes are small relative to the inter-school spacing that the distances between schools and their clustering can be studied (e.g. point processes - see Section 6). Only then will the variability intrinsic to the observational method become insignificant relative to the variability in the physical dimensions measured (i.e. distances between schools). Therefore, one must be mindful of the limitations of the vertical echo-sounder data to precisely measure school parameters and select appropriate analysis tools to avoid misinterpretation of the many potential measurement artefacts.

To solve this problem we need to be able to collect data in three dimensions. For this we require to use sonar equipment rather than vertical echo-sounders. There have been considerable advances in the development of relatively cheap, high quality sonars for use in fisheries science. To some extent fisheries science has benefited here from developments in defence based technology. The main difference for our purposes is that echo-sounders sample only below the vessel and along its track (2D), while sonars are also able to sample to the side of the vessel track (3D). Section 7 describes the various developments which have been made and the technology now available. In essence, the task of Echo Trace Classification (ETC) remains the same for both technologies. However, with sonars we are able to get closer to the true dimensions of the school, and critically, we avoid the problem of seeing a large school as a small relative to the inter-school spacing that the variability intrinsic to the observational method become insignificant relative to the variability in the physical dimensions measured (i.e. distances between schools). Therefore, one must be mindful of the limitations of the vertical echo-sounder data to precisely measure school parameters and select appropriate analysis tools to avoid misinterpretation of the many potential measurement artefacts.

To solve this problem we need to be able to collect data in three dimensions. For this we require to use sonar equipment rather than vertical echo-sounders. There have been considerable advances in the development of relatively cheap, high quality sonars for use in fisheries science. To some extent fisheries science has benefited here from developments in defence based technology. The main difference for our purposes is that echo-sounders sample only below the vessel and along its track (2D), while sonars are also able to sample to the side of the vessel track (3D). Section 7 describes the various developments which have been made and the technology now available. In essence, the task of Echo Trace Classification (ETC) remains the same for both technologies. However, with sonars we are able to get closer to the true dimensions of the school, and critically, we avoid the problem of seeing a large school as a small one simply because we only passed over the edge of the school.

There are a number of problems to be addressed before the use of sonars can become routine. One is the significantly greater amount of data collected. A fan beam sonar with fifty beams will produce fifty times more data than an echo-sounder with the same ping interval and resolution. Given the rate of development in processing power this should not be a major problem. A related problem is that many sonars have not been designed with the acquisition of high quality digital data in mind. In many cases the systems provide an image only, which can be recorded, but no digital data. This problem is being addressed and new systems are being made available from which digital data can be acquired. Another problem is the interpretation of acoustic data off the vertical axis. We have a reasonable understanding of the target strength (TS) of some organisms in their dorsal aspect. However, this is less well established for fish seen at other angles. This has an impact not only on the integration of the returned acoustic signal but also on the morphometry and energy descriptors of a school. For instance, if a fish had a dramatically different TS from above than from the side, a school may be above the detection threshold directly below the vessel and below the threshold when off the track. While this subject lies outside the scope of this report, its encouraging to note the good progress being made in the calculation of TS from a theoretical basis in a number of different studies.

In the near future it is unlikely that sonars will be routinely employed in stock assessment surveys and so echo sounder data will continue to be collected. We will, therefore, continue to need to carry out Echo Trace Classification (ETC) on these data. It can be argued that, in the short term, sonars will be used mostly in research situations. In this role, they should provide valuable information to allow us to interpret the 2D information more accurately. As an illustration, it would be very useful to know if a particular species under study had schools which tended to be circular in plan view. Preliminary work suggest this may be true for some species e.g. North Sea herring. If this is proven, then we can correct the observed school widths to give a better statistical representation of the real school dimensions. If not, then we must be more cautious in our use of such data.

2.5 How do we analyse Echo Trace Classification (ETC) data?

In the above discussion we have considered the questions of what Echo Trace Classification (ETC) is and what we can use it for, as well as some of the difficulties in interpreting the data. The question - How do we collect data for Echo Trace Classification (ETC)?- has been covered inter alia within this. The next question pertains to the tools for the analysis of this type of data.

A fundamental and often overlooked aspect of analysis is the relatively simple examination of the scrutinised, validated and processed acoustic data. Here we have termed this as data visualisation. Essentially the first step of analysis is to simply look at the survey data in the wider context (spatial, temporal, environmental or biological) of the area surveyed. A great deal of valuable information can be derived during this process particularly in relation to the spatial distribution of the target species (mapping); the variability in school/aggregation structure (echogram viewing); and relationships with external variables (e.g. using Geographic Information Systems GIS) A wide variety of tools have been developed in recent years allowing such visualisation of echo-sounder survey data. Given the variety of tools and their
different methodological approaches, it was decided that it was unnecessary and probably impossible to produce a single template for a suitable visualisation protocol. As an alternative a catalogue of the different tools and their capabilities was compiled. This allows the scientist to choose the most appropriate tools for their situation and gives details and contacts to obtain those tools.

The next step is to construct meaningful classifications of schools/aggregations and to analyse the inter-relationships between them and their surroundings. This is termed post processing.

The tools described can be classified into two distinct groups:

- Tools for classification of the schools or patches into identifiable groups, such as species, functional groups etc.;
- Tools for modelling, analysing or mapping the spatial distribution of the schools and relating them to external variables. These are aimed at developing a more general representation of real fish distributions to help test survey design strategies and understand fish behaviour.

A series of appropriate tools for each of these types of analysis are described in detail in Section 6. The introduction to that chapter details which tools are most appropriate in relation to the desired output from the analysis.

2.6 What is the future for Echo Trace Classification (ETC)?

Finally the report considers how Echo Trace Classification (ETC) will proceed in the next few years. As detailed above, much of the work in this field of research has concentrated on the analysis of vertical echo-sounder data. This has probably come about for a number of reasons. Firstly, most acoustic surveys are carried out within the context of stock assessment, and thus far, these almost invariably use vertical echo-sounders. Thus the bulk of the data available for analysis is derived from this type of instrument. Secondly, the availability of reasonably priced sonars, and the possibility of acquiring digital data from these, has been limited until recently. Thirdly, the ability to convert sonar data to biomass, particularly for side aspect TS problems, has prevented the use of these instruments in most stock assessment surveys.

It should be anticipated that in the medium term future (5–10 years) most of these problems will have been solved, and sonars will be in routine use on stock assessment surveys and the data available for Echo Trace Classification (ETC) studies. In the interim, research based sonar studies, should provide valuable calibration information to improve the quality of the data derived from the use of vertical echo-sounders. The state-of-the-art in sonar, and possible future developments are discussed in detail in Section 7.

The other main development path of importance to Echo Trace Classification (ETC) is that of multi frequency sounders and wide-band systems. Both of these technologies provide a wider range of descriptors for the observed schools, which should allow more detailed classification. One of the main difficulties in species identification, for instance, has been the limited number of uncorrelated descriptors available for each school. Given the known TS/frequency dependence of many biological scatterers it is reasonable to hope that these technologies may improve the accuracy of the discrimination possible and allow reliable species identification to be carried out remotely. Many acoustic surveys are already carried out using a number of different echo sounder frequencies, although relatively little use has been made of these data in Echo Trace Classification (ETC). Wide band systems have been developed in a number of research institutions, however, these are technically complex and have not yet been used in routine survey situations. A description of the state-of-the-art for these systems and their potential development and application in the future is detailed in Section 7.

In summary, this report presents detailed coverage of the main lines of research in the collection, analysis and interpretation of Echo Trace Classification (ETC) data. The main aim of the report is to provide the potential user (both new and experienced) of this kind of analysis with a guide to the state-of-the-art and promising lines of research to follow. It is hoped that given the rapid developments in this field, particularly in the use of 3D sonar data, a further review will be required within the next ten years.


3 Echogram visualisation and analysis software

3.1 Introduction

Acoustic data management (both for acquisition and processing) has become an increasingly computer intensive task in recent years. The increase in information provided by digital echo-sounders and other equipment has coincided with the development of faster and cheaper computers. Increased processing speed and improvement in storage devices together with the development of new software tools has allowed new concepts in the analysis of acoustic data. However, the management and presentation of such large amounts of information is not an easy task. The presentation and understanding of this information in an integrated fashion requires the development of new tools and concepts. Standards are also required not so much in specific tools, but in concepts, formats and structures (e.g. file structures, classification criteria, methodologies, variables to be collected, their attributes etc...), to allow comparison between data collected by different vessels and scientists in a wide variety of situations.

An important aspect of the role of computer tools is the integration and co-presentation of the collected acoustic data with positional, oceanographic (environmental) and biological data. When presented and analysed together, these can provide valuable information about the behaviour of the species observed and population dynamics.

The development of such tools and applications is generally conducted by either, acoustic research groups or commercial companies. It should be noted that, in general the commercial companies usually work in a continuous collaboration and feed-back process with the research community.

As part of their remit, the Study Group on Echo Trace Classification (SGETC) agreed to collate information on currently available software which had been developed for the acquisition and visualisation of acoustic and ancillary information. To this end, a questionnaire was sent out to the whole acoustic research community. The questionnaire was intended to be simple but also to cover the many different objectives and philosophies of the various software tools which have been developed. It should be recognised that no questionnaire can cover all the points of interest. The main objectives of the questionnaire were:

- To determine which groups are involved in developing software, or have developed software;
- To determine the coherence in objectives and structure of the data analysis tools;
- Obtain information on the availability and scope of software, which could be used for ETC rather than just data visualisation;

A list of the contributing researchers is presented in Table 3.1, together with email addresses and institutions. The left-hand column gives an ordinal number to facilitate rapid cross-reference to the table giving the summary of the questionnaire (Table 3.2).

A summary of the responses to the questionnaire is given in Table 3.2. Two important points should be noted:

- the questionnaire separates “Acquisition software” (AS) from “Processing software” (PS). The reason for this is that data from different echosounders are acquired using a variety of different AS and that these are often “echosounder dependent”. For example, commercial tools, such as the BH500 and EP500 software from Simrad, or Biosonics ESP or DT Software. For the purposes of this report we were most concerned with “Processing software, however it was agreed that it is important to be aware of the acquisition process as a starting point for the processing software;
- some commercial software, which is now available, is not represented in this survey. As mentioned in the introduction, this is a rapidly developing field, and some commercial software will have appeared during the period prior to publication. For this reason we have differentiated between commercial software and non-commercial software. Evaluation of the suitability and application of these packages is presented here, but we have not attempted to critically assess them.

3.2 The questionnaire

Questionnaires were sent to all research groups active in this field to obtain a general view of what hardware, software and approaches were actually being used in the field.

The questionnaire was divided into two main topics:

- Acquisition software (AS);
- Processing software (PS);

One immediate observation was that most groups are using commercial software for acquisition and developing in-house software for processing.

This report does not attempt to determine the utility of particular software. The choice of a particular echosounder system will, in most cases, determine the selection of the software used for acquisition. Again, different objectives within different projects or studies will determine the selection or development of the tools and software. However, a broad analysis of the methodologies used is helpful in defining trends in methodologies and may allow us to define some standards for the analysis of acoustic data.
3.3 Acquisition and processing software

In this report we define acquisition software (AS) as being those packages that are used to acquire acoustic data from echosounders in real time, and storing this information in a standard format on some type of digital medium (Hard disk, CD, tape, etc.).

A complete AS system must include not only the echo (acoustic) information but should also include the echosounder settings and configuration parameters such as transceiver parameters, range and bottom variables, etc. This data should be time and position referenced allowing the data to be included in a relational database along with other parameters e.g. water depth, ship attitude (heave compensation data), or environmental parameters from other instruments such as ADCP, CTD, thermosalinograph etc.

The processing software (PS) package provides post-processing of acoustic data to obtain suitable information for biomass estimation and the study of fish or plankton distribution and behaviour. Packages for statistical or geostatistical analysis or specific image analysis software are not considered.

It should be noted that some of the software considered in this chapter is "commercial" software – where it is a commercial product with full legal status and licences and is distributed as "closed" versions. Other software can be considered "non commercial" software. These have been developed by research groups for their own purposes. While these may include elements from "commercial" applications (e.g. Dynamic Link Libraries – DLL and commercial programming languages) they are more "open" software, which have a continuous evolution and are likely to be more "developer dependant".

3.4 Commercial software

3.4.1 Echosounder dependent packages

These software packages are dedicated to the acquisition, visualisation and processing of data from a particular echosounder. In these groups we can include Simrad BI500 and EP500 and BioSonics ESP and DT software. It was not possible to evaluate all these software packages and some of the information is based on published material. The companies concerned offer web services giving operation and file specifications of the software for downloading.

Simrad: BI500 (For Unix Work Stations) and EP500 (for PC). The Bergen Integrator (BI) is widely used for acquisition and visualisation of acoustic data. In some cases, the whole process is carried out using the BI500. It allows the operator to scrutinise the data, carry out echo-integration, determine single target TS distribution, and some on screen editing. The EP500 is used mainly for acquisition of EK500 and EY500 echosounders, and has a reduced functionality (Knudsen 1990). Web site www.simrad.com


3.4.2 Echosounder independent packages

These software packages can acquire and process acoustic data from a number of different echosounders. These include EchoView from SonarData and the Movies family from IFREMER for ETC and the EDSU oriented Echobase from C-MAP.

IFREMER MoviesB and Movies+, (PC DOS and Win 95). MoviesB permits the acquisition of data from any analogue echosounder and requires an electronic interface. Movies+ can acquire data from digital echosounders such as the Micrel Ossian, Simrad EK500 and BioSonics systems. The main importance of Movies+ in the context of ETC is that it can routinely identify and extract all echo traces above set thresholds and record these in a database for subsequent analysis. Uses HAC file format. http://www.ifremer.fr

Sonar Data EchoView. (PC Windows). This package can acquire acoustic data from a variety of echosounders, often in real time (EK500). Files from Simrad, Kaiko and BioSonics DT echosounders and HAC files can be imported for post-processing. Image processing modules are in development to allow echo trace identification and extraction. Data can be edited on screen. Web site: http://www.sonardata.com


3.5 Non-commercial software

We have included in this category all those packages that have been developed by different research groups for specific studies. The feedback from the questionnaire reflects mainly this type of package and is intended to provide a new worker entering the field with a gazetteer of what could be useful when looking for a specific data analysis. In most cases these packages are developed using mixed programming tools or sets of programs which permit a dynamic link with other commercial software such as statistical, data base, graphical or image processing packages. This type of application is generally in the later stages of processing and is usually structured to allow quick modification of functions or methods in a continuous style. Matlab, Labview, Arcview, ArcInfo, Modula, C, C++, Visual Basic, Pascal etc. are among the programming or application languages used. Many of the functions and methods developed within these tools (e.g. school classification) could be implemented in more sophisticated and potentially commercial software.

3.5.1 Echo-trace, school, and species classification software

AVS, British Antarctic Survey, UK.
Can acquire and process data from Simrad EK500, EK400 and BioSonics echosounders. It connects to an Oracle database, which allows relational links with environmental and haul information. This system also allows species classification and graphical corrections. Developed mostly for use with krill swarms. Multi-frequency.

**ECHO**, CSIRO Division of Marine Research, Australia.

Acquisition and processing of EK500 echosounder echo-gram data. Data are stored in an Oracle database. Multi-frequency, and graphic editing. Developed for benthic fish biomass studies.

**SCHOOLS**, Limnological Institute Univ. of Konstanz, Germany.


**SCHOOL**, Institute of Marine Biology, Crete, Greece.

This package uses various integrated sets of applications on both Work Station and PC platforms. It can process EK500 data acquired by BI500. It provides automatic biomass estimation with echo-trace, school and species classification. Graphic editing. It makes extensive use of image processing methodologies and Artificial Neural Networks methods. Georgakarakos and Paterakis (1993).

**NO NAME**, Danish Institute for Fisheries Research, Denmark.

Set of programs for fish biomass estimation and for the study of fish behaviour. Environmental data is included in the analysis. ETC, school classification and species classification tool.

**CH1 CH2**, Department of Fisheries and Oceans, Canada.

CH1 and CH2 are part of a suite of applications designed to acquire and analyse hydro-acoustic data produced by analogue or digital multi-channel (multiple frequencies and beams) echosounders under a standard, upgradable and versatile data format (HAC). (Simard et al., 1998)

**SCHOOLBASE**, Marine Laboratory Aberdeen, UK

This package uses commercial image processing software built into a Visual Basic framework. It can process BI500 files and works in a supervise automatic mode. Identified and tagged schools are transferred to a Paradox database along with EDSU and area based data, which are cross reference to the school database. It can be used for echo trace extraction and classification. (Reid and Simmonds 1993).

### 3.5.2 Other software

Other software has been developed by a number of research groups and was outlined in the questionnaire replies. These have not been included as they are not school classification or ETC tools. These include other functions such as automatic biomass estimation and coupled acoustic-environmental databases.

### 3.6 Conclusions

Although the diversity of tools and applications is high, general trends in the use of these software tools can be seen. Automatic echo-integration is one of the main objectives of all the packages. Echo-trace, school classification also are important objectives. Environmental coupled information systems seams to be secondary. One of the most important conclusions from this collated information is that a standard file format for data exchange is a priority to allow the relative performance of these tools to be investigated. The Study Group investigated the possibility of carrying out a study on how well the main ETC tools worked on a variety of data sets. This proved practically impossible, as all the main systems used data in different formats, and no suitable exchange format then existed. HAC format files (Simard et al., 1997) may represent such a common format. It has already been implemented in a number of tools e.g. Movies+ and EchoView. If a wider integrated approach to this type of study is to occur, then it is important that HAC or some other standard format is adopted in the near future.

### 3.7 References


Table 3.1. Contributors to the questionnaire with affiliations and contact addresses.

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<td>18</td>
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Table 3.2. Resumé of the responses to the questionnaire.

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### ACQUISITION

| 1.1 Echosounder: | EK500, EY500 | EK400 | EK500, EY500 | EK500 | EK500 | EK500 | All analogue | Numeric (Ossian, EK500, BIOSONICS) |
| 1.2 Frequencies: | 38, 120 kHz | 38 kHz | 38, 120 kHz | 38, 120, 200 kHz | 12, 38, 120 kHz | 18, 38, 120, 200 kHz | 12 to 200 kHz | Any |
| 1.4 Variables acquired: | Sa, Sv, TS | Sa, Sv, TS | MSBS, SBS, MVBS, VBS | Ping & Integrator data | Echogram telegram | Echogram VBS, ind. TS | Echo traces | Echo Traces |
| 1.4 Ping or EDSU based: | Both | Both | Both | Ping | Ping | Ping | Ping |
| 1.7 Data storage: | Binary | Binary Proprietary format | Binary | B1500 files | Binary files | Binary files |
| 1.10 Echos. Param. Stored with acoustic data | Yes | Cal. Const. & Settings | None | Yes | Yes | Yes (manual) | Yes (Automatic) |

### PROCESSING

<p>| Acquisition Software | B1500 | AIDA | EP500 | AVS | ECHO | EP500 | B1500 | MOVIESB | MOVIES+ |
| 2.1 Echosounder Model(s): | EK500, EY500 | EK400 | EK500 | EK500 (EK400 BioSonics) | EK500 | EY500 | EK500 | All analogue | OSSIANS, EK500, BIOSONICS |
| 2.2 Frequencies | 38, 120 kHz | 38 kHz | 38, 120 kHz | 38, 120 kHz | 12, 38, 129 (all) | 70 kHz | 18, 38, 120, 200 | 12 to 200 kHz | Any |</p>
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</table>

2.3 Ping or EDSU based:

- **EK = Log Based, EY = Time based**
- **Ping (time based)**
- **Ping**
- **EDSU**
- **Ping**
- **Ping**

2.4 Pixel (graphic processing) or Signal (numeric processing):

- **Numeric**
- **Signal (numeric)**
- **Pixel**
- **Signal**
- **Pixel based**
- **Signal**

2.5 Data processing:

- **EK & EY to BI500 or EP500**
- **EDSU** (ping for filtering, Shoal analysis and patch estimation)
- **EDSU Sa, Sv**
- **Time/Depth matrix**
- **Ping based analysis**
- **EDSU process.**
- **EDSU by distance**
- **EI by layers or schools (time or distance EDSU, Echotrace descrip., Ping Tomography)**
- **EI by layers or schools (time or distance EDSU, Echotrace descrip., Trace class. Ping Tomography)**

2.7 Database and storage:

- **Oracle**
- **Hierarchial flat file database**
- **Hierarchial flat file database**
- **Sometimes ORACLE, SAAS**
- **Oracle**
- **Echobase**
- **Ingress**
- **No DBASE. Propri. files**
- **HAC format**

2.9 Is it introduced in a GIS?

- Yes, ArcView
- None
- None
- Not used
- No
- Echobase
- No
- Not direct. Another software needed
- Not direct. Another software needed

2.10 Other data stored:

- Separate Databases, environmental data integrated w. Matlab, Surfer, P-wave, ArcView
- GPS + altitude + SST + fluor + meteo
- GPS + bottom depth, HDG, speed
- Connection w. Envir. Database
- No. Merged in another Dbase
- CTD
- GPS
- GPS, Vessel speed, Heading
- GPS, Vessel speed, Heading

2.12 How haul information is introduced?

- Database
- Separated, manually. Fish length
- Separated, manually. Fish length
- Database of net information
- Georeferenced tables
- Separated Dbase, merged in post-process.
- Manually w/ another Soft.
- Manually w/ another Soft.

2.14 Acquis. Environmental data:

- Manually
- Other manually
- Manually
- DataBase routines SAS
- Another Dbase
- Georeferenced Dbase
- Separated mapas
- No
- No (? w. Another soft.)
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<th>AVS</th>
<th>ECHO</th>
<th>EP500/Echobase/…</th>
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<th>MOVIESB (+OEDIPE)</th>
<th>MOVIES+ (+FISH-VIEW)</th>
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<td>2.15 Environmental data:</td>
<td>ADCP, CTD, salinity, fluor.</td>
<td>CTD, ADCP, SST, salinity, fluor, Egg and plankton</td>
<td>CTD, ADCP, SST, salinity, fluor, Egg and plankton</td>
<td>CTD, SST, nutrients</td>
<td>CTD, ADCP, SST, Bottom discrimin. XBT</td>
<td>CTD</td>
<td>CTD, SST</td>
<td>No</td>
<td>Bottom Class.</td>
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<td>2.16 Ship attitude:</td>
<td>AshTech Log, speed, distance, heading, GPS</td>
<td>Heading, Vessel log, GPS.</td>
<td>No info.</td>
<td>GPS, Vessel log</td>
<td>Heading, Vessel Log, GPS, Heave.</td>
<td>GPS</td>
<td>Vessel speed, Heading</td>
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<td>2.18 Information processed:</td>
<td>EI, TS</td>
<td>EI, BS</td>
<td>EI, BS, TS</td>
<td>EI, TS, BS</td>
<td>BS, TS, Hauls</td>
<td>EI, TS, species (hauls)</td>
<td>EI, BS, hauls (Other soft)</td>
<td>EI, BS, hauls (Other soft)</td>
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<tr>
<td>2.19 Process of information:</td>
<td>Fish behaviour-manual; Stock = database</td>
<td>Automatic each EDSU</td>
<td>Manually Excel</td>
<td>Automatic</td>
<td>Mapping, Geo-statistics.</td>
<td>Visual scrutin, and edited. SA values per species</td>
<td>Automatic school param extraction</td>
<td>Automatic school param extraction</td>
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<tr>
<td>2.20 Outputs</td>
<td>Abundance/biomass by length/age; plus various</td>
<td>EI tables 1 to 5 m depth channels</td>
<td>EI tables, Echo-tracerogram</td>
<td>Mapping w. confidence intervals.</td>
<td>Date, Time, logg, GPS, SA(EDSU)</td>
<td>Processed Files and echograms</td>
<td>Processed Files and echograms, school, bottom image.</td>
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<td>2.21 Graphic software:</td>
<td>ArcView, Excel, Matlab, Surfer, etc.</td>
<td>Yes</td>
<td>Yes, graphic corrections</td>
<td>Yes, Noise and absorption corr. Bottom editing,</td>
<td>Yes</td>
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<td>2.22 Echo Trace, School Species classification</td>
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<td>None</td>
<td>Species class</td>
<td>Yes, Multi-frequency</td>
<td>No info.</td>
<td>Echo Trace and School class.</td>
<td>Echo Trace and School class.</td>
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<td>2.23 Integrated oceanographic and acoustic</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>No</td>
<td>Yes (echobase)</td>
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<tr>
<td>2.25 Brief description</td>
<td>Stock Assesment, Buoy, TS and fish avoidance</td>
<td>Biomass estimation, stock assessment</td>
<td>Data collection, integration, analysis</td>
<td>Benthic biomass, fish, multi-frequency.</td>
<td>BI500</td>
<td>Acquir., EI, biomass per schools. Echo Trace</td>
<td>Acquir., EI, biomass per schools. Echo Trace</td>
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<td>Computer requirements</td>
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<td>AqAq</td>
<td>T-Echo Viewer</td>
<td>Various</td>
<td>BI500+ 2.2</td>
<td>Khoros</td>
<td>No Name</td>
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<td>2.2 Frequencies</td>
<td>All BI500</td>
<td>38 kHz</td>
<td>38 kHz</td>
<td>38, 120, 200 kHz</td>
<td>38,120,200 kHz</td>
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<td>38, 120 kHz</td>
<td>38, 120 kHz</td>
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<td>2.3 Ping or EDSU based:</td>
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<td>Ping</td>
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<td>EDSU</td>
<td>Ping based</td>
<td>EDSU</td>
<td>Both</td>
<td>Both</td>
<td>Both</td>
<td>Ping based</td>
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<td>2.4 Pixel (graphic processing) or Signal (numeric processing)</td>
<td>Sv values</td>
<td>Signal</td>
<td>Pixel</td>
<td>Pixel</td>
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<td>Signal</td>
<td>Signal?</td>
<td>Both</td>
<td>Signal</td>
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<td>2.5 Data processing</td>
<td>Ping data process. School detect. by image analysis w./ Sv values.</td>
<td>Numerical analysis. (SV, phase angles)</td>
<td>Distance EDSU process., descriptors: depth, threshold integrals, temp, salinity, Roxanne data</td>
<td>EDSU time related during constant speed survey</td>
<td>Sv values are computed and output as graphic and ascii files</td>
<td>Ping based, EDSU based (both distance and time)</td>
<td>Ping based</td>
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<td>2.7 Database and storage</td>
<td>Relational Dbase PostgreSQL 95</td>
<td>Binary BI500 files</td>
<td>Paradox, Relat. With salinity and temp. references.</td>
<td>Data Base spreadsheet (SMART)</td>
<td>Proprietary Database</td>
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<td>Developing</td>
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<td>2.10 Other data stored:</td>
<td>GPS</td>
<td>CTD and Xducer direction</td>
<td>School/EDSU ID as reference to other Dbase.</td>
<td>Fish length and age length keys</td>
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<td>CTD, Hauls, GPS</td>
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<td>CTD, Hauls, ADCP, GPS and meteorology</td>
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<td>Haul data is independent, i.e added in post processing</td>
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<td>Another Dbase ID ref.</td>
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<td>MLA(b)</td>
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**Application Name:**

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<th>CTD+ XBT + Thermosalin.</th>
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<th>CTD, SST, Bottom classification</th>
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<th>CTD, Hauls, ADCP, GPS and meteorology</th>
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<td>AqAq</td>
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<td>Various</td>
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**Ship attitude:**

| 2.16 | None | None | None | No | Pitch, Roll, Heading, GPS, Vessel Log. | Pitch, Roll, Heading, GPS, Vessel Log | Pitch, Roll, Heave, GPS |

**Application to:**

<table>
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<th>2.17</th>
<th>Detection of fish schools. Analysis of school echo signals. EI.</th>
<th>Distribution of fish schools.</th>
<th>Fish biomass</th>
<th>General biomass estimation.</th>
<th>Fish biomass estimation</th>
<th>Fish biomass estimation and behaviour</th>
<th>General application</th>
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**Information processed:**

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<th>2.18</th>
<th>BS, TS, School EI, echo trace descrip. School numbers.</th>
<th>SV and phase angles</th>
<th>BS.</th>
<th>Echo integration or backscatter, Echo trace and hauls</th>
<th>EDSU</th>
<th>EI, BS,TS, EchoTrace, Hauls.</th>
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<th>All</th>
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<td>AqAq</td>
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**Process of information:**

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**Outputs:**

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**Graphic software:**

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<td>2.22 Echo Trace, School, Species classification</td>
<td>School detection and class. (species class. With school descriptors)</td>
<td>No</td>
<td>Yes. School descriptors. Species class. as user decision.</td>
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<td>Echotrace, school and species class.</td>
<td>Developing (species.)</td>
<td>Echo trace, school and, species classification</td>
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<td>2.23 Integrated oceanographic and acoustic</td>
<td>No</td>
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<td>No</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
<td>No</td>
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<tr>
<td>2.25 Brief description</td>
<td>Autom. School detection and description, interactive opera. Dbase connection.</td>
<td>Discrimination of fish target strength</td>
<td>Dbase of descriptors for individual schools, local environment and wider environment. (EDSU descrip.)</td>
<td>Echo trace data with fish size age and maturity</td>
<td>Biomass distribution related with environmental data</td>
<td>Automatic Biomass estimation with species identification</td>
<td>Khoros is Image Process. system with statist. and graph. tools</td>
<td>acquisition echosounder data under a standard, upgradable and versatile data format (HAC1)</td>
<td></td>
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</table>
4 Standard protocols for the analysis of school based data from echo sounder surveys

4.1 Introduction

Ever since the introduction of acoustic methods for the quantification of fish biomass there has been an interest in what other sorts of information can be extracted from acoustic surveys. One of the most obvious is the study of the fish schools as seen in echograms. Data on the school's size, shape, structure, position and immediate environment can be extracted. These data can then be used, for instance, to give information on species composition or on the mesoscale distribution of the fish; the pattern of fish aggregation into schools and the clustering of those schools. Particularly important in the fisheries context is how aggregation patterns have changed historically in relation to stock level, exploitation pattern and the environment, and what impact these changes have on commercial fishing and assessment surveys.

This approach is the subject of the current EU CLUSTER project. To investigate these phenomena a protocol has been designed for the compilation of a standard database incorporating data on the school itself, its immediate surroundings and its wider context.

The most common approach to extracting data from echograms at the school level has been to use image processing algorithms or software applied to digital echogram data collected ping by ping and with the return signal from each ping collected in a number of depth bins. The data can then be treated as an “image” analogous to a visual image acquired using a frame grabber, each pixel in the image represents a single depth sample from a single ping. Again, a variety of approaches can be adopted to this process. The most common approaches are to analyse the data either ping by ping, or frame by frame, where a frame is made up of a number of pings. Detailed descriptions of these methodologies have been published elsewhere (Richards et al., 1991; Harabolous and Georgakarakos 1993; Kieser et al., 1993; Reid and Simmonds 1993; Diner et al., 1994; Scalabrin et al., 1996; Swartzman 1997) and it is not our intention to examine the imaging methodologies here.

A number of papers have been published in recent years describing the results of the application of image processing to the extraction of school parameters. While in general these studies have used the type of algorithms described above, they have involved the extraction of a wide variety of different school parameters. The type of parameter extracted from the image analysis process can be classified into four different groups;

- Positional - temporal, geographical and vertical (i.e. position in the water column);
- Morphometric - shape etc;
- Energetic - total acoustic energy reflected and indices of internal school variation;
- Environmental - water depth, temperature etc.

To place the extracted schools in their proper geographical and environmental context, it is also necessary to combine these school specific parameters with a range of appropriate biological and environmental parameters. In some cases these will be available in sufficient resolution to be applicable at the school level e.g. species composition of the school. In most cases this type of data will only be available at a coarser spatial resolution. The next level at which data is available is usually at the EDSU level. We, therefore, propose that in addition to a database of schools and associated parameters, the researcher also produce an EDSU level database, containing information which is only available at this wider spatial scale, or which is more appropriate to collate at this scale. With cross-referencing, the individual school can then be considered in the context of the appropriate EDSU. Further, some data are only available on a wider scale again, usually in the form of point or station data, or mapped and regional data sets. Examples of mapped data sets would include remote sensing data or seabed substrate maps. Using either mapped or gridded interpolated data it is then possible to cross-reference the EDSU database to the wider spatial scale. This can be considered as a three-tier nested structure. Each school will have a set of unique associated parameters. It can be placed in the context of an EDSU which will allow the inclusion of further (but no longer unique) parameters which in turn are placed in the context of maps or gridded data at the third spatial scale.

The aim of this chapter is to describe this process and the most appropriate set of parameters to extract. The school level parameters chosen can be described as primary parameters, i.e. they cannot be derived indirectly from any of the other parameters. These school level parameters will mostly be derived from an image processing type analysis. At the EDSU and mapped data levels the parameters will mostly be obtained from ancillary data sources.

A number of researchers have been working in the field of image processing of echograms and relating these findings to the environment for some years (Harabolous and Georgakarakos, 1993; Reid and Simmonds, 1993; Diner et al., 1994; Scalabrin et al., 1996; Masse et al., 1996). The primary parameters described here have been chosen as being the most useful over a wide range of different aggregation patterns and as presenting a relatively simple extraction task.

4.2 Methods

Three levels of data extraction have been defined:

1. **The school level** - parameters associated with each individual school - mostly derived from image processing of the echograms;
2. The EDSU level - where parameters are extracted over a fixed distance of the survey track - mostly derived from analysis (mostly manual) of the echogram as a whole, but including data from ancillary underway data collection e.g. Thermosalinograph data;

3. The region level - parameters which are only available in mapped form over large parts of the survey area, e.g. satellite derived temperature or sea colour data, or derived from point samples e.g. trawl hauls or CTD stations.

Each level is appropriate for different types of data and all are relevant to the understanding of school typology and its relationship to the local and wider scale environment.

4.2.1 School level parameters

It is assumed that the echogram will be presented for analysis as a raster image with each pixel representing a single sample from a single ping. In the text we will henceforth refer to these as pixels. A pixel will have a standard set of properties defined by the performance of the system; ping rate, sampling rate, operating frequency and vessel speed. These properties are:

- $P_h$ The vertical dimension of a single sample. This is taken to be the time separation between adjacent samples (in milliseconds) multiplied by the speed of sound in water (m.ms$^{-1}$).
- $P_w$ The horizontal dimension of a single sample. This is taken as the distance travelled by the vessel between adjacent pings.
- $P_{csa}$ The cross-sectional area represented by a single sample ($P_h \times P_w$).

School level parameters fall into five general categories:

- Positional - temporal, geographical and vertical;
- Morphometric - shape, etc;
- Energetic - total acoustic energy reflected and indices of internal school variation;
- Environmental - hydrographic and physical (seabed substrate and topography);
- Biological - species, age structure, other species, etc.

**Positional parameters (SP$\text{subscript}$)**

The positional parameters are defined either in terms of latitude, longitude and date/time in the vertical plane or depth in the horizontal. On the echogram, each school is defined as having a vertical and a horizontal beginning (BV and BH) and end (EV and EH).

In the vertical plane, the beginning (BV) is the first ping on which the school was detected and the end (EV) is the last ping. Some echo sounders record data digitally, ping by ping, with each ping tagged with navigation data, usually from a GPS receiver. Alternatively, the position of a particular ping can be interpolated from whatever navigational data is available. The school position is defined as either the mean of date/time (SP$\text{time}$), latitude (SP$\text{lat}$), and longitude (SP$\text{lon}$) of BV and EV or as the mean of the date/time, latitude, and longitude of all pings between BV and EV. The choice will depend on how much trust can be placed in the validity of the navigational stamp. The time is determined in the same way from the navigational data associated with each ping.

In the horizontal plane the beginning (BH) is the shallowest depth sample in any ping in which the school was detected and the end (EH) is the deepest sample. The horizontal school position (SP$\text{dep}$) is defined as the mean of BH and EH.

**Morphometric parameters (SM$\text{subscript}$)**

1. School Height (SM$V$): The distance (number of pixels $P_h$ between BH and EH expressed in meters;
2. School Width (SM$W$): The distance (number of pixels $P_w$ between BV and EV expressed in meters;
3. School cross sectional area (SM$csa$): $P_{csa}$ multiplied by the total number of pixels in the school ($P_{tot}$);
4. Centre of rotation: Three values:
   i. Mean latitude of all samples in the school (SM$cr$-lat);
   ii. Mean longitude of all samples in the school (SM$cr$-lon);
   iii. Mean depth of all samples in the school (SM$cr$-dep).

While these are essentially positional parameters, they are included under morphometric because they are an expression of the deviation of the actual shape from an ideal circle.

5. School perimeter (SM$P$): The perimeter of the school should be expressed in meters. It should be remembered that the pixels (i.e. the samples) have different vertical and horizontal dimensions ($P_h$ and $P_w$). The image processing system used is expected to be able to produce an outline description. This will usually be a series of x and y coordinates of successive pixels around the perimeter of the school. The procedure should then be to define an algorithm to "walk" around the perimeter pixel centre by pixel centre. Choosing a starting pixel, the algorithm will then look for the next pixel, and calculate the x and y displacement to that pixel. If the displacement is in only one direction (x or y) the perimeter value is incremented by the appropriate value ($P_h$ in the x axis and $P_w$ in the y axis). If the displacement is in both directions (i.e. diagonal), the perimeter value should be incremented by:

$$val = \sqrt{(P_h^2 + P_w^2)}$$

This procedure should then be continued for all perimeter pixels. A perimeter pixel can be defined as one that has at least one edge on the outside of the school (see Figure 4.1.).

$$val = \sqrt{(P_x^2 * P_h^2 + P_y^2 * P_w^2)}$$
1. Roughness of the school perimeter (SMr): This is expressed as the Coefficient of Variation (CV) of the distance in all directions between a perimeter sample and the centre of rotation. As in the perimeter value calculations, each distance should be calculated using: the horizontal and vertical dimensions of the pixels (P_h and P_v) and the x and y displacement in pixels (P_x and P_y) between a perimeter sample and the centre of rotation, using the relationship:

$$ SM_{r} = CV $$

A schematic of these measurements is presented in Figure 4.1.

Energetic parameters (SE_{subscript})

1. The total acoustic energy from the school (SE_{tot}): Calculated from:

$$ SE_{tot} = \sum PE_i $$

Where: PE_i is the energy from the i^{th} pixel. NB. All system calibrations should be applied prior to this stage.

2. The average pixel energy value (SE_{av}): Calculated from:

$$ SE_{av} = \frac{\sum PE_i}{P_{tot}} $$

3. The variability in the pixel energy values within the school SE_{cv}: Calculated as the CV;

4. Centre of mass: again, as in the calculations for the centre of rotation, these parameters are expressed as positional data (latitude, longitude, and depth of the school). These data can be compared to the positional data (SP_{lat}, SP_{lon} and SP_{dep}) and to the centre of rotation data (SM_{cr-lat}, SM_{cr-lon} and SM_{cr-dep}). The centre of mass is calculated as weighted average of the latitude, longitude, and depth of all the pixels in a school. The weighting is by the energy of each pixel relative to the total.

Mean latitude of all samples in the school (SE_{cm-lat})

Mean longitude of all samples in the school (SE_{cm-lon})

Mean depth of all samples in the school (SE_{cm-dep})

$$ SE_{cm-lat} = \sum_i \left( PE_i \cdot PP_{cm} \right) $$

$$ SE_{cm-lon} = \sum_i \left( PE_i \cdot PP_{cm} \right) $$

$$ SE_{cm-dep} = \sum_i \left( PE_i \cdot PP_{cm} \right) $$

Figure 4.1. Schematic representation of a typical school. BH and EH are the horizontal beginning and end. BV and EV are the vertical beginning and end. SMh is the height and SMw is the width. The dotted line is the perimeter as described in the text. The radial lines represent the distances from the geometric centre (black circle) to all the perimeter pixels used to calculate the perimeter roughness.
Figure 4.2. A single herring school from an acoustic survey identified in the image processing system. The table on the right gives the descriptors calculated for this school.

where:

\( SE_{\text{cm-lat}} \) = the mean weighted latitude of the school.

\( PP_i \) = the mean weighted latitude of the \( i \)th pixel

The same calculations can be performed for longitude and depth.

School Environment (SD subscript)

1. Minimum depth of the seabed under the school (SD\text{min});
2. Maximum depth of the seabed under the school (SD\text{max}).
Biological parameters

Biological parameters cannot be extracted by the image analysis procedure. However, in many implementations, it is possible to tag individual schools as belonging to a particular species or species assemblage. This will depend on the information available to the researcher and their understanding of the fish distribution and biology. Under special circumstances the researcher may also be able to tag schools as belonging to a particular age or length class of a species. We feel that, in general, biological parameters are best dealt with in this type of analysis at a wider spatial scale, either at EDSU or regional levels.

An example of the output from this analysis approach is presented in Figure 4.2. The school itself (outlined in black) is shown on the left and the parameters extracted for this school are given in the table on the right. Some of the parameters are presented as pixels (x and y coordinates in the image) to allow direct comparison. In normal practice the horizontal values would be converted to latitude and longitude for archiving. Examples of the type of output for complete surveys are presented in Figure 4.3. School databases were extracted for herring from four acoustic surveys in the northern North Sea, and the cumulative frequency distribution of four descriptors are presented here. A fuller analyses of these data is presented in Aukland and Reid (1998).

4.2.2 EDSU level parameters

The elementary distance sampling unit or EDSU is the distance (time) over which acoustic data are integrated to form a single sample (MacLennan and Simmonds 1993). Many potential data sources which are difficult or impossible to express at the school level may be better presented at the EDSU level. Each individual school can be easily associated with an EDSU by means of time, date and position.

Again these fall into a series of categories:

1) Position;
2) Energy;
3) Hydrography;
4) Acoustic typology;
5) Sea Bed.
Positional parameters

1) Date and time: at the centre of the EDSU if possible;
2) Vessel Log: number of elapsed miles along survey track: at the centre of the EDSU if possible;
3) Latitude: at the centre of the EDSU if possible;
4) Longitude: at the centre of the EDSU if possible.

Energetic parameters

At the simplest level, this would be the total echo-integral for the whole water column across the EDSU. With some systems (e.g. SIMRAD EK500) it may be possible to divide the integral into sub-categories (e.g. the echo integrals from fish (either total or by species) or from plankton). It may also be possible to subdivide these into depth layers e.g. the echo-integral from fish in a layer 100–200m. The decision on how detailed such sub-categorisation should be will depend on the particular situation. As a minimum we would recommend that a total integral subdivided between plankton and fish be included where possible. This should allow the comparison between schools from different areas dependent on the local fish or plankton backscatter.

Hydrographic parameters

Research vessels will normally record sea surface temperatures and salinities (SST and SSS) under way during the survey. The mean SST and SSS should be recorded for each EDSU.

Acoustic typology

Many details of the fish or plankton within an EDSU will be lost if the data acquisition is restricted to only those schools which are picked up and retained by the image analysis process. Some aggregation patterns will also not be amenable to image processing systems, e.g. long continuous layers. We would recommend that the EDSU be manually assigned based on visual examination of the echogram. Where such data are not available, this value could be the average of these values across the whole EDSU. To record the depth ping by ping, this should be the average of these values across the whole EDSU. Where the echo sounder is able to record the depth ping by ping, this should be the average of these values across the whole EDSU.

1. Scattered fish: EDSU characterised by large numbers of single fish echoes where the fish are not aggregated into structures;
2. Fish in schools: EDSU characterised by a number of discrete and identifiable schools. This information can come directly from the school database described above. Instead of a binary factor this could be recorded as the number of schools in that particular EDSU;
3. Fish in aggregations: in some echograms fish can be seen to form into loose aggregations, which are difficult or impossible to define using the IA approach. These are often diffuse and of a fairly low energy level and with pixel S_v values close to the recording threshold. Such aggregations are often described as "clouds";
4. Fish in pelagic layers: these are often fairly dense layers of fish in mid-water which can continue for many miles. Such layers are difficult to describe using frame/image based IA systems. There are often apparent small breaks in such layers. We feel that such structures, even if they can be handled as a series of separate schools are best seen as a layer structure. In this context it should be remembered that the echogram is effectively a slice through the water column. A layer, even if it has occasional breaks, is probably best represented in three dimensions as more like a pancake with occasional holes through it. The breaks do not represent separations between discrete groups but thinner, less dense, areas of the overall structure;
5. Fish in demersal layers: these can be considered as similar to the pelagic layers but occur close to, or in contact with the seabed. The same arguments about spatial continuity hold for demersal as for pelagic layers;
6. Other: we have attempted to define the major aggregation patterns experienced by this group of authors; however, it is inevitable that other patterns exist and they should be incorporated in this part of the database.

Sea bed parameters

The topography and substrate structure of the seabed is well known to have an important effect on the local spatial distribution of fish, particularly demersal or semi-demersal species. The EDSU can be characterised in a number of ways:

1. Water depth: Expressed as the average depth of the seabed in the EDSU. Where the echo sounder is able to record the depth ping by ping, this should be the average of these values across the whole EDSU. Where such data are not available, this value could be manually assigned based on visual examination of the echogram.
2. Topography of the seabed: This is an expression of how variable the seabed appears in this particular EDSU. There are four categories:

   Flat: generally continuous - with little or no change;
   Undulating: characterised by relatively small changes over the EDSU;
   Bumpy: characterised by more marked changes over the EDSU;
   Spikes: characterised by rapid and dramatic changes in depth over the EDSU.

These descriptions are obviously highly subjective, and have been restricted four categories for this reason. The first and last represent the extremes, and
the other two the transitional state. If depth data were available on a ping basis, it would be possible to include a CV value of the seabed depth as a more objective seabed roughness parameter. However, compensation for heave and roll due to weather would need to be incorporated in this calculation.

3. **Slope of the seabed:** Again this is a subjective parameter, and so we have opted for three categories: flat, medium, and steep. These should be defined in terms of the range of slopes encountered during the surveys to be studied. In combination with the roughness parameter, this should adequately express a useful range of different types of seabed.

4. **Seabed substrate:** a number of acoustic instrumentation packages are now available to allow remote seabed substrate discrimination (e.g. RoxAnn Chivers et al., 1990, Schlagintweit 1993). Alternatively, visual examination of the echogram is often sufficient for the experienced user to determine if the seabed is soft or hard (i.e. mud or rock). Based on experience in both domains we would recommend four substrate categories: Soft (muds, clays and sands), medium (gravels and small stones), and hard (boulders and rock). Additionally, a mixed category should be included where more than one of these types occurs within one EDSU. Again without a well grounding truthed discrimination system, this will be a subjective interpretation, but should still prove valuable.

### 4.2.3 Strata or regionalized parameters

Some data which may be important in the understanding of fish aggregative behaviour will only be available in a regional or strata form, not at the school or EDSU level. The most obvious examples would be biological data derived from trawl hauls during the survey (e.g. species assemblage, age or length frequencies). These are effectively point data, but can be interpolated to give maps over the entire survey area. Other point sample data which may be interpolated over the entire survey area include; plankton tows and CTD (conductivity, temperature and depth) stations. Other parameters, such as satellite derived data on SST or sea colour will only be available in a synoptic mapped format. In all such cases, the requirement is to be able to give each EDSU a value based on such mapped or point data.

There are two methods for handling such data. In the first the data can be reduced to a series of strata. For example, CTD data might be used to define three types of hydrographic stratum: mixed waters, frontal zones and stratified waters, based on presence and type of thermocline. Each EDSU could then be assigned to one of these three strata. Alternatively the data could be transformed to a grid using a commercial software package such as SURFER (Golden Software, Colorado, USA). This grid could then be used as a look-up-table from the EDSU file. Each EDSU could be assigned the value at the nearest node on the grid.

The data sets which we feel are most important in the study of fish assemblage patterns are:

1. Biological, derived from trawl hauls: Presence or absence of common species, age and length compositions and maturity state;
2. Biological, derived from plankton tows: Presence or absence and abundance of major food or indicator species/taxa;
3. Hydrographic, derived from CTD stations: Presence/absence, depth and gradient of thermocline and presence/absence of major water types defined from TS profiles;
4. Hydrographic, derived from satellite data: SST and ocean colour;
5. Meterological, derived from vessel log or weather service maps. Occasionally this type of data may be available at the EDSU level;
6. Anthropogenic: Fishing activity and exploitation information;
7. Seabed substrate: derived from hydrographic service maps.

4.3 Discussion

The aim of the present chapter is to provide users and potential users of image processing systems for application to echogram data with a standard and simple framework (set of descriptors), which should allow a direct comparison of results from different species and situations. The aim is emphatically not to constrain innovation in the field. The image processing technology and/or software used and the application of specific algorithms are deliberately not covered here. The potential user can either design his or her own algorithms and programmes or can build an application based on commercially available software packages. There is a wide range of appropriate packages available, and trial versions are often available over the World Wide Web.

The parameters described here are not exclusive. At the school level, a restricted set of parameters has been chosen. The choice was made to provide as wide a range of descriptors as possible (i.e. covering as many aspects of the school as possible) while avoiding those which were likely to be correlated. Ease of extraction and calculation was also a criterion. In our experience to date, usable school descriptors are largely restricted to shape and energy plus positional parameters. Furthermore, there is a strong tendency for parameters within these categories to be strongly correlated. So, a wider school will also tend to be taller and have a greater area and perimeter. It will also tend to have a more complex shape. This conclusion is borne out by analyses of school descriptors using Principle Component Analysis - PCA - (for an example see Nero et al., 1990). The first component is generally a collection of morphometric criteria, and the second a collection of energetic criteria. Within each of these general categories it is possible to define a range of descriptors from simple to complex. Simple descriptors include: height, length, area etc and total, mean and peak energy. Complex shape descriptors include fractal dimension (Nero et al., 1993; Harabolous and Georgakarakos, 1993) and perimeter roughness. Essentially, these descriptors are designed to parameterise shape further than simple dimensional descriptors (height, width etc.). Complex energetic descriptors include: pixel CV, acoustic roughness, kurtosis, skewness, standardised peak to trough distance (SPT) and mean distance between voltage peaks (PP) (Rose and Leggett, 1988; Nero and Magnuson, 1989; Nero et al., 1993). These descriptors are designed to parameterise the internal structure of the school. In the interest of simplicity and standardisation, we have chosen perimeter roughness and pixel CV, but it seems probable that all these parameters will adequately describe shape and structure complexity, and we do not intend to imply any judgement on other possible choices. The main difficulty with these complex descriptors is that they are all likely to work well with large schools (e.g. Figure 4.3) but are likely to become increasingly invalid with smaller schools. In the studies illustrated in Figure 4.4, 85% of the schools were made up of five samples or less, making the use of complex descriptors problematic.

At the EDSU and regional level, we chose those parameters which have been shown to have an effect on the distribution and behaviour of some species.

There are two main research applications for the type of school database described in this chapter; species identification and the study of aggregation patterns. For the purpose of species identification it is assumed that particular species will display a specific range of schooling behaviour patterns which are characteristic and diagnostic. This approach has been examined by Rose and Leggett (1988), Nero and Magnuson (1989), Nero et al. (1990) Richards et al. (1991), Reid and Simmonds (1993), Harabolous and Georgakarakos (1993), Diner et al. (1994) and Barange (1994). While some success has been achieved, particularly where only a few species are involved (Richards et al., 1991), there can also be considerable difficulties (Scalabrin et al., 1996). The second main application is for the study of fish aggregation patterns themselves. In this approach the fish schools are assigned to species (where possible) based on trawl hauls and the operators experience. The main interest is then in how the schools themselves vary under different oceanographic, biological or anthropogenic scenarios. Examples of this type of approach include; relationships to seabed topography (Richards et al., 1991); spatial and temporal variability (Scalabrin and Masse, 1993); relationships to environmental parameters (Swartzman et al., 1995 and Swartzman, 1997); variation according to species present (Masse et al., 1996); and variations with time of day and water depth (Petitgas and Levenez, 1996). The impact of commercial exploitation activities on aggregative behaviour has not been well documented, however, see Potier et al. (1997). There are numerous anecdotal reports of fish schools being broken up by fishing and remaining so for some time afterwards. Some anecdotal evidence suggests that fish schools of a particular species are chronically smaller and more scattered in areas of high exploitation as compared to adjacent, less exploited areas.

As well as the structures, positions, etc. of the schools, it is important to consider how the schools themselves aggregate or cluster in space, and how this, in turn, is effected by external parameters. There are good arguments to suggest that clusters can be seen as the functional level of fish aggregation as schools can break and coalesce, but clusters may stay together for longer periods (Petitgas and Levenez, 1996; Swartzman, 1997).
An important aspect, from the point of view of fisheries management, is the relationship between aggregation patterns and the state of the stock at both the school and the cluster levels. As a particular stock increases or decreases, one would expect concomitant changes in the fish distribution and aggregation patterns. McCall (1990) has proposed the "basin" effect where fish would concentrate in preferred areas at low stock levels and spread out as the stock increases. This raises the question of what, if any, effects occur at the smaller spatial scales. Do schools become smaller or further apart at lower stock sizes, or does the "basin" effect mean that the aggregation patterns stay the same but over a narrower area? These questions have implications for both commercial fishing activity and for assessment surveys, as catchability (i.e. chance of encounter) will depend on the aggregation patterns.

In the image processing parts of this chapter we have considered only the extraction of school shape and energy parameters from the echograms as they have been collected. It is important to understand that the image as seen on the echogram is not a true representation of the actual school. Firstly, the image is best considered as a two-dimensional slice through a particular school, and not the whole school. However, given a reasonable number of sampled schools it is reasonable to assume that we have a representation of the variability in size, shape etc. of the real population of schools. Additionally, this slice is likely to cut across the school away from its centre. This would tend to bias the observed school dimensions, giving smaller widths and heights than the actual school. It is possible to apply a correction for this bias, given that the schools are assumed to be cylindrical (Reid and Simmonds, 1993). The second main problem lies in the acoustic instrumentation used to observe the schools. Each sample (or pixel on the image) is derived from a volume of water and not a point. This sample volume will increase with depth as the beam spreads. This has the effect of making a school appear wider on the echogram the deeper it is observed (Reid and Simmonds 1993). In turn, the scale of this bias will depend on the volume backscattering strength ($SV$) of the observed school. The higher the $SV$ the wider the effective beam angle of the transducer. Bias corrections for this have been suggested by Reid and Simmonds (1993), Kieser et al. (1993), and in this volume (see chapter 3). A further problem lies in the threshold values chosen by the operator to analyse and view the echogram. Many echosounder systems e.g. SIMRAD EK500 can collect samples down to a value of -100dB. Clearly what is seen by an image processing system as a school will depend on the threshold chosen, the lower the threshold the larger the perceived school. It is not our intention to examine these question here, however, it is important to understand that the observed characteristics of fish schools on echograms have inherent biases due to the system design. Simulation and modelling studies addressing this question are presented in section 4.

The final question to be addressed is "what is a school?". This is a topic of intense debate both among behavioural biologists as well as those working with acoustic data. We believe it is impossible to resolve. For the purposes of this type of study we have chosen to define the "acoustic school". This is not necessarily the real school, but is the representation of that assemblage as seen on the echo sounder. The best definition we have seen was given by Kieser et al. (1993) as "an acoustically unresolved, multiple fish aggregation".

Given the problems described above, the question must arise to how useful shape, size and energy parameters are when extracted from digitised echogram data. The answer to this question largely depends on the questions the researcher wishes to ask. The parameter values collected will contain substantial and currently unknown biases: however, it is our view that they can still be regarded as reasonable correlates of the genuine school values. Provided that the equipment, system settings, and image analysis parameters are kept constant, and that appropriate steps are taken to reduce the known biases, we believe that useful information can be derived on the variability of aggregation behaviour. If the researcher wishes to draw inferences about the exact dimensions of fish schools, then the data should be treated with caution.

In conclusion, this chapter presents a proposed standard approach to the extraction of fish school descriptors from acoustic survey data. These standard protocols are primarily intended as a guide for new workers in the field and to allow existing workers to directly compare their results. Much of the work in this field has been directed at the identification of aggregation to species/species assemblage in the context of a specific survey series or situation, where comparison to other studies is relatively unimportant. The potential gains in the understanding of fish aggregative behaviour in the wild from being able to compare results from different species and different environments are enormous and explicitly require such a standardised approach.

### 4.4 Summary

This chapter presents a set of standard extraction parameters and protocols for the use of image analysis techniques in the processing of echo sounder data. The chapter includes parameters at the school, EDSU and regional levels. The school level parameters, which are mainly derived from the image analysis, fall into four main categories; positional, morphometric, energetic and environmental. At the sampling unit level (i.e. standard integration units, commonly 1 or 2.5 nautical miles) parameters used include: school structures, protocols for including layers and general scatter plus ancillary (e.g. environmental) variables. These variables are derived mostly from visual examination of the echogram and from ancillary data collected underway. Regional level parameters include those mapped from point samples (e.g. trawls) or which are available as maps. Each school thus has its own unique parameters and is associated with an EDSU and through that to regional data. We discuss the application of such databases to the analysis of echo surveys at a school level in relation to aggregation patterns (school, school cluster and population) and to changes in those aggregation patterns with stock biomass and exploitation pattern.
4.5 Acknowledgements

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4.6 References


5 Correction of school geometry and density: an approach based on acoustic image simulation

5.1 Introduction

For some years interest has been increasing in the use of acoustic image analysis to carry out automatic classification of detected echo-traces (Souid 1988, Scalabrin 1997). Such classification is important as it may allow direct acoustic stock evaluation, species by species, and school by school. This would be a great improvement on the classical method which produces a global biomass estimate which must be split into its different specific components, for instance by using catch results.

However, because of the restricted resolution power of the measurement tool - the vertical echo-sounder - a single image could represent a number of field situations or, alternatively, the same kind of aggregations may produce various different acoustic images according to its position. Therefore, without appropriate correction of the descriptors extracted from the acoustic image, acoustic classification could be quite inaccurate and misleading.

In the past, some authors (Olsen 1969, Johanesson & Losse 1977) have proposed school size (and size dependent) correction based only on nominal beam spreading. In practical situations, on a great number of schools, the inaccuracy of this type of correction was evident. Threshold dependency of effective detection angle has also been demonstrated (Aglen, 1978) and it appears that any correction algorithm must also take account of this parameter.

5.2 Approach to the problem

Resolution of vertical echo-sounders is defined by its confusion volume, which is determined by the pulse duration and, at a given depth, by the beam width. As the acoustic sampling unit is a volume that may be relatively large compared to the size of fish schools; the processed acoustic image of a school is a poor representation of its actual size, shape and density. The vertical echo-sounder acts like a distortion filter with the result that:

- the section length of the school image is increased by a value depending on the basic angle value of the directivity function of the echosounder but also on the school depth (Figure 5.1);
- the average fish density computed from the acoustic school image is systematically underestimated. Intensity values from pings at the beginning and end of the school detection (where confusion volumes are not entirely filled up with fish) are used together with those of pings from the centre of the school (where the sampling volume is fully occupied by the target) to compute the average density.

Of course, other descriptors like area, perimeter and energy, which are correlated to length and density, may also be affected by similar systematic errors or bias.

![Figure 5.1. Echo-traces of the same school - length : 20 m and Rv : - 35 dB - at different depths (30, 80, 130 and 180 m) for 2 nominal beam angles : 5° on the left (schools 1 to 4) and 15° on the right (schools 5 to 8). The different colour rings surrounding the traces are the reflect of lower echo levels when the school don't occupies the whole beam ("unfulfilled" pings). For 15° at depth higher than 100 m, no ping contains echo-levels (brown colour) reflecting the real volume back scattering strength of the school.](image-url)
An important factor, which must be taken into account when extracting school parameters from acoustic data, is the effective detection angle as, due to the directivity function of a transducer (Figure 5.2): (i) targets with a high Target Strength are effectively sampled with a larger beam angle and (ii) targets with a high Target Strength are also sampled by more pings.

The parameter which affects the effective detection angle is not only the school volume back-scattering strength \( R_v \), but the difference between school “VBS” and processing threshold \( S_v \).

Due to the directivity function (see Figure 5.2.), the effective detection angle varies continuously according to the difference between density and threshold. For instance, a high threshold excludes from analysis the lower amplitude values which surround the school image (see Figure 5.1) producing a decrease in the apparent school image length.

Three different angles important to this problem can be defined (Figure 5.3):

- the nominal angle, \( \theta \), which is determined by the directions for which a 6 dB attenuation (two ways) is observed compared to the on-axis sensitivity level;
- the detection angle, \( B \), which can be defined as the top angle of the cone including all the fishes contributing, at a given time, in the echo amplitude. This angle depends on the difference between the mean school density and the processing threshold;
- the “attack” angle, \( A \), defined as the angle between a vertical line, from the transducer, and another line, towards the school edge, measured at the moment when the school detection is just beginning. This happens when the number of fishes, within the acoustic beam, is high enough to produce an echo signal amplitude just above the processing threshold. The school length increase, \( dL \), is directly related to this angle:

\[
dL = 2 \times P \times \tan \left( \frac{A}{2} \right)
\]

where \( P \) is the mean school depth.

The two first angles, \( \theta \) and \( B \), depend on the directivity function of the transducer. \( B \) is also related to the difference between school back-scattering strength and processing threshold. Estimating the value of these angles seem quite straightforward. It is not really the case for the third angle which is mostly determined by fish density located in a border zone of the acoustic beam. Simulations of acoustic school images based on a priori well known configuration of schools might provide a general expression allowing to estimate the “attack” angle \( A \) by taking into account all relevant parameters.

### 5.3 Description of the acoustic simulator

A vertical echo-sounder image simulator was developed in part to explain the variability in descriptor values which are extracted from school images by the software MOVIES-B, developed over many years by IFREMER (Weill et al., 1993). The simulator software was developed for PC computer applications (Diner and Scalabrin, 1997). All the parameters required for image construction can be defined for a given simulation:

- up to 5 different species, each defined in terms of: \( TS \) to length relationship and weight/length characteristics,
- performance and settings of the echo-sounder: \( (SL+Vr) \), pulse duration, nominal beam angle, frequency, ping rate and vessel speed,
- settings for display: range, absolute threshold in dB and colour range,
up to 10 different schools, each defined in terms of: length, width and height, species (length and density), position in the water column along the vessel route (depth and distance), directly under the transducer or some meters offset. The shape of all these schools was taken as ellipsoid and the density inside the school was taken as uniform.

The software first calculates the individual $TS$ of the fish, the mean "VBS", $R_v$, the volume and the weight of each school.

Using all these parameter values, it is possible to obtain:

- an image of the real situation, displayed on the computer screen with the same scales as on the echosounder, depending on vessel speed and ping rate;
- a file (*.SBC) of almost all the school’s MOVIES-B descriptors, calculated for the real situation;
- a simulated image of the school echoes. This simulation takes in account the directivity function of the transducer (rectangular shape only) and works, step by step, according to the pulse duration for the vertical direction and to a fixed cell value in the horizontal plane;
- a file (*.MOV), in the same format as MOVIES-B (or MOVIES+) of this simulated acoustic image is also offered. This kind of file can be analysed in order to extract, from the simulated images, the MOVIES-B descriptors and allows comparison with the real descriptor values of the file *.SBC.

## 5.4 Processed simulated data

Variability in school descriptor values, extracted from acoustic images, depend on several parameters (see above), mainly: beam angle, school dimensions, density and depth.

A main set of six different schools has been defined a priori in order to perform simulations. Some other type of schools have also been studied to verify the stability of some relations against morphological parameter variation. Table 5.1 presents the characteristics of the main set of six schools with:

\[
B = f\{d(R_v - SV)\}
\]

\[
dL = 2P\tan(A/2)
\]
The depth of each school has been systematically determined to: 30, 80, 130 and 180 m. Some other schools have also been simulated to verify the stability of some relations against morphological parameter variation.

These values of school size and density have been chosen so as to include the main population of descriptors contained in the school data base gathered from data collected in the Bay of Biscay over more than 10 years.

To cover all the situations described above, four different beam widths have been simulated: 5, 7.5, 10 and 15°. The pulse duration was fixed at 1 ms and the acoustic properties.

Table 5.1. Six main school types used in the simulations.

<table>
<thead>
<tr>
<th>Type</th>
<th>L (m)</th>
<th>W (m)</th>
<th>H (m)</th>
<th>Species</th>
<th>TS (dB)</th>
<th>Rv (dB)</th>
<th>Volume (m$^3$)</th>
<th>Weight (kg)</th>
</tr>
</thead>
<tbody>
<tr>
<td>A3</td>
<td>20</td>
<td>20</td>
<td>10</td>
<td>Sardine</td>
<td>-48</td>
<td>-35</td>
<td>2096</td>
<td>896</td>
</tr>
<tr>
<td>A4</td>
<td>20</td>
<td>20</td>
<td>10</td>
<td>''</td>
<td>-45</td>
<td>-35</td>
<td>2096</td>
<td>90</td>
</tr>
<tr>
<td>B3</td>
<td>50</td>
<td>50</td>
<td>10</td>
<td>''</td>
<td>-35</td>
<td>-45</td>
<td>13100</td>
<td>5601</td>
</tr>
<tr>
<td>B4</td>
<td>50</td>
<td>50</td>
<td>10</td>
<td>''</td>
<td>-35</td>
<td>-45</td>
<td>13100</td>
<td>560</td>
</tr>
<tr>
<td>C3</td>
<td>100</td>
<td>100</td>
<td>20</td>
<td>''</td>
<td>-35</td>
<td>-45</td>
<td>104800</td>
<td>44808</td>
</tr>
<tr>
<td>C4</td>
<td>100</td>
<td>100</td>
<td>20</td>
<td>''</td>
<td>-35</td>
<td>-45</td>
<td>104800</td>
<td>4481</td>
</tr>
</tbody>
</table>

Figure 5.4. Echo-trace length for a school Lr: 50 m and Rvr: -35 dB and various dRS (30.1, 20.1, 16.1, 13.1 and 10.1 dB):
- A: versus mean school depth for a nominal angle 7.5°,
- B: versus mean beam angle for a constant depth 80 m.

Rv: "VBS" of the school.
performances have been varied so as to obtain the same echo-sounder constant in each case, which represents the acoustic performance of the equipment and is defined by the relation:

$$C_s = \left( (SL + V_r) + 10\log \psi + 10\log \frac{C \tau}{2} \right)$$

with:

- $(SL + V_r)$: source level plus voltage response
- $10\log \psi$: equivalent beam angle
- $\tau$: pulse duration
- $c$: sound velocity

Vessel speed and ping rate were fixed respectively at "5 knots-2 pings/sec" for ranges down to 100 m and "2.5 knots-1 ping/sec" for ranges between 100 and 200 m.

These settings give a constant inter-ping distance, $e$, of 1.3 m.

Every simulated image has been processed using MOVIESB, over a range of processing threshold values, $\delta v$, of:

-65.1, -55.1, -51.1, -48.1, -45.1, -41.1, -38.1 and -35.1 dB.

These values, combined with the "VBS", $R_v$, of the different schools, give possible differences "$dRS = R_v - S_v$" of:

30.1, 20.1, 16.1, 13.1, 10.1, 6.1, 3.1 and 0.1 dB.

The maximum $dRS$ value studied is thus 30.1 dB. Higher values appears not sensible to use because, if considering the directivity function (see Figure 5.2.), it

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Figure 5.5. Echo-trace volume back scattering strength, $R_{vi}$, for same school and various $dRS$ as Figure 5.4:

- **A**: versus mean school depth for a nominal angle of 7.5°
- **B**: versus nominal beam angle at a constant depth of 80 m.

could induce detection angles high enough to include the secondary lobes.

A major data set (more than 700 school situations) has thus been generated giving a good idea of the scale of variability. For example, substantial changes can be seen in both the acoustic image school length and in the reverberation index (Figures 5.4 and 5.5). This is dependent on beam width, school depth, but also of $dRS$, which appears to be a key parameter when corrections of the descriptors are required.

5.5 Problem analysis

The complexity of the problem required that many parameters be taken into account. This results in a large amount of data of various types, from which it became quite difficult to extract general relationships.

As the $dRS$ difference is one of the keys and as the threshold $Sv$ is known, it is possible to focus on the parameter $Rv$. The bias present for this descriptor as extracted from the school image, is related to the ratio between fulfilled and unfulfilled pings, i.e. the school length compared to the beam width. A standardisation of the image length by the beam width at the school depth allows the possibility of processing all the data together whatever the school length and depth or the nominal beam opening. Establishing general variation laws then easier by using the normalised school dimension in terms of beam-width number, $NB$

This data set gives the evidence of a close relation between the angles $A$ and $B$ and the "key" $dRS$ values. It is particularly evident when using $Rv$, true "VBS" of the considered school when calculating $dRS$. However, it is only the image value, $Rvi$, which can be extracted from the echo-traces, and this parameter is known with a systematic bias.

It is the reason for which an approach composed of three main steps has been considered:

- **Step 1**: determine, with the highest possible accuracy, a temporary value $Rvp$ for "VBS". This leads the possibility of computing a first detection angle $Bp$, used for calculating the number of beam-width, $NBp$, corresponding to the school image;
- **Step 2**: computation of the "attack" angle $A$ that allows the definitive corrections of the school length and reverberation index;
- **Step 3**: corrections concerning area, perimeter and energy are then be processed.

5.6 Suggested algorithm

Algorithm expressions might include the following subscripts:

- "$r$": for the parameter values of the real school as defined for the simulation,
- "$i$": for the values concerning descriptors extracted

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- "$r$": for the parameter values of the real school as defined for the simulation,
- "$i$": for the values concerning descriptors extracted
directly from the acoustic image,
"c": for descriptor values after correction,
"p": for temporary values appearing only in the first phase of the algorithm.

**Step 1:**

a - Calculation of the difference: \[ dRS_i = R_{Vi} - S_v \]

b - Calculation of a detection angle:

\[ B_i = 0.44 \times \theta \times (dRS_i)^{0.45} \]

Figure 5.7. Graph of dRVi versus \(N_{Bi}\). The function \(d(\text{RV}_i) = f(N_{Bi})\) allows the calculation of a first correction for the volume back scattering strength of the echo-traces.

Figure 5.8. Plot of the different mean points, for each studied school, of the ratio attack on nominal angles (A/\(\theta\)) versus dRS. The function \(A/\theta = f(dRS)\) allows the calculation of the attack angle. The relation giving the ratio of detection angle on nominal one (B/\(\theta\)) is plotted for comparison.
This relation is in fact an approximate inverse relation of the directivity function of the transducer. It fits quite well with the true function for attenuation range between 0 and 30 dB, which are those concerned by the present study (Figure 5.6).

c - Calculation of a normalised length in terms of beam width number:
\[
N_{Bi} = \frac{L_i}{2 \times P_i \times \tan(B_i/2)}
\]
where \(P_i\) is the mean depth of the echo-trace.

d - Calculation of a raw correction for the image "VBS" (Figure 5.7):
\[
dRv_i = \frac{2.56}{(N_{Bi} - 1)}
\]
This relationship has been derived by processing the parameters \(N_{Bi}\) and \(dRv_i\) for all the simulated data (all schools and beams at any depths) There is an asymptotic value of 1 for \(N_{Bi}\).

e - Calculation of a temporary "VBS":
\[
Rv_p = Rv_i + dRv_i
\]

f - Calculation of the corresponding difference:
\[
dRS_p = Rv_p - Sv
\]

Step 2:

a - Computation of the "attack" angle (Figure 5.8):
\[
A_C = \theta \times \left[ 1.04 \times (dRS_p)^{0.33} - 1.52 \right]
\]
As for \(dRv_i\), this attack angle relation is the result of a processing on all the simulated data.

This relation gives a 0° angle when \(dRS_p\) value is equal to 3.18 dB, which means that the school then occupies a little bit less than half of the acoustic beam. This looks realistic as, at this particular point, the transducer is just on the vertical line of the school edge.

b - School length correction :
\[
L_c = L_i - 2 \times P_i \times \tan\left(\frac{A_c}{2}\right)
\]
This angular correction becomes very important when school depths and difference, \(dRS\), are high (Figure 5.9). In some cases when the \(dRS\) value is lower than 3.18 dB, the angle \(A\) becomes negative and the school image length is smaller than the true length.

e - Calculation of a new normalised school length in term of beam width:

Figure 5.9. Length increase, \(dL\), versus depth of echo-trace image for a nominal angle 7.5° and \(dRS\) 1, 3, 10, 20 and 30 dB, calculated by using the attack angle. For \(dRS < 3.2\), the image length is smaller than the real one.
In this step, the attack angle, which is known, has been used instead of the detection angle $B$. It would seem preferable as it allows, for a specific school, a better ratio between fulfilled and unfulfilled pings, a ratio which directly influences the bias of $R_v$.

d - New correction of the "VBS":

$$dR_v = \frac{4.09}{(NBc)^{0.88}}$$

by the updated relation, which was established using the whole simulated data set (Figure 5.10). For negative values of the angle $A_c$ when $dR_S$ is less than 3.18 dB, $N_{bc}$ is also negative and the calculation of $dR_v$ becomes impossible. It can be observed that, in this special case due to low values for $dRS$, the $R_v$ values are very close to the true one and no correction is required.

e - Calculation of the corrected "VBS":

$$R_{vc} = R_{vi} + \Delta R_{vc}$$

Step 3:

a - Correction of the height: $H_c = H_i - \frac{ct}{2}$

b - Correction of the surface: $S_c = S_i \times \frac{L_c \times H_c}{L_i \times H_i}$

c - Correction of the perimeter: $P_{rc} = P_{ri} \frac{L_c + H_c}{L_i + H_i}$

d - Calculation of the corrected energy:

$$E_{nc} = E_{ni} \times \frac{S_c}{S_i} \times 10^\left(\frac{dR_{vc}}{10}\right)$$

This relation is established taking in account that the school energy is the product of its surface by a factor equivalent to the square mean amplitude, term equal to the antilog of the "VBS" $R_v$.

5.7 Results and limitations

By operating this algorithm on the image descriptors of the set of simulated schools it appears that:

- the final corrected values for length are very close to the true values: relative errors less than 2% are very common, this correction being independent of nominal beam angle or school depth. A slight variation (c. 1%) is observed according to the nominal $dR_S$ value (Figure 5.11). However, significant errors can appear when the school size, expressed in terms...
Figure 5.11. Echo-trace lengths and corresponding corrected values (doted lines) for various dRS:

- **A**: versus mean school depth for a nominal angle 7.5° and school L: 20 m and Rv: -35 dB,
- **B**: versus nominal beam angle for a constant depth 80 m and the same school as in "A",
- **C**: versus school depth for a nominal angle 7.5° and school L: 50 m and Rv: -45 dB. In this last example, a "3 dB" dRS produces echo-trace lengths very close to the real ones; for dRS: 0.1 dB, the attack angle is negative, the echo-trace lengths are less than the real ones, but the corrected values are not so different from the true one.
Figure 5.12. Same legend as on Figure 5.10 but for volume back scattering strength Rv. For greater depths (e.g. 180 m), there are still some significant errors on the corrected values for the "20 m" school ("A" and "B"). When the "attack" angle is negative, (dRS: 0.1dB in "C"), the image values are not substantially different from the true ones, and there will be negligible impact if correction is not possible.
of beam width, gets smaller. This point is explored in more detail later;
- the corrected "VBS" values, \( R_v \), are very close to the true values: differences were less than 0.3 dB in most of the studied cases. However, as with the school length, increasing errors were observed when the school size became smaller (Figure 5.12).
- with regard to area and perimeter, larger errors were obtained (Figure 5.13). This seems to be due to the method of computation of these descriptors by MOVIES-B. For the energy errors, which result from the sum of the errors on surface and reverberation indices, the results are not at the level of those observed for length and index (Figure 5.14). Thus, it would be better to use the uncorrected values which are probably more accurate.

The limitations of these types of corrections have also been studied, as follows. Simulations were carried out using another school, which was smaller than those studied above. The main characteristics of this school were:

\[
\begin{align*}
L: 14 \text{ m} & \quad W: 20 \text{ m} & \quad H: 6 \text{ m} & \quad R_v: -35 \text{ dB}
\end{align*}
\]

Simulations have been done with the same echo-sounder parameters and then processing, by MOVIESB, with the same thresholds as above. This school was placed at 20m depth intervals between 20 and 180 m (Figure 5.15). For a nominal angle of 5°, the parameters of this school are quite well corrected for all depths \( P \). However, in the case of a nominal angle 10° and a \( dRS \) of 6.1 dB, the algorithm gives inaccurate corrections for depths greater than 140 m. For high \( dRS \) values and wide beam angle, for example 30 dB and 15°, the corrections
become inaccurate for depths over 100 m. Expressed in terms of beam width, the limitations of this algorithm can be seen more clearly in Figure 5.16. Thus, the limitation for using this algorithm appears to be for schools whose relative dimension of $N_B$ is approximately equal to 1.5. The practical impact of this limit on the length of the echo-traces is illustrated for a 7.5° nominal beam angle in Figure 5.17.

The detection and attack angles defined above are directly dependent on the difference between school "VBS" and processing threshold, $d_{RS}$. While the threshold, determined by the operator, is well known, it is not the case of "VBS". Only an image based value of this parameter is known. This value can be subject to substantial errors (e.g. low $N_B$ values). It appears thus interesting to calculate the error induced for the angle $A$ value by a "1" dB systematic error in determining $R_v$. This has been studied for $d_{RS}$ values between 0 and 30 dB (Figure 5.18).

Roughly speaking, when $d_{RS}$ is less than 3 dB, the angular error increases rapidly: in this case only the central part of the acoustic beam being involved, the angle values are small and the relative error becomes more important. Inversely, for $d_{RS}$ values between 10 and 30 dB, the angular errors are reduced. This seems thus the best field to operate analysis on school descriptors. As the average $R_v$ of the schools encountered in open sea seems to stand between -45 and -35 dB, a threshold value of -60 or -65 dB will give the best chance of precision.

The simulated images, studied above, have been obtained by using a constant ping interval, $e$, of 1.3 m (see Section 4.2). This ping interval effect may also affect the image length by supplementary errors as this length is determined at $\pm e$. This parameter can be computed by:

$$e = \frac{1852 \times V_v}{3600 \times p}$$

with:

$V_v$: vessel speed in knots
$p$: ping rate in number per second.

Typically this means an error of $\pm 5.1$ m when, for instance, the vessel speed is 10 knots, in 200m of water and with a ping rate 1/sec. The variation in school length on the echo-trace is equal to the ping interval. Of course, the relative supplementary error that will affect the length decreases with depth for the image. However, after correction by the algorithm, the error in school length, is approximately the same as the relative ping error compared to the real school length (Figure 5.19). Concerning, volume back scattering strength, a combined effect of length variation of echo-trace and relative small dimension of school (low $N_B$ values) may increase the variation of the corrected $R_v$.

![Eni and Enc = f(Depth) for various dRS and nominal angle 7.5°](image)

Figure 5.14. For a school length 20 m and $R_v$: -35 dB, it appears great differences for the image energies. The corrected values (dotted lines) are worst than the image ones.
Figure 5.15. Length and volume back scattering strength for a school of relatively small dimension compared to the beam width, simulated using dRS of:

- 30 dB in "A" for school length,
- 6 dB in "B" for volume back-scattering strength.

When the beam is too large compared to the school length, the accuracy of the corrections is reduced.

- for $N_b$ values above 2, $R_v$ is corrected with differences less than 0.5 dB and the maximum relative error for length is 10%,
- for $N_b$ values under 2, these error levels increase rapidly. There is an asymptotic value for $N_b$ equal to 1.
Figure 5.16. Plot of many values of the differences $dR_{vc} (R_{vc} - R_{v})$ and of school length relative errors, $dL_{c}$, (in %) versus $N_{bi}$. For $N_{bi}$ above 2, the errors are generally low. Under 1.5, an important increase of inaccuracy is observed for corrected values. There is an asymptotic value for $N_{bi} = 1$ and 1.5 seems the lower acceptable limit for operating the proposed correction algorithm.

Figure 5.17. Length limit of echo-traces versus depth, corresponding to a value 1.5 for $N_{bi}$ and for a nominal angle 7.5°. For an accurate algorithm correction, a school length must be at least:

- 20 m at 50 m depth for $dRS$ 30 dB,
- 80 m at 200 m depth for $dRS$ 30 dB,
- 24 m at 100 m depth for $dRS$ 10 dB,
- 9 m at 100 m depth for $dRS$ 1 dB.
Figure 5.18. Error on the attack detection angle, “A” versus dRS for a constant potential error of 1 dB when determining the difference dRS. Curves are plotted for 2 nominal angles: 5° and 15°. The errors are minimal for dRS values above # 10 dB: in this part of the transducer directivity function, a given variation of dRS induces a minimum angle change.
Figure 5.19. Effect of ping interval on length and volume back scattering strength of school echo-traces (image and corrected). These results are for 2 schools - 20 and 50 m length with Rv : -40 dB - simulated at vessel speed of 2, 6 and 12 knots (e : 1.0, 3.1 and 6.2 m) and then processed with a dRS : 16.4 dB. It appears that:

- in "A" for length : the maximum variation on school length increases with vessel speed and is approximately equal to the ping interval. This variation is the same after correction by the algorithm even if, for the smaller school (20 m) at great depth (180 m), the correction accuracy is decreasing.

- In "B" for back scattering strength: speed and depth result in additional inaccuracy in corrected values, especially for the smaller school.
5.8 Discussion

By using acoustic image simulation, which allows the comparison of descriptor values extracted from acoustic images and real situations, it has been possible to produce an algorithm for correcting many parameters whose errors are mainly due to the beam pattern effect.

However, the databases used to develop the correction algorithm were composed of idealised schools with a single shape (ellipsoid) and furthermore with a uniform density. This is certainly not a perfect reflection of the field situation echo-trace shape and internal density can vary widely.

The simulation takes account of the directivity function of the transducer, which is required to obtain precise information on the different detection angles. However, only rectangular transducers have been used thus far for image simulation. In the case of circular transducers, there are some differences, for instance for the nominal angle, which would be slightly larger, or for the secondary lobe level, about 4 dB lower. However, it seems unlikely that this has a major impact on the main conclusions of this work and the proposed algorithm.

The energy descriptor of the schools can be considered as the product of school area by mean squared echo amplitude. For this parameter the proposed corrections do not appear to be very efficient. This is mainly due to the cumulative effect of errors in the correction of both area and Rv. In all cases, it does not appear to be necessary to correct the image energy value. It must be emphasised that this kind of descriptor, concerning only a school of limited dimensions, must be considered differently to the same kind of parameter calculated for the purpose of echo-integration and stock evaluation. In this case, there is no evaluation bias as it is only a sampling of the water column that is done.

Nevertheless, if the school image dimensions are large enough compared to the beam width (Nbi ≥ 1.5), the proposed algorithm gives corrected descriptor values with low relative errors. Any classification based on school morphological or energetic descriptors will be improved if this type of correction is undertaken first. Indeed, depending for instance on echo-sounder characteristics or school depth, there may be a very important difference between image and real values (cf. Figure 5.9). School image length increase with depth may be very important: for example up to 40 m at 200 m with a dRS of 30 dB and a nominal beam angle of 7.5°. Without any previous correction, it would be difficult to compare different echo-traces and to carry out advanced ETC.

It is also recommended to use processing threshold values high enough to avoid possible detection through the side lobes. However this settings must be determined for obtaining dRS values greater than 10 dB. Thresholds between -60 and -65 dB seem adapted at least for school "VBS" values commonly encountered in the Bay of Biscay.

5.9 Corrections on the school geometry and density descriptors: use of the algorithm on real detected schools

In Section 5.6, a new algorithm was described for the correction of morphometric and energetic descriptors, which can be extracted from school echo-traces obtained by vertical echosounders. This algorithm was established using simulated images to allow the accuracy of the proposed corrections be compared over a number of different scenarios. These scenarios would have been impossible to obtain in real life as the true structure of the schools would remain unknown.

Nevertheless it is clearly necessary to test this algorithm on real school detections with field data to understand the validity of the different corrections. This has been carried out following two main approaches:

- using well individualised schools, detected by the same echo-sounder. By varying the processing threshold value, it is possible to obtain various differences between volume back-scattering strength, Rv, and threshold, Sv. This difference, dRS, is a key value which has a direct impact on the effective detection angles and thus on the corrections values. Usually the corrected lengths and Rv are the same whatever the threshold;

- on schools detected simultaneously by 2 echosounders with substantially different directivity patterns.

5.9.1 School detection with one echosounder and using various processing thresholds

This first application of the algorithm concerns echo-trace data obtained with a single echo-sounder. When processing the same schools using different thresholds, we would expect the corrected values for length and volume back-scattering strength to be the same for any given school.

The data set used were sardines schools observed in the Bay of Biscay. The mean bottom depth was 35 m, the mean school depth was 22 m. The main characteristics of the echo-sounder used were:

- frequency: 38 kHz
- nominal beam angle: 8°x8°
- pulse duration: 1 m

This set of 9 schools was interesting as many of them are quite dense and present a regular shape: schools n° 1, 4, 8 or 9 for example (Figure 5.20). So they are similar to the simulated schools used when designing the correction algorithm. These were ellipsoidal and of uniform density.

The thresholds used (absolute), Sv, when extracting the school descriptors, were:

- 51 dB - 45 dB - 40 dB

-51 dB corresponds to the original digitisation threshold.
This gives a variation of dRS values between 3.8 and 20 dB.

The limitations of the algorithm are given by the school length relative to the beam width - $N_{Bi}$. This parameter must exceed values of (cf. Diner, 1998):

- 1 to produce the different corrections,
- 1.5 to reach an acceptable accuracy for the corrected descriptors.

For this group of schools, detected by a beam with an angle of 8°, in shallow waters, the minimum $N_{Bi}$ value was 1.8 and the maximum was 16.5.

The conditions required for accurate use of the algorithm have been achieved for these sardine schools. The results are summarised on the right part of Table 5.2 and in Figures 5.21 and 5.22 for school length and volume reverberation index $R_v$.

In general, for each school, the corrected lengths gave similar mean corrected values whatever the processing threshold. The corrected values were closer for the schools whose shapes were regular and whose density was more uniform. There were some exceptions due to major changes in the image itself, caused by the increase in the threshold:

- School n° 6 was separated into 3 different parts when using a -40 dB $Sv$ threshold,
- The shape of school n°2, which did not have a uniform internal density, was substantially changed when the threshold was increased: thus the right part of the school, which was less dense, was lost when the threshold was -40 dB.

Concerning volume backscattering reverberation, $R_v$, the results were not as satisfactory as for length. The most dispersed corrected values were observed for those schools where the corrected lengths varied the most: schools n° 7, 5, 6 and 2. As for length, the best results were observed for those schools with a regular shape and uniform internal density. It appears that the algorithm cannot compensate very well for large changes in the image $R_v$ induced by a threshold increase and change due to the removal of the low density parts of the echo-traces.

### Table 5.2. Main characteristics of the processed school echo-traces (38 kHz - 8°) and limit values of the corrections obtained for length and $R_v$.

<table>
<thead>
<tr>
<th>Thresh DB</th>
<th>Rv dB</th>
<th>DRS dB</th>
<th>Length m</th>
<th>$N_{Bi}$</th>
<th>Corrections</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>min</td>
<td>Max</td>
<td>Min</td>
<td>Max</td>
<td>Min</td>
</tr>
<tr>
<td>-51</td>
<td>-41.3</td>
<td>-31.0</td>
<td>9.7</td>
<td>20.0</td>
<td>10.6</td>
</tr>
<tr>
<td>-45</td>
<td>-39.5</td>
<td>-30.4</td>
<td>5.5</td>
<td>14.6</td>
<td>9.6</td>
</tr>
<tr>
<td>-40</td>
<td>-36.2</td>
<td>-30.0</td>
<td>3.8</td>
<td>10.0</td>
<td>5.6</td>
</tr>
</tbody>
</table>

Figure 5.20. Echogram (MOVIES+) of the sardine schools used for a first test on the algorithm. The processing threshold is here -51 dB.
Figure 5.21. Lengths of image ("Li" - continuous lines) and corresponding corrected lengths (Lc - dotted lines) for the set of sardine schools. There are 3 pairs of curves for -51 (Θ), -45 (□) and -40 dB (Ο) thresholds.

Figure 5.22. Image volume reverberation index, Rvi (continuous lines) and corresponding corrected values, Rvc (dotted lines) for the set of sardine schools for thresholds Sv: -51 (Θ), -45 (□) and -40 dB (Ο).
5.9.2 Algorithm test on data obtained simultaneously by transducers with different directivity patterns

It is possible to operate two different echosounders with different directivity patterns simultaneously without interference provided that they operate on widely spaced frequencies. This was done on R.V. THALASSA by using the following echo-sounders with the data processed simultaneously by MOVIES+:

a - Frequency: 38 kHz, Nominal beam angle: 5.7°, Pulse duration: 1 ms
b - Frequency: 12 kHz, Nominal beam angle: 16°, Pulse duration: 1 ms

The echo-traces were processed using the same absolute threshold: -60 dB.

Algorithm tests have been conducted on 2 main sets of echo-traces:

- Relatively large echo-traces, at a mean depth of 140 m (horse-mackerel)
- Smaller echo-traces at a mean depth of 45 m (sardine).

5.9.2.1 Large schools

The main difficulty in this case, working on relatively deep echo-traces, was to make sure that the same echo-traces were analysed by the two echo sounders. Due to its poor angular resolution, the 12 kHz beam (16°) tends to combine adjacent echo-traces which would appear as separated with the narrower beam (5.7°). This occurred for much of the available data, and had an important effect on the number of schools detected (Figure 5.23).

For this group of echo-traces, the main characteristics are summarised on Table 5.3.

For this reason special attention was given to selecting the echo-traces for comparison. However, for some echo-traces there were still significant length variations between 38 and 12 kHz, e.g., for schools n° 33, 28 and 41, (Figure 5.24). In Table 5.2, it can be seen that some corrections are relatively large and these often correspond to lower values of the factor NBi.

For schools at a depth of around 140 m, detected by a 16° nominal beam, the mean length correction may be as great as 40 m for a NBi value of 4. For the same echo-traces, detected with a 5.7° beam, the corresponding

<table>
<thead>
<tr>
<th>Freq.</th>
<th>Beam °</th>
<th>Rv dB</th>
<th>dRS dB</th>
<th>Length m</th>
<th>NBi</th>
<th>Corrections</th>
</tr>
</thead>
<tbody>
<tr>
<td>12</td>
<td>16</td>
<td>-53.3</td>
<td>-43.5</td>
<td>6.7</td>
<td>16.5</td>
<td>32.1 231 1.25 4.4 9.0 62.5 0.77 14.0</td>
</tr>
<tr>
<td>38</td>
<td>5.7</td>
<td>-53.7</td>
<td>-42.1</td>
<td>6.3</td>
<td>17.9</td>
<td>27.6 181 1.63 11.7 3.1 17.7 0.26 4.2</td>
</tr>
</tbody>
</table>

Figure 5.23. Comparison between echo-traces (MOVIES+) at 12 kHz-16° (top) and 38 kHz-5.7° (bottom) obtained on large echo-traces of horse-mackerel. At 12kHz, schools n° 17, 19, 25 and 29 are obviously aggregations of a number of schools seen on the upper echogram.
mean corrections are between 10 and 15 m for $N_{Bi}$ values around 5.

As in the previous examples, the corrections appear to be better for length than for $R_v$. Concerning length (Figure 5.25), corrections were good for the 2 schools in mid water, n° 16 and 14 (see Figure 5.24, "12 kHz"), and generally acceptable for the others with the exception of 31, 33 and 41. It should be noted that these last three schools were also the least uniform in internal density. Concerning $R_v$ (Figure 5.25), there were some important differences: for example more than 3 dB for schools 10, 42 and 48. The best results (giving differences between the two frequencies < 1.3 dB) were observed for the mid water echo-traces (16 and 14) and also for other, apparently inhomogeneous schools, e.g. 46, 27, 2 and 33.

**5.9.2.2 Small schools**

This type of correction becomes inaccurate when the echo-trace dimensions are small compared to the beam width (factor $N_{Bi}$). It is possible to study the validity of the corrections for the two different directivity patterns. Some schools can be processed on the 5.7° echogram as the $N_{Bi}$ number is above the limit value of 1.5 while this is not the case using the wide 16° beam. The echogram used for this part of the study is shown in Figure 5.26.

Table 5.4 gives the main characteristics of the set of echo-traces used. Here, $N_{Bi}$ numbers are generally small and, in many cases for the 16° sounder, it was not possible to use the correction algorithm.
The \( N_{\text{Bi}} \) values for schools detected with the 5.7° and 16° sounders are plotted on Figure 5.27 and some clear differences can be seen in \( N_{\text{Bi}} \) for small traces, e.g. schools 11 and 13.

Figure 5.28 shows the corrected lengths. For school n° 14b and the others on the right of the plot, where \( N_{\text{Bi}} \) was greater than 1.23 for 16° (and 1.8 for 5.7°), the correspondence between the corrected lengths is better. The limits of the algorithm can clearly be seen here. Echo-traces whose lengths were too small compared to the beam width resulted in poor corrections and these often appeared as negative lengths.

Figure 5.29 shows the corrections for volume back scattering strength \( R_v \). As for the other cases above, the corrections for this parameter were not as accurate as those made for length. For the smaller schools, it was impossible to calculate corrections for the 16° beam.

<table>
<thead>
<tr>
<th>Freq. (KHz)</th>
<th>Beam (°)</th>
<th>( R_v ) dB min</th>
<th>( R_v ) dB max</th>
<th>dRS dB min</th>
<th>dRS dB max</th>
<th>Length m min</th>
<th>Length m max</th>
<th>( N_{\text{Bi}} ) Min</th>
<th>( N_{\text{Bi}} ) Max</th>
<th>Corrections</th>
</tr>
</thead>
<tbody>
<tr>
<td>12</td>
<td>16</td>
<td>-47.7</td>
<td>-33.5</td>
<td>12.9</td>
<td>26.5</td>
<td>8.8</td>
<td>25.5</td>
<td>1.03</td>
<td>1.84</td>
<td></td>
</tr>
<tr>
<td>38</td>
<td>5.7</td>
<td>-51.8</td>
<td>-26</td>
<td>8.2</td>
<td>34.0</td>
<td>2.3</td>
<td>12.0</td>
<td>1.33</td>
<td>4.1</td>
<td>4.3 (•)</td>
</tr>
</tbody>
</table>

(•): among the schools for which corrections were possible.

5.9.3 Conclusions from real schools

This practical exercise using real echo-traces was carried out to provide an investigation of the validity of the suggested descriptor correction algorithm. It is not surprising that the corrections do not provide the same level of accuracy as that obtained with simulated data. This is mainly due to the variability encountered in the echo-traces particularly the more complex shapes and variable internal densities.

The comparison between the two very different directivity patterns - 16° and 5.7° - was not always simple as the equipment gave very different echo-traces. Nevertheless, it can be concluded that:

- It is better to use narrow beam echo-sounders: in this way a greater number of traces can be processed.
Figure 5.27. Comparison between $N_{Bi}$ values for 12 kHz-16° ($\Phi$) and 38 kHz-5.7° (□). In this last case, the narrower beam angle gives $N_{Bi}$ values greater than for 16°, which allows better corrections for length and $R_v$.

Figure 5.28. Comparison between length corrections for small schools at 12 kHz-16° ($\Phi$) and 38 kHz-5.7° (□). The schools are arranged in ascending order for a $N_{Bi}$ factor of 5.7.
with an acceptable accuracy;

- Corrections for length are generally more accurate than those for volume back scattering strength;

- It is necessary to calculate the $N_{Bi}$ value. When it is lower than 1.5, the accuracy of the algorithm is reduced. It is probably best not to apply any corrections on these schools.

5.10 References


6 Post processing tools

6.1 Introduction

The section on post processing tools is divided into conceptually distinct sections. Here we consider tools and techniques for use after the schools have been identified and a database of these and the school parameters that have been extracted. The tools can be classified into two groups:

- Tools for classification of the schools or patches into identifiable groups, such as species, functional groups etc.
- Tools for modelling, analysing or mapping the spatial distribution of the schools and relating them to external variables, with the aim of developing a more general representation of real fish distributions to help test survey design strategies and understand fish behaviour.

6.1.1 Tools for school classification

These consist of tools that attempt to place any school, based on information about its location, morphometry, energy and immediate environment into one of a predefined set of classes. To this end, they all usually require a sample of known entities, referred to as a training set. The most straightforward of these tools are cluster analysis and its derivatives (Discriminant function analysis, Classification and Regression trees, k-means clustering). The most commonly used of these methods for species classification is discriminant function analysis. Section 6.2 provides an overview of clustering techniques and a more detailed appraisal of Discriminant Function Analysis. One benefit of clustering algorithms is that they provide quantitative descriptors of the classes in terms of the external variables. A more complex, and potentially more powerful technique for school classification is artificial neural networks. These methods have few underlying assumptions, and can accommodate almost unbounded complexity (e.g. Bayesian Priors). However, the underlying model leading to the final classification is unknown and it is not possible to extract the relationship between the classes and the external parameters. An appraisal of artificial neural networks is presented in Section 6.3.

These tools can also be used in an unsupervised mode, providing groupings without basing them on predefined classes. For example, they can be used to produce classes of similar water body types and of bottom types based on measured attributes of these variables.

6.1.2 Spatial description tools

All these techniques can be used to model the spatial distribution of schools and can accommodate the effect of external parameters on this distribution. The three classes of tools presented here differ in their underlying assumptions. In point processes (see Section 6.4) the schools are treated as points in space, or more generally as points with a multivariate suite of attributes called marks. Geostatistical (see Section 6.5) methods look at the autocorrelation between values of some attribute (e.g. school area) as a function of the distance between the schools and fit an explicit model to the empirical autocorrelation (e.g. an exponential model). Generalised additive models (GAM) are a generalisation of linear regression, which models the mean of school descriptor (e.g. length) as an unspecified additive function of some of the available covariates (see Section 6.6).

In essence, point processes look for pattern in the distances between the objects and attempt to find a stochastic model, which adequately defines this pattern. Geostatistics (kriging) applies the model of autocorrelation to map the chosen attribute of the schools. GAMs are used to test hypotheses about the relationships between attributes of schools and environmental covariates.

6.2 Cluster analysis

6.2.1 Introduction

Cluster analysis is defined as: "The analysis of data with the object of finding natural groupings within the data either by hand or with the aid of a computer."

Cluster analysis involves the identification of significant sub-groupings of variable values relative to a selected dependent variable. These "Clusters" are examined at different significance levels e.g., 90%, 95%, 99%. As the significance level increases, the number of clusters generally decreases.

This type of analysis is helpful in developing segmentation strategies as well as identifying the variables that most influence the dependent variable under study. This is also referred to as Data-Mining, Fuzzy Sets or Rule-Based systems. Expert Systems are also developed with this methodology.

The automatic classification of the n row--objects of an n by m table generally produces output in one of two forms: the assignments to clusters found for the n objects; or a series of clusterings of the n objects, from the initial situation when each object may be considered a singleton cluster to the other extreme when all objects belong to one cluster. The former is non--hierarchical clustering or partitioning.

The latter is hierarchical clustering. A sequence of n-l agglomerations are needed to successively merge the two closest objects and/or clusters at each stage, so that we have a set of n (singleton) clusters, n-l clusters, 2 clusters, 1 cluster at successively higher levels of the clustering. This is usually represented by a hierarchic tree or a dendrogram, and a "slice" through the dendrogram defines a partition of the objects. Unfortunately, no rigid guideline can be indicated for deriving such a partition from a dendrogram except that large increases in cluster
criterion values (which scale the dendrogram) can indicate a partition of interest.

In carrying out the sequence of agglomerations, various criteria are feasible for defining the newly-constituted cluster: These include: minimum variance criterion, minimum variance hierarchy, single link method, complete link method, average link method, weighted average link method, median method, and centroid method.

The Minimal Spanning Tree, which is closely related to the single link method, has been used in such applications as interferogram analysis and in galaxy clustering studies. It is useful as a detector of outlying data points (i.e. anomalous objects).

A hierarchical classification method akin to clustering called Classification and regression Tress (CART) provides an underlying regression model for dealing with the splits between classes. For more information go to: http://www.pitt.edu/~csna/www.cart

### 6.2.2 Applications in fisheries

Clustering Analysis has been applied in classifying environmental conditions into similar water-body regions (Swartzman et al., 1994). They have obvious direct application to classifying fish schools into categories, providing a training set to set up the classification splits and a separate testing set to test the method against. The training set can consist of individual schools of known composition an any attributes that can be helpful in distinguishing the classes. Some examples are size parameters (e.g. area, width, height), shape parameters (e.g. eccentricity, perimeter/area, fractal dimension) backscatter parameters (e.g. average sv, variance in sv, average TS) and environmental parameters (e.g., depth, location with respect to thermocline). For hierarchical classifiers pruning the tree will produce clusters with multiple schools in them and there will be incorrect classifications. The frequency of these can be used as a measure of the probability of a correct classification. Alternatively, school clusters can be used as the basis for classification, with the advantage that multi-species school aggregations can be included. Distributions of school parameters in the cluster as well as ensemble averages can be used as parameters in the classification.

Discriminant Analysis is actually a non-hierarchical clustering method, which has been used in several classification programs with reasonable success (see Section 6.4.3. below).

One disadvantage of classification methods is their lack of use of explicit spatial information (e.g. distance from the closest "known" shoal or shoal group). An attempt is currently being (Hammond 1999, Hammond et al., 1999) to combine the parameter-based classification with information about shoal composition from trawl data, using a Monte Carlo Markov Chain model.

### 6.2.3 Discriminant Function Analysis

#### 6.2.3.1 Introduction

Discriminant Function Analysis (DFA) is a multivariate technique that can classify unknown entities (e.g. species, aggregation types) into one of a number of possible discrete groups. Classification is made on the basis of multifaceted observations (e.g. depth, density, location) of the unknown entity. The possible groups to which the entity can be allocated are themselves defined by analysing the same multifaceted observations from entities taken from known groups (“training” the classification). The unknown entity is ascribed to the group to which it is most similar.

Good descriptions of DFA, and guidelines for its application, are given by Manly (1986) and Krzanowski (1988).

#### 6.2.3.2 Fisheries/acoustics applications

DFA has been used with varying degrees of success to classify acoustic data from both fish and zooplankton aggregations into species (entity) groups. DFA is relatively simple to perform, and can be undertaken in numerous proprietary software packages (e.g. Minitab, SPSS). The technique works by calculating the distance (vector) of a single multivariate observation (comprising, for example, several characteristics derived from echo data from a school) from the means of all such observations (group centres) for each of the possible source groups (predictors, e.g. schools of several species). The single observation is then allocated to the group to the centre of which it lies closest. One commonly used measure of distance is the Mahalanobis distance (squared distance).

The greater the number of characters that can be included in the analysis (e.g. echo-strength at several frequencies, depth of school, length of school etc.), the more likely it is that the analysis will allocate an individual observation to the correct group.

<table>
<thead>
<tr>
<th>Study</th>
<th>No. of species/sizes</th>
<th>No. of characters*</th>
<th>Classification rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>Haralabous and Georgarakos (1996)</td>
<td>3 fish species</td>
<td>&gt;25 (echo / physical)</td>
<td>89% correct</td>
</tr>
<tr>
<td>Scalabrin et al. (1996)</td>
<td>3 fish species</td>
<td>9 (echo / physical)</td>
<td>57% correct</td>
</tr>
<tr>
<td>Simmonds et al. (1996)</td>
<td>5 fish species (plus 1 species at 2 sizes)</td>
<td>8 (frequency bands)</td>
<td>80% correct</td>
</tr>
<tr>
<td>Brierley et al. (1998)</td>
<td>5 zooplankton species</td>
<td>2 (echo)</td>
<td>77% correct</td>
</tr>
</tbody>
</table>

*echo = echo intensity or a derivative thereof; physical = school dimension e.g. depth, length.
A summary of the effectiveness of DFA in some recent studies of classification of fish and zooplankton echo data into species/size groups is given in Table 6.2.1 below:

Another example of the use of DFA in fisheries can be found in Rose & Legget (1988).

### 6.2.3.3 Example of a practical application

Brierley et al. (1998) collected 3 frequency (38, 120 and 200 kHz) acoustic data from essentially monospecific aggregations of five zooplankton species which were fished in the Southern Ocean. A plot of the difference in mean volume back-scattering strength at 200 and 120 kHz against the difference at 200 and 38 kHz (Figure 1 in Brierley et al., 1998) for all species revealed that the acoustic data fell into five groups that were only partially overlapping.

The data were split into 2 groups, one of which was used to train a DFA. The resulting confusion matrix (Table 6.2.2) shows that, overall, the DFA was able to classify acoustic data into species groups with a success rate of 77%.

### 6.2.3.4 Limitations

Although DFA works best with large numbers of characters, the characters must not be correlated, since this causes problems of multi-collinearity. One way to avoid this with multi-frequency data, for example, is to derive differences between frequencies and use these instead of absolute echo intensity values. This approach also serves to remove density effects from signals.

Strictly speaking discriminant function analysis requires that data sets be normally distributed, and that the within-group covariance matrix be the same for all groups. If data are not normal, then the statistical significance of any group differences cannot be established. However, effective discrimination may still be achieved even if both these conditions are violated (Manly, 1986) and, in these cases, the rate at which individuals are mis-classified can be used as a pragmatic evaluation of the effectiveness of the discriminant function (Krzanowski, 1988). Unbiased estimates of discrimination error rates can be obtained by splitting data sets at random into two portions and using one part to train the discriminant function, i.e. to establish the allocation rule, and one portion to assess the performance of the rule by determining the proportion of individuals mis-classified. Different sample-splitting ratios (training: validation) can be used (e.g. 1:1 and 3:1) to assess whether or not the discriminant function is subject to large sampling fluctuations (see Krzanowski, 1988).

Given that volume scattering strength and back-scattering cross-sectional area data may not be normally distributed, it may be statistically more robust to use non-parametric functions for discriminating classes. Demer (1994) used a two-sample Kolmogorov-Smirnov (KS) test to evaluate the probability that ensembles of differences in back-scattering cross-sectional areas at two frequencies came from a krill cdf (cumulative non-parametric probability density functions), a salp cdf, a krill and salp cdf, or not a krill nor salp cdf. This approach was functionally similar to classical DFA, without the assumptions of normality.

### 6.2.3.5 Future developments

Classification rates using DFA are encouragingly high. Haralabous and Georgarakos (1996) and Simmonds et al. (1996) have though compared artificial neural networks (ANN) and DFA, and have both found ANN analysis to be more effective. Furthermore neural networks do not suffer from the requirements for data normality. Although DFA is a proven technique for classification of acoustic data, it seems likely that in the future this technique will be replaced by more widespread use of ANNs.

### 6.2.4 Overview

In summary, DFA is a relatively simple and accessible technique that has proved to be effective at classification of multivariate, acoustic-based data. The mathematics underlying the technique are well described and under certain conditions statistically robust significance levels can be attached to group differences. ANNs are at present less well understood. Although the latter represents a “black box” approach to data classification, available comparisons suggest that this is a more effective technique than DFA.
6.2.5 References


6.2.6 Software

Simple introductory text on:

www.ph.tn.tudelft.nl/PRInfo/books/msg00101.html

Link to a passel of web-accessible clustering

www.pitt.edu/~csna/software.html

Another clustering specific link:

www.astro.psu.edu/statcodes/sc_multclass.html

Numerical Algorithm Group (NAG) library in Fortran:

www.nag.co.uk/numeric/FLOLCH/mk17/G03ECF.html

Minitab multivariate Macro Library

www.statslab.cam.ac.uk/~steve/minitab.html

6.3 Artificial neural networks as a tool for ETC

6.3.1 Introduction

A significant source of error of the acoustic estimated pelagic biomass is mainly due to the uncertainty of the biological sampling procedure, namely the gear catchability and the selectivity concerning species and body length of the fish. The importance of the biological sampling can be varied from one region to another. Areas of continuous change in the species composition and length distribution need a denser sampling grid compared to areas with less variability. Especially in a mixed multi-species environment, judging the species composition by scrutinising the echogram is the main source of serious bias (MacLennan and Simmonds, 1992). Therefore a concentrated effort should be made to develop methods supporting a more objective species identification procedure.

Schools represent the most important forms of fish aggregations taking into account the higher concentration of biomass in a relatively restricted area. Modern acoustic equipment provides a continuous monitoring of isolated schools until the trawl mouth, allowing the interpretation of the echogram images in the case of monospecific samples. However, the development of the appropriate Knowledge-Database is difficult, especially in mixed multi-species environment, with very rare monospecific samples. In most cases, the sample contains more than one target species or the catchability for some species is contestable.

Species identification of fish schools is more or less adequately provided only at stations of trawl sampling. Outside these stations, no species membership can be assigned to a school, unless certain "pattern recognition" procedures take place. Regardless of their variations, these procedures aim at statistical modelling and prediction of fish species based on fish school features. Several methods have been developed in order to perform automatically the school isolation from digitised echograms and eventually species recognition and classification. We may cite techniques based on wide-band spectral analysis (Zakharia and Sessarego, 1982; Simmonds and Copland, 1989), on echogram image analysis (Reid and Simmonds, 1991), or on extraction of school descriptors (Diner et al., 1989; Scalabrin C., 1991; Georgakarakos and Paterakis, 1992). More detailed information is provided by Weill et al. (1993).

Recently the automatic extraction of the school parameters accelerated the publications of studies testing the hypothesis that school features can be used for school species identification (Scalabrin et al., 1992 and 1996, Haralabous and Georgakarakos 1993 and 1996). Standard multivariate procedures, such as Principal Components Analysis or Discriminant Function Analysis
as well as Artificial Neural Networks (ANNs) have been applied. The fundamental concept is based on the fact that some behavioural characteristics of the insonified schools, which are related to the above descriptors, are species specific.

Artificial Neural Network methods are characterised by a particular focus on pattern recognition and pattern generation. Many types of ANNs can be viewed as generalisations of classical pattern-oriented techniques in statistics and engineering areas of signal processing, system identification and control theory. The notion of "pattern" in neural network research is essential probabilistic and numerical. In this context, neural networks can best be viewed as a class of algorithms for statistical modelling and prediction (Jordan and Bishop, 1996).

Based on a source of training data, the goal of the method is to produce a statistical model of the process from which the data are generated, to allow the best predictions to be made for new data.

### 6.3.2 Neural - networks overview

Artificial Neural Networks (ANNs) are information processing paradigms, which mimic the densely interconnected parallel structure of animal’s brain. From the technical point of view ANNs can be interpreted as collections of mathematical models that emulate some of the known properties of the neurones and their processing elements, namely the synapses.

Density estimation (also referred to as unsupervised learning), classification and regression (both often referred to as supervised learning) are three broad types of statistical modelling problems that can be successfully approached by ANNs. We are interested here in the application of ANNs for classification problems. General references to ANNs can be found in Rumelhart and McClelland 1986, Ripley 1994–1996, Venables and Ripley 1994, Bishop 1994, MacKay 1992a-b, Neal 1996–1997 (most of them have a Bayesian approach to ANNs). A brief overview of ANNs, concerning the standard back-propagation algorithm applied in feedforward neural networks (also called Multi-Layered Perceptrons, MLPs), given below in section 6.3.7. For an application of MLP algorithms on species classification based on morphometric, energetic and bathymetric features extracted from school echograms, see Haralabous and Georgakarakos 1996. The MLP algorithms have also been applied to species identification using wide-band backscatter by Simmonds et al. (1996).

The most important properties of ANNs among others are their non-linear behaviour, their capability of learning from examples by constructing an Input-Output Mapping, their adaptivity, even operating in a non-stationary environment and their ability to provide information about the confidence in the decision made (Haykin 1994).

#### 6.3.2.1 Introduction to Bayesian neural networks

Bayesian techniques have been developed over many years in various fields, but have only recently been applied to the problem of learning in neural networks. Here only an introductory overview can be provided on these developments. For further reading the key references can be found in MacKay 1992a-c, Bishop 1994 and Neal 1996.

The two ideas, i.e. classical neural network modelling and Bayesian statistics, share several similarities (MacKay 1992a-b). Both methods generate models that closely fit the data. Many popular ANNs are essentially non-linear or semi-parametric estimators that are based on general and power functional forms such as a linear combination of sigmoid or radial basis functions. The parameters are the weights that are "learned" or estimated using training data. Due to the specific types of non-linearities used, such forms are very flexible and can model complex variations in the data better than simple linear methods (Ripley 1993).

However, with increased flexibility comes the potential problem of over-fitting and poor generalisation. The usual approach is to set aside data to form a test or validation set and optimise the model complexity to give the best validation set performance. Bayesian methods, with their inherent preference for simpler models over complex ones, can complement neural networks by providing information about the amount of flexibility that is warranted by the data without the need to set data aside in a validation set. Interpreting neural networks as probabilistic models can facilitate this process (Neal 1996). For example, the objective function (plus some generalisation parameter) that is minimised during training (weight change) of a neural network can be regarded as the negative log of the probability assigned to the observed data by the model with the current weights. As more is seen, this objective function is updated to get the most probable weights given the data, using the Bayes' theorem.

From a practical point of view, the Bayesian optimisation of model control parameters for a neural network has four major advantages summarised by MacKay (1992a):

- No ‘test set’ or ‘validation test’ is involved, so all available data can be devoted to both model fitting and model comparison;
- Regularisation constants can be optimised on-line, i.e., simultaneously with the optimisation of ordinary model parameters;
- The Bayesian objective function is not noisy, in contrast to a cross-validation measure;
- The gradient of the evidence with respect to the control parameters can be evaluated, making it possible to simultaneously optimise a large number of control parameters.

The Bayesian learning of neural networks can be implemented using mainly two different methods:

- the Evidence Framework (EF) of MacKay (MacKay 1992a, 1992b) which uses Gaussian processes and is similar to the Type II maximum likelihood method and;
- a Markov Chain Monte Carlo (MCMC) method (Neal, 1996), that uses the Hybrid Monte Carlo sampling of the posterior distribution of the network.
parameters and hyperparameters. For small data sets the MCMC method has been reported to perform better than EF (Vivarelli 1996), thus it was selected in the current project.

6.3.2.2 The Automatic Relevance Determination (ARD)

One of the most important new features that can be incorporated in the Bayesian neural networks is the use of the automatic relevance determination (ARD). This method, proposed by MacKay (1992b) and Neal (1996), is able to detect the relative importance of the feature vectors by looking at the distribution of the synaptic weights that connect one input unit to all of the units in the next layer. Actually the variance of this distribution is informative of the size of the weights controlled by each one of the input units.

Usually the variance of the distribution of weights is controlled by a so-called hyperparameter $h$, where $h$ is proportional to the square root of the actual variance. Within the Bayesian framework of neural networks the values of this hyperparameter $h$ are adaptively optimised in the light of the available data.

6.3.2.3 The softmax model

In order to define species probability in a classification problem, it is considered appropriate to use the ‘softmax’ model (Bridle, 1989). When the target species $y$, is a single discrete value indicating one of $K$ possible species, the ‘softmax’ model can be used to define the conditional probabilities of the various species using a network with $K$ output units, as follows:

$$P(y = k|x) = \frac{\exp(f_k(x))}{\sum_k \exp(f_k(x))}$$

where $x$ is the input vector, $k$ is one possible species from $K$ and $k'$ indicates all possible values of $k$. This method of defining species probabilities is also used in generalised linear models and especially corresponds to the generalised logistic regression model of statistics (McCullagh and Nelder, 1983).

6.3.3 Species identification using ANNs

All types of ANNs applied and discussed in this text concern “supervised feed-forward” networks using the “back-propagation” learning algorithm (See 6.3.7). The data used for development and evaluation of the presented neural networks have been collected in Norway, Scotland and Greece during the joint research project “Acoustics” (Project AIR3-CT94-2142 (1995–1998)).

6.3.3.1 Data pre-processing

The SIMRAD EK-500 – BI-500 platform has been used for data acquisition and visualisation; however the developed software can co-operate with any other BI compatible data format. The developed software includes an interface allowing selective data extraction from the echogram (BICS), an image processing tool for identifying and characterising schools (SCHOOL) and several Artificial Neural Networks (ANNs) with learning capabilities. The Bergen Integrator Classification System (BICS) is a software module designed to support the classification of acoustic objects in several groups. It transforms standard BI binary data into a common ASCII-based format used by all other modules. The user can identify the echogram area of interest by drawing a window around the acoustic object (school, cluster or scattered fish) (Figure 6.3.1). BICS then produces as output ASCII files describing the data inside the square. As portrayed in Figure 6.3.2, BICS is made of two sub-modules:

- The WIN sub-module, which access BI500 data and extracts the appropriate input format of the SCHOOL module;
- The META sub-module, responsible for maintaining and storing meta-information.

The SCHOOL module is an image analysis tool, responsible for the detection of the school aggregations inside a given echogram or window inside an echogram. The main routine of the module “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 continuity. The continuity function is based on the minimum vertical and horizontal gap parameters. Namely the maximum distance between neighbourly pixels above the basic threshold which is accepted inside an isolated single school. Finally, a second threshold is applied filtering out aggregations of plankton with very low mean integration level. The same algorithm implemented however in an earlier version of this software, is in details described in Georgarakakos and Paterakis (1993). A procedure similar to the SCHOOL algorithm is used for bottom detection in combination to the nominal bottom depth provided by the EK-500.

6.3.3.2 Neural network simulators

The following ANNs simulators have been tested in order to assess their performance and user-friendliness both on PC and UNIX machines:

- Brainmaker® Professional (California Scientific Software ©) for MS-DOS;
- NeuroShell® and NeuroWindows® (Ward Group©) for Windows;
- MATLAB® Neural Network Toolbox (MathWorks©) for Windows;
- SNNS© (SNNS Group, Institute for Parallel and Distributed High-Performance Systems) for UNIX;
- SFBM environment for UNIX (Neal, 1996).
Most of the non-Bayesian ANN implementations are

Figure 6.3.1. Schematic diagram of a scrutinised echogram.

Figure 6.3.2. Bergen Integrator Classification System (BICS).

BI-500 Data Files

DATA
[Echo]
[Pelagic]
[Bottom]

Ping Indexes

Vlog Indexes

Info

Work & Snap

BICS

WIN
Window - Data
Extractor

META
Organiser
Pings, depth and
objects per window

Standardised
Output

WIN - Data
(ASCII, csv format)

TW=E-Trace
PW= Pelagic
BW=Bottom

WLog-file
Most of the non-Bayesian ANN implementations are based on the commercial 32-bit neural network simulators “NeuroShell 2” and “Neuro-Windows” DLL (Ward Systems Group®). This platform provides a source code generator in ANSI-C and Visual Basic, which allows to control the learning parameters of the ANNs like: training tolerance, learning rate, noise thresholds, smoothing factors, adjusting of the momentum algorithm, etc.

The Bayesian ANNs are developed under the UNIX environment using the SFBM simulator.

### 6.3.3.3 General design of neural networks

The descriptor values extracted from a certain fish-school define a vector *pattern* that represents this school. Three examples of descriptor patterns of sardine schools are displayed in Figure 6.3.3. The main idea behind the application of ANNs in the species classification problem is based on the ability of ANNs to learn these patterns.

As a general rule (Lawrence 1993) the number of patterns of each output (i.e. the number of schools of a certain species) should not be less than 10 times the number of all possible outputs (species used) in the training set of a neural network. Thus using three – four species in the output layer, the minimum requirement is about 40 schools from each species, summing to a minimum total number of 160 schools from all species.

The available descriptors generated by the SCHOOL programme and used as a whole or as a subset are summarised in Table 6.3.1. The table includes also an example of the data separation in training and testing subsets.

<table>
<thead>
<tr>
<th>Input layer</th>
<th>Output layer</th>
<th>Number of schools</th>
</tr>
</thead>
<tbody>
<tr>
<td>Type</td>
<td>School descriptors</td>
<td>Species</td>
</tr>
<tr>
<td>M 1 Height</td>
<td>1. Herring</td>
<td>111</td>
</tr>
<tr>
<td>M 2 Length</td>
<td>2. Norway pout</td>
<td>83</td>
</tr>
<tr>
<td>M 3 Area</td>
<td>3. 0 pout</td>
<td>31</td>
</tr>
<tr>
<td>M 4 Perimeter</td>
<td>4. Blue whiting</td>
<td>14</td>
</tr>
<tr>
<td>M 5 Radius Mean</td>
<td>5. Sprat</td>
<td>3</td>
</tr>
<tr>
<td>M 6 Radius Max</td>
<td>TOTAL</td>
<td>242</td>
</tr>
<tr>
<td>M 7 Radius Variance</td>
<td></td>
<td>86.4%</td>
</tr>
<tr>
<td>M 8 Circularity</td>
<td></td>
<td></td>
</tr>
<tr>
<td>M 9 Rectangularity</td>
<td></td>
<td></td>
</tr>
<tr>
<td>M 10 Elongation</td>
<td></td>
<td></td>
</tr>
<tr>
<td>M 11 Fractal Dimension</td>
<td></td>
<td></td>
</tr>
<tr>
<td>B 12 Altitude Mean</td>
<td></td>
<td></td>
</tr>
<tr>
<td>B 13 Altitude Min</td>
<td></td>
<td></td>
</tr>
<tr>
<td>B 14 Altitude Max</td>
<td></td>
<td></td>
</tr>
<tr>
<td>B 15 Depth Max</td>
<td></td>
<td></td>
</tr>
<tr>
<td>B 16 Depth Min</td>
<td></td>
<td></td>
</tr>
<tr>
<td>B 17 Depth Mean</td>
<td></td>
<td></td>
</tr>
<tr>
<td>B 18 Bottom Mean</td>
<td></td>
<td></td>
</tr>
<tr>
<td>B 19 Bottom Min</td>
<td></td>
<td></td>
</tr>
<tr>
<td>B 20 Bottom Max</td>
<td></td>
<td></td>
</tr>
<tr>
<td>E 21 Energy Total</td>
<td></td>
<td></td>
</tr>
<tr>
<td>E 22 Energy Mean: m</td>
<td></td>
<td></td>
</tr>
<tr>
<td>E 23 Energy CV</td>
<td></td>
<td></td>
</tr>
<tr>
<td>E 24 Energy Max</td>
<td></td>
<td></td>
</tr>
<tr>
<td>E 25 Index of Dispersion: ns²/m</td>
<td></td>
<td></td>
</tr>
<tr>
<td>E 26 Crowding: m=[s²/(m-1)][(1+s²)/(nm²)]</td>
<td></td>
<td></td>
</tr>
<tr>
<td>E 27 Clumping coefficient: m²/(s²-m)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>E 28 Patchiness: crowding/m</td>
<td></td>
<td></td>
</tr>
<tr>
<td>T 29 Time</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

| Table 6.3.1. Neural network input and output structure for training and testing 280 schools (Shetland Islands 1996). The type of a descriptor is indicated by a letter: M= Morphometric, B= Bathymetric, E= Energetic, T= Temporal. The symbols used in the equations are n= number of pixels, m= mean school energy, s²= variance of school energy. |

The input layer

A single table containing the descriptors extracted from the “known” fish schools, serves as the input layer of the network. From the total number of the descriptors extracted, a subset of 13-20 of them is used. The amount of the available “known” schools limits the number of the concurrently in use descriptors. Bayesian Neural networks are less sensitive in this limitation.

- **The input layer**
- **The hidden layer(s)**

After some preliminary tests the number of the needed hidden layers is selected. Most ANNs contain only one hidden layer. The designed network in Figure 6.3.4 is developed with the simulator “NeuroShell 2” and it is based on 1 hidden layer, containing 3 sub-layers (Slab 2, 3 and 4). Different activation functions can be applied to the 3 slabs in order to detect different features in a pattern processed. In addition to the classical sigmoid function in one sub-layer, a Gaussian function is used on the second
sub-layer in order to detect features in the mid-range of the data. In the third sub-layer a Gaussian complement is used for detecting features from the upper and lower extremes of the data set. Combining the three feature sets in the output layer can lead to a better prediction. Thus, the output layer will get different “views of the data”.

- **The output layer**
  The unit in the output layer are the number of different groups of species. Each output unit, corresponding to a certain category (species or subgroup of species) takes the value of 1 if the school belongs to this category, else the value of 0. The creating of separate network outputs when using back-propagation networks can increase the precision of the network.

6.3.3.4 ANN testing procedures

To measure the classification efficiency of the ANNs the actual output of the network is compared to the correct output over a number of testing trials. This requires additional randomly selected examples beyond those used for training the networks. The most widely used method to obtain this test set is to reserve a separate representative subset of the available examples. These example patterns must be new because, if the same examples are used both for training and testing, all that is determined is how well the network learned the training patterns. What is really required to know is how well the networks learned the “mapping” function for arbitrary input values (Hecht-Nielsen 1991). Subsets ranging from 5% to 30% of the available data were tested.

For the evaluation of the accuracy of a trained ANN some statistics are calculated, the most important of which is the $R^2$: the coefficient of multiple determination, a statistical indicator usually applied to multiple regression analysis. It compares the accuracy of the model to the accuracy of a trivial benchmark model wherein the prediction is just the mean of all of the samples. A perfect fit would result in an $R^2$ value of 1, a very good fit near 1, and a very poor fit near 0. If the neural model predictions are worse than could be predicted by just using the mean of your sample case outputs, the $R^2$ value would be 0.

$R^2$ is not the ultimate measure of whether a net produces good results, especially for classification nets such as those used. For example, if the ANN generates output values of 0.5, 0.6 and 0.4 in the three outputs, the $R^2$ value will not be very high, but the classification would be correct if the second output was the answer. The successfulness of a net may be decided on by the number of correct classifications.

All non-Bayesian Neural Networks simulations applied in the data sets provide a high predictability just in cases where trained and test data belong to the same spatio-temporal schema. In addition it was found that they had a limited ability to recognise schools of the same species, but encountered in different school depths, due to the increased beam effect in deeper waters.

However, the importance to predict the species of schools in an area, applying ANNs, trained with data from another area is a very useful test for the generalisation power of the developed Neural Network. A comparison between non- and Bayesian Neural networks (see Table 6.3.3) convinces, that Bayesian neural networks permit a more robust and generalised prediction against schools encountered in different areas or depths.
6.3.3.5 Development of Bayesian Neural Networks

The Bayesian Neural Networks have been chosen due to their strong ability to generalise the patterns encountered in the data sets and their potentiality to take into account more descriptors than classical networks. As example, the test output of a Bayesian Neural Network is summarised in Table 6.3.2. The used network is trained and tested with data collected from the same area under study (Shetland, 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, the two species that had enough representatives in the training set (45.8% and 34.3% of cases respectively).

In order to test the “generalisation power” of the Bayesian Network, the previously trained with the Shetland data network is used for predicting Norwegian herring schools. The predictions of this network on the Norway data are given in Table 6.3.3.

The high prediction rate (88.3%) of the Bayesian Neural Network concerning herring schools of another survey area (Norway) emphasises its good generalisation properties. Note that the pure representation of the B. whiting both in training and testing data sets generates a significant reduction in the predictability concerning this species.

One of the most important features of the Bayesian Networks is the estimation of the probability assigned to the prediction made in each “unknown” school. This allows to the user to decide with different confidence limits the probability threshold of accepting or not the network prediction. An example of Box-plots displaying the distribution of the school-species prediction probabilities shows Figure 6.3.5. In all species, the distribution was skewed to the high values (close to 1). As the median value of all box-plots indicated, more than 50% of the predictions of each species had probability higher than 0.90 and in most species higher than 0.95. Especially for the prediction of herring schools the highest quartile (25%) had probability values in the range of 0.98 to 1.0.

![Diagram of Neural Network](image)

Figure 6.3.4. Partial view of Neural network structure.

Table 6.3.2. 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.

<table>
<thead>
<tr>
<th>True species</th>
<th>0-group Pout</th>
<th>N.Pout</th>
<th>B.whiting</th>
<th>Herring</th>
<th>Total correct predicted</th>
</tr>
</thead>
<tbody>
<tr>
<td>0-group Pout</td>
<td>4</td>
<td>10.5%</td>
<td>3</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Norway Pout</td>
<td>12</td>
<td>31.6%</td>
<td>0</td>
<td>12</td>
<td>0</td>
</tr>
<tr>
<td>Blue whiting</td>
<td>3</td>
<td>7.9%</td>
<td>0</td>
<td>3</td>
<td>0</td>
</tr>
<tr>
<td>Herring</td>
<td>19</td>
<td>50.0%</td>
<td>0</td>
<td>0</td>
<td>19</td>
</tr>
<tr>
<td>TOTAL</td>
<td>38</td>
<td>100.0%</td>
<td>3</td>
<td>12</td>
<td>3</td>
</tr>
</tbody>
</table>
More than 75% of schools (the 3 highest quartiles) in all species except Norwegian pout had maximum probabilities higher than 0.80. Very few schools had a probability lower than 0.70 and could therefore be considered weakly classified but not necessarily mis-classified.

6.3.3.6 Relevance of school descriptors

The hybrid Markov Chain Monte Carlo (MCMC) simulation algorithm, incorporated in the SFBM software, produced a sample of 100 networks and gave a distribution aspect of all parameters and hyperparameters. Through this sample of 100 networks, it was possible to evaluate the differences in the value of hyperparameter \( h \) between descriptors. The estimated “importance” of the selected descriptors has been found in all trials that are not significantly different from the others between the same simulation experiment. Therefore, it was no descriptor that could be considered as *key feature* (highly separable from the others) in species classification. This absence of a single ‘strong’ descriptor confirms the multivariate approach to species classification.

6.3.4 Conclusion

The final impression gained from the described experiments, especially using Bayesian Networks, is that despite the existing differences between the schools of two geographic areas, a proportion of the corresponding discrimination pattern of the species remains the same, still able to recognise their “relatives”. On the other hand these experiments indicate that the encountered deviations from a species “common” school pattern in the two survey areas are enough to hinder the discrimination capability of standard analytical procedures including non-Bayesian ANNs.

Concerning the impact of depth on the estimated de-

![Figure 6.3.5. Box-plots of the distribution of maximum probability assigned to the predictions of the Bayesian neural net for each of the four output species in Shetland 1996 test data set. The gray box represents the central 50% of the cases and the vertical line inside this box indicates the median value.](image)
scripts, the current strategy used to avoid this bias is to select for the analysis and the ANN development only data from the same depth range. The observed improved recognition efficiency, when Bayesian Networks are applied, seems to offer a promising way to overcome this problem.

Finally, a further aspect for improving the methodology of school species identification could be the incorporation in the training phase additional to the mono-specific also of multi-species trawl samples. Predicted species identities, which are in accordance with the catch of a multi-species sample can be used as training data.

### 6.3.5 Acknowledgements

This research was partially supported by the Commission of the European Union within the framework of the AIR Project “Acoustics” (AIR3-CT94-2142 (1995–1998), N, UK, and GR. The authors thank their partners E. Ona (Institute of Marine Research, Bergen), D. MacLennan and E. J. Simmonds (SOAFD Marine Laboratory, Aberdeen) for the submission of the data and valuable advice and suggestions during the project.

### 6.3.6 References


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### 6.3.7 Neural network overview

Artificial Neural Networks (ANNs) mimic the brain's own problem solving process: just as humans apply knowledge gained from past experience to new problems or situations, so a neural network takes previously solved examples to build a system of "neurons" that makes new decisions, classifications, and forecasts. They look for
patterns in training sets of data, learn these patterns, and develop the ability to correctly classify new patterns or to make forecasts and predictions.

There are two basic types of neural networks: supervised and unsupervised:

- **Supervised** networks build models that classify patterns, make predictions, or make decisions according to other patterns of inputs and outputs they have "learned." They give the most reasonable answer based upon the variety of learned patterns. In a supervised network, we show the network how to make predictions, classifications, or decisions by giving it a large number of correct classifications or predictions from which it can learn. Multi-layered Perceptrons (MLPs) using back-propagation are supervised network types.

- **Unsupervised** networks can classify a set of training patterns into a specified number of categories without being shown in advance how to categorise. The network does this by clustering patterns. It clusters them by their proximity in N dimensional space where N is the number of inputs. The user tells the network the maximum number of categories and it usually clusters the data into that number of categories. However, occasionally the network may not be able to separate the patterns into that many distinct categories. The most well known unsupervised networks are the Kohonen networks.

Neither type of network is guaranteed to always give an absolutely "correct" answer, especially if patterns are in some way incomplete or conflicting. Results should be evaluated in terms of the percentage of correct answers that result from the model. In this regard, the technology is similar to biological neural functioning after which it was designed, and differs significantly from all other conventional computer software.

![Network Structure Diagram](image)

**Network Structure**

The basic building block of neural network technology is the simulated neuron (also called processing node or element) depicted in Figure 6.3.6 as a circle. Independent neurons are of little use, however, unless they are interconnected in a network of neurons. The network processes a number of inputs from the outside world to produce an output, the network's classifications or predictions. The neurons are connected by weights, (depicted as lines) which are applied to values passed from one neuron to the next. A group of neurons is called a slab. Neurons are also grouped into layers by their connection to the outside world. For example, if a neuron receives data from outside of the network, it is considered to be in the input layer. If a neuron contains the network's predictions or classifications, it is in the output layer. Neurons in between the input and output layers are in the hidden layer(s). A layer may contain one or more slabs of neurons.

**Learning in multi-layer perceptrons (MLPs)**

A typical MLP network is a back-propagation network that usually has three layers of neurons. Input values in the first layer are weighted and passed to the second (hidden) layer. Neurons in the hidden layer "fire" or produce outputs that are based upon the sum of weighted values passed to them. The hidden layer passes values to the output layer in the same fashion, and the output layer produces the desired results (predictions or classifications). The network "learns" by adjusting the interconnection weights between layers. The answers the network is producing are repeatedly compared with the correct answers, and each time the connecting weights are adjusted slightly in the direction of the correct answers. Eventually, if the problem can be learned, a stable set of weights adaptively evolves and will produce good answers for all of the sample decisions or predictions. The real power of neural networks is evident when the trained network is able to produce good results for data which the network has never "seen" before.

Building successful neural networks is closely related to criteria for "stop training". If we train too little the net will not learn the patterns. If we train too much, the net will learn the noise or memorise (over-fitting) the training patterns and not generalise well with new patterns. The network performance on separate "test sets", along with cross-validation or bootstrap procedures, are the usual ways applied here for model validation.

**6.4 Spatial point processes and the spatial distribution of schools**

**6.4.1 Introduction**

After extracting school objects from an echogram of acoustic surveys, each school can have at least four parameters for location (Latitude, Longitude, Depth, Time) and various parameters for energy, density, morphology, species identification. A Point process approach for analysing the spatial distribution of schools is of interest when schools can be considered as point-events in the sea separated by empty areas which are large in comparison to school dimensions. However this assumption may not always be valid, particularly when (i) small
schools fill space on the echogram and (ii) distance between schools are of the same order of magnitude as school dimensions. In such case, a random function approach (geostatistics) where school parameters are averaged over small blocks would be a more realistic approach, as school parameters would be considered as continuously variable in space. Then the pool of schools could be separated into two groups, one category of schools filling space in a continuous manner and the other one occurring in space as point events. At present, studies of schools with a point process approach are rare. The development of school databases is a recent departure in fisheries acoustics and point processes represents a new method for this new type of fisheries data.

6.4.2 Method - description

This section describes the current state-of-the-art in point processes in general. Aspects directly related to the use of these techniques for ETC are dealt with in Sections 6.3.3 and 6.3.4.


The standard reference for point processes is Ripley (1988). Cox and Isham (1992) is also very useful. For new users Diggle (1983) or Stoyan and Stoyan (1994) may be more approachable as they have more worked examples.

In point process jargon, “point” will be used for any point of space whereas “event” will used for a process point, here a school.

The homogeneous Poisson process plays a major role in point process theory and analysis as it represents complete spatial randomness (CSR). In analysing point process data, the general approach followed is first to show that the studied process differs from CSR. The test for departure from CSR can be performed by quadrat counts or by computing a second order statistic. Second, the process spatial structure is usually characterised by the second order statistic. Inference of models is not simple and is generally performed by assuming a model and testing whether the studied process differs significantly from it.

Structural functions (second order characteristics)

All events of the point field need to be recorded in order to characterise its spatial structure. Different types of distances can be computed to characterise structure, between two events or between a randomly chosen point and an event. Here, we shall consider distances computed between events only. There are two classes of structural functions, those based on the number of neighbouring events or emptiness around events and those based on the distribution of the distance between events.

The I or K functions:

The I function is the average number of events at distance R from any event. Scaled by the point process intensity it is known as Ripleys’s K-function. Border effects have been proposed to account for unseen neighbours of events located near the borders.

The G-function:

Is defined as the cumulative frequency of the distance to the nearest neighbour. Along a 1D line, the G-function differs from the cumulative distribution of the distance to the next event.

The pair correlation function:

Is the probability that a segment of unit length 1 has 2 point events at its extremities. It does not suffer the problems of border effect as the K function. It is useful to apply kernel estimators.

The marked pair correlation function:

Is the correlation function (or variogram function) of marked event values at unit distance 1 conditional to the presence of events at distance 1. It is based on the definition of the pair correlation function. This function measures how alike schools are in the considered parameter.

The pair correlation function does not tell whether the position of neighbours is related to the value of the mark (i.e. if large schools have for instance fewer neighbours around them). Such relation can be checked by simple plots or by testing whether K functions for large schools differ from K functions for any schools.

Such analyses are simple enough to be performed using Excel, Fortran or C. S_Plus in its spatial statistics module provides routines to compute the G and K-functions. Petitgas and Lafont have developed a software named SPP (Spatial point process (Petitgas et al., 1999) to allow point process analysis in 2D and in 1D along acoustic transects. This software can be obtained from the authors free of charge (Pierre Petitgas, IFREMER Centre de Nantes. http://www.ifremer.fr. or email: pierre.petitgas@ifremer.fr.).

Different models

Homogeneous Poisson model:

This is defined by its intensity \( \lambda \), which is the number of events per unit area of the field where the process happens. Events happen at random homogeneously and independently from each other over the field. The intervals between events are independent from each other. The G-function is an inverse exponential in 2D. In 1D, the distance to the nearest event (this is different from the distance to the nearest) is an inverse exponential. The K-function is quadratic in 2D and linear in 1D.

NB. In most point process analyses the distance used is that to the nearest neighbour. However, when working with data in 1D it is essential to use the distance to the NEXT neighbour, as statistically this behaves as NERA neighbour in 2D or 3D.

Inhomogeneous Poisson model:

This is defined as a Poisson process in which the intensity \( \lambda \) is not a constant. For instance, the intensity \( \lambda(x) \) has a pattern of variation in space. The variation of \( \lambda(x) \) may be a deterministic relation of a function of \( x \) or may be random. In this case, the process is referred to as a Cox process. The random variation of \( \lambda(x) \) may also
show a structured variogram. In each cell of the map, the events follow a homogeneous Poisson process of intensity \( \lambda(x) \). Such processes have few parameters and can account in a simple manner for many situations such as clustering and decrease in intensity with an ancillary variable. But the clustering is not parameterised directly with one parameter.

Cluster models:
These are defined as models composed of two additive processes. The first process gives the location of parent events. It can be a Poisson homogeneous or inhomogeneous process. The second process defines the location of child events around each parent event: homogeneous Poisson inside a disk centered on the parent event, or following a bigaussian spatial distribution centered on the parent event or another. The final process is the process of the child and parent events. The process of child events directly defines the clustering parameters. Such a process can be difficult to infer from data as clusters of child events may overlap. The so-called Neyman-Scott process is frequently used: it is a cluster process where the parent events are homogeneous Poisson and the child clusters are all independent and generated by the same rule.

Thinned and inhibition models:
These are defined as models made up of two processes that are subtractive. The first process can be any type of point process. The second process defines which events derived from the first process are to be deleted. The final process is made of the resulting events. Such a process is believed to be potentially interesting when it is known that schools cannot be in some locations and a map of mortality can be superposed on a map of school events. Inhibition processes are thinned processes where the events removed are those found too near to other events.

Markov models:
Here the probability of an event occurring at point \( x \) depends on a specified rule which only concerns the neighbouring events around point \( x \). A Markov process has more flexibility than an Inhibition process and thus is more adapted to model point patterns that are less regular.

Renewal or survival models along 1D line transects:
The distance from one school to the next along the line is considered to be a survival time. The hazard function for school occurrence is the probability that a new school occurs at time \( t + dt \) when one has already occurred at time \( t \). In the Poisson homogeneous process, the distance to the next event is a random variable which has no spatial structure (i.e. no memory in the occurrence of events) and an exponential histogram (pdf). The repetition rate of school occurrence is \( 1/\lambda \). A renewal process has the property of independence (no memory) but the distribution for the distance to the next event can be of any type. For instance, if we consider a process with a repetition rate of school occurrence that is accelerated in comparison to a Poisson, say a/t, the pdf of the distance to the next school follows a Weibull distribution. Renewal processes have few parameters and can account for clustering in a simple manner. Clustering is then parameterised by the skewness of the distribution of the distance to the next event.

Marked processes:
These are defined as point processes where each event has a value called the mark. One example would be the biomass of the schools. Such processes are characterised by the point process of the events, the probability distribution of the marks and the spatial autocorrelation of the marks. Mark correlation (or variogram) functions characterise the spatial correlation between two marks at distance \( h \), conditional to the probability to have two events separated by this distance. Models where the value of the mark influences (positively or negatively) the number of neighbouring events were not found to be standard models in the methodological literature and thus potentially represent a new field of research for fisheries science.

6.4.3 Questions for analysing fish school spatial patterns

Analysis in 2D or 1D?

The Point Process analysis requires that all events (at least those that do not escape the acoustic beam) have been recorded in the field studied. This is true in 2D on sonar images. This is also true in 2D along transect lines and depth for standard echo sounder surveys of fish stocks. However, in using data from echo sounder surveys carried out along transects, the 2D latitude and longitude point field of schools cannot be studied because information of school location between transects is lacking. Hypotheses must then be made and stereological methods used to reconstruct the 2D-point field from 1D lines, which is complex and would need many assumptions. One-dimensional data of school occurrence are obtained simply by collapsing the depth or vertical dimension and studying the occurrence of schools along the transect lines, without reference to depth. This provides a description of school occurrence at large spatial scale. A 2D analysis of school occurrence is possible in the along transect and depth planes. However, it is reasonable to assume that the biological processes controlling a schools position horizontally and vertically are quite different. Furthermore, distances between schools in the vertical plane are in the order of tens of metres (in shelf seas) while horizontally distances are likely to be much greater. One possible approach is that school depth could be included in the analysis as a covariate and be considered in marked process (see above).

An important point to note when using transect data collapsed to a single (along transect) dimension is the difference between nearest neighbour and next neighbour. A major difference between 1D and 2D processes is that the 1D-line can be oriented with time when such orientation does not occur in 2D. Thus in 2D, the next event is also the nearest. But in a 1D point process, the next is not necessarily the nearest because of the orientation of the line. Therefore, 1D line processes are easily related to occurrence of events in time and survival type of analysis. The distance to the next neighbour (event) is
then a parameter that can be modelled and that has a practical meaning when considering orientation with time. But in either 2D or 1D, the intensity of the process, i.e. the number of points per unit area, relates to the average distance between events.

**Inhomogeneous Poisson, Renewal or Cluster type of analysis?**

In the Inhomogeneous Poisson and Renewal processes the number and dimension of clusters are not model parameters. They result from the values of other parameters that specify the model. The number of clusters of schools, their number and the number of schools in them can be presumed to include important mesoscale biological information. Thus should we not infer these parameters directly from data? How feasible is this type of approach? At the time of writing these questions were under study as part of the EU CLUSTER project.

### 6.4.4 Point processes and fish schools in the fisheries literature

**Clustering of schools**

**Clustering of schools evidenced with a survival approach:**

MacLennan and MacKenzie (1988) used a Renewal Process to model the occurrence of schools along a 1D acoustic survey line. The pdf. of the distance to the next event was shown to be a Weibull distribution. Petitgas and Samb (1998) also found that a Weibull distribution was appropriate for their data. The Weibull model is certainly flexible enough to be appropriate in different situations. But it also shows that the occurrence of schools along transect lines is more aggregated than for a Homogeneous Poisson distribution. Swartzman (1997) also evidenced clusters of schools by the skew of the histogram of the distance to the next neighbour. This was also shown for schools extracted from a series of echo-integration surveys in five different geographical areas (Reid et al., 1999, Petitgas et al., 1999). For all these surveys, the skew of the histogram of the distance to the next school along the transect, showed a clear clustering of schools.

**Clustering of schools evidenced with an Inhomogeneous Poisson approach:**

Marchal and Petitgas (1993) evidenced a structured variogram for the number of schools per 1Nm. EDSU and proposed an Inhomogeneous Poisson model for the spatial distribution of schools. Swartzman et al. (1994) evidenced relationships between environment and schools, their occurrence and their descriptors and this was modelled using a Generalised Additive Model (GAM). Petitgas et al. (1999) evidenced a spatial variation of the number of schools per EDSU with latitude, longitude, depth or time using GAM. These results suggest the possibility of modelling school occurrence at a large spatial scale using an Inhomogeneous Poisson model by fitting a response surface on the number of schools per EDSU (i.e. \( \lambda(x) \)).

**Grouping schools in clusters along 1D transect lines:**

Schools can be grouped in clusters by forming a new cluster when the next neighbour along the transect is too far from the present school event, otherwise the next neighbour is added to the present cluster. In the past, a fixed threshold distance has been used to group schools in clusters, e.g. 460m by Swartzman (1997) and 1000m by Soria et al. (1998). Petitgas and Samb (1998) suggested an algorithm which groups the schools in clusters, which will have the same, average number of schools per unit length. In this algorithm, the threshold distance may vary from survey to survey. The algorithm was refined by (Petitgas et al., 1999) to give coherence between the number of solitary schools, number of homogeneous clusters, constant \( \lambda \) inside clusters, and variogram of the number of schools per EDSU.

**Density dependence of school cluster parameters:**

Petitgas and Levenez (1996) evidenced very little interannual change in the variogram for the number of schools per 1Nm EDSU in a series of surveys where the stock abundance varied greatly and suggested that the spatial distribution of schools has density independent properties. Petitgas and Samb (1998) grouped schools in clusters along transect lines and showed that the number of clusters and their length were also density independent in their data series. Cluster intensity \( \lambda \) was density dependent. Swartzman (1997) also grouped schools in clusters, for one survey only and studied the effect of differences in environmental conditions. Cluster intensity \( \lambda \) was not related to environmental factors. However, environmental differences did affect school parameters and spacing between clusters (i.e. cluster length). Auckland and Reid (1998) found no density dependence for the total number of schools or for the nearest neighbour distance. This is an important subject and should be a priority for future research in this field of fisheries science. It should be noted that results also depend on the algorithm used to group schools into clusters to an extent that has not been acknowledged.

**Underlying biological processes generating clusters of schools:**

Fish density (biomass) is distributed heterogeneously in space and when present is usually aggregated into schools or other assemblages. Environmental conditions in an area can influence the biomass level, the average number of schools and biomass per school as indicated by regression analysis (Swartzman 1995 and 1997, Maravelias and Reid 1997). Schooling dynamics (i.e. the structure of a school) is variable at short spatial and temporal scales (tens of meters to a few miles, tens of minutes to hours) (Fréon et al., 1992, Swartzman 1991) which can add noise to the ecological relations described above. Schooling dynamics also shows a day/night cycle of aggregation/disaggregation (Fréon et al., 1996) which can also add complexity.
Spatial variation of school parameters (mark point values)

Correlation between mark values:
Results here are very rare and represent a new field of study in fisheries science. Petitgas et al. (1996) analysed the small scale (up to 1000m) spatial distribution of schools recorded by an omnidirectional sonar: Ripley’s K-function revealed clustering of schools for all images but the pair variogram function revealed high variability in the spatial correlation between school geometric size (surface) from image to image. The dynamics of schooling was thought to be the reason of this variability in spatial correlation.

Relation between the school point process and the mark values:
Again, relatively little work has been carried out to date and this area should reward future study, as there is some confusion in the findings. Some authors have evidenced no correlation while others have. MacLennan and MacKenzie (1988) modelled the size (biomass) in schools using a Weibull distribution. They modelled the school occurrence process and the school biomass process independently and assumed no correlation between the two. They derived an estimate of fish stock abundance with its estimation variance by combining both processes. Marchal and Petitgas (1993) also considered the two processes as if independent and argued that the assumption of no correlation was compatible with their observation that the probability of encountering larger schools was greater in areas where school number was higher. But Petitgas et al. (1996) working on sonar images at small scale (up to 1000m) showed that bigger schools had fewer neighbours around them. Soria et al. (1998), working on lateral sonar data, grouped schools in clusters along transects. They considered different types of school clusters depending on whether the spatial distribution of the schools within the clusters was homogeneous or heterogeneous. They found school parameters to be related to cluster types. Petitgas et al. (1999) found that the distance to the nearest neighbour was related to the school biomass for some stocks and not for others. They also found no relation when schools of all species are considered. Point patterns where the mark values are correlated to the number of neighbouring school events may suggest the potential value of Markov point fields and the introduction of new models for fisheries acoustic data.

6.4.5 References

References - theory:


References - case studies:
Swartzman, G. 1997, Analysis of the summer distribution of fish schools in the Pacific Eastern Boundary


6.5 Geostatistics

6.5.1 Introduction

Geostatistics was born out of the disciplines of mining engineering, geology, mathematics and statistics, to provide techniques which analyse and predict values of a variable distributed in space or time. The prefix ‘geo’ is derived from applications in geology which spurred its inception (Matheron 1963). Today it is more universally applied to any data where two adjacent observations are more alike than those further apart, a characteristic known as autocorrelation which is typical of ‘natural populations’ (Cochran 1977). Such data might include pollutant concentrations, rainfall, soil properties, worm density, bird distributions, as well as the case considered here - fish distributions.

Typically geostatistics is used to estimate a quantity of a surveyed variable (global estimation) and provide a map of its distribution (local estimation); this is most often implemented by a technique known as kriging. In analysing the results of ETC, mapping of school descriptor variables, such as school size, is probably the most obvious case where geostatistics can be usefully employed. A measure of the precision with which the quantity was obtained can also be acquired by calculating the global estimation variance: this is one of the principal benefits of using geostatistics when estimating abundance – it is unlikely to be particularly useful for ETC studies. However, prior to either of these end-processes, there is a vital stage known as structural analysis, where the autocorrelation is quantified and modelled using a structural tool such as the variogram. This stage in itself may produce useful results which may be directly applicable to studies of ETC: it can yield information about the dimensions of school clusters and, on a finer scale, the associated internal (spatial) structure.

The subject of geostatistics has been covered extensively in many texts. For an introduction for biologists Rossi et al. (1992) is relatively short and uses terms that are more familiar to non-geologists. A natural progression from this would be Isaaks and Strivastava (1989), which is the most readable of the dedicated (mining) geostatistics texts. Brooker (1991) is also recommended as it provides a very clear and practical overview of fundamental concepts – particularly with regard to the implications of the variogram parameters. More comprehensive explanations can then be sought from Journel and Huijbregts (1978), Goovaerts (1997), or for the more statistically minded Cressie (1993). The definitive geostatistical reference, although somewhat cumbersome to the non-mathematically minded, is Matheron (1971). Finally, it is worth noting that a fisheries specific text entitled ‘Geostatistics for estimating fish abundance’ is in preparation (Rivoirard et al., in press): this covers all aspects of methodology as well as providing examples of geostatistical analyses from fisheries acoustics data.

The practise of geostatistics is computationally intense and requires appropriate software. ‘EVA2’ is highly recommended (Petitgas and Lafont 1997), as it is dedicated to fisheries data and is also very cheap. Other readily available (cheap) software include ‘VARIOWIN’ (Pannatier 1996), ‘GEO-EAS’ (Englund and Sparks 1991), and the comprehensive suite of Fortran codes in ‘GSLIB’ (Deutsch and Journel 1992). In the mid-range of the market are packages such as ‘S+SpatialStats’ which is an add-on module for ‘S+’ (Mathsoft), and ‘Surfer’ (Golden Software) which although does not include variography, does have extensive visualisation and mapping tools, including kriging (for mapping and abundance evaluation). At the top end of the market and therefore the most comprehensive package available is ‘ISATIS’ (Geovariances, France), which is now available for PC (Windows NT). There are also a number of websites which provide information and, in some cases, software routines for geostatistical analyses. Most of these can be accessed through the ‘ai-geostats homepage’ located at: http://curie.ei.jrc.it/ai-geostats.htm. One site in particular, is dedicated to applications in fisheries research; this can be found at: http://www.cqs.washington.edu/~gordie/gordie.html.

6.5.2 Basic methodology

A full description of the techniques involved in geostatistics is beyond the scope of this brief review and the reader is referred to the references cited above for an appropriate introduction. However, some of the basic principles and techniques are described below.

Geostatistics deals with variables which are distributed in space; Matheron (1971) defined these as regionalised variables. These are denoted as z(x) where z is the value of the variable and x describes its location (in 1, 2 or 3 dimensions). The steps in a geostatistical study fall into four categories carried out in the following order:

1. exploratory data analysis;
2. structural analysis (variography);
3. prediction for estimates of abundance and mapping (kriging);

The use of the variogram is an implementation of intrinsic geostatistics. This is the more common approach to dealing with two-dimensional data and differs from transitive geostatistics. Transitive methods have been used primarily with data reduced to a single dimension, e.g. acoustic transect cumulates (Williamson 1996). Petitgas (1993a) provides a full description of the alternative theories. The discussion throughout the current text refers to intrinsic theory.
4. calculation of precision (global estimation variance).

**Exploratory data analysis**

This is a preliminary and necessary step. It includes: visualisation of raw data (histogram, scatterplot, post-plot), including locations (e.g. vessel track); identification of extreme values; basic statistics, such as the mean and range of values; and checking for consistency (e.g. sum of proportional data = 1). The potential for small errors in large datasets such as those typically collected in fisheries acoustics surveys is considerable.

Data should be in real (x, y) co-ordinates (i.e. not longitude and latitude) and in certain circumstances should include an appropriate projection (e.g. gnomonic for high latitudes). A domain or area has to be delineated around the sample points by construction of a polygon. Except for known natural frontiers, such as the coastline or shelf edge, it is advisable to make the outside edge of the domain as regular as possible.

**Structural analysis**

Capturing the spatial structure is widely regarded as the most critical step in a geostatistical analysis (Cressie 1993). The basic structural tool of geostatistics is the variogram which measures the variability between any two sample points as a function of their distance. The experimental variogram is obtained from the samples z(x) using Matheron’s (1971) classical estimator:

$$\gamma(h) = \frac{1}{2n} \sum [z(x) - z(x + h)]^2$$

where:

- $\gamma(h)$ = semi-variance value at lag $h$ = gamma (h)
- $z(x)$ = value of z at location x
- $z(x+h)$ = value of z at (displaced) location $x + h$

The variogram is usually computed for distance classes or lags, i.e. a value $h$ plus or minus a tolerance (e.g. half the distance of the class interval). The lag should approximate the distance between samples and $\gamma(h)$ should be calculated to a distance of approximately half the maximum dimension of the domain. To capture orientational differences in structure, variograms can be computed along chosen directions (plus or minus a tolerance in angle). If these directional variograms differ then the process is *anisotropic* and appropriate geometric corrections are required. If directional variograms are similar then the process is *isotropic* and a single omnidirectional variogram is sufficient.

In the presence of autocorrelation, values of gamma are small at short distances (h) and increase with h. If this increase continues, the variogram is said to be unbounded; this is typical of a spatial trend (e.g. high densities inshore decreasing to low densities further offshore). If gamma increases up to a certain distance (the range) and then levels off (at the sill), the variogram is bounded (Figure 6.5.1); this typifies a patchy spatial structure where the range defines the maximum diameter of patches. The value of the sill will be close to the value of the sample variance when the range is small, as the range increases the sill is expected to be higher than the sample variance. There may also be a discontinuity at the origin (i.e. $\gamma(0) \neq 0$): this is known as a nugget effect and is due to: (1) variability occurring beyond the spatial scale sampled (i.e. less than the distance between samples); and (2) measurement error. When gamma is constant regardless of h, such that the variogram is a flat line, a random spatial process can be inferred. This, often described as 'pure' nugget, implies that spatial autocorrelation is absent and gamma should then be equal to the sample variance.
A function is then fitted to the experimental variogram to produce the model variogram. There are a variety of functions from which to choose but for most purposes unbounded variograms can be fitted using a linear model, and bounded variograms either a spherical or exponential model. A nugget effect model can be added to either of these and combinations of models into nested structures may be required. The fitting process is accomplished by inspection (by ‘eye’) or by using an automatic procedure such as weighted least squares (Fernandes & Rivoirard 1999). The fitted model represents the hypothesis of spatial structure formulated for the variable and it is this model, defining gamma as a function of h and model parameters (range, sill and nugget), that is used for further applications.

In cases where fisheries acoustic data are considered, structural analysis is often hampered by the highly skewed nature of density distributions which may lead to poor variographic structure (Murray 1995; Porteiro et al., 1995; Maravelias et al. 1996). Poor variographic structure may resemble pure nugget and subsequently may be misinterpreted as lacking spatial structure. This is often a drawback of the simple classical variogram estimator: it is not robust. There are techniques which have been reported as methods for establishing a variogram from fisheries data with highly skewed amplitude distributions (Petitgas 1993b; Simard et al., 1993). However, these have not been universally received because they are seen as ad hoc solutions to specific datasets. Other methods of dealing with this problem include: the use of alternative estimators such as the non-centred covariance (Petitgas & Lafont 1997) and the log backtransform (Guiblin et al., 1995; Fernandes and Simmonds 1997); as well as using mean variograms (Fernandes and Rivoirard 1999).

Abundance estimation and mapping

The abundance estimate of a sampled variable in a domain is determined by global estimation. This should be distinguished from local estimation which provides predictions of values of the variable at unsampled locations i.e. interpolation; which can also be described as mapping. It is possible, and in many cases preferable, to derive a global estimate by integrating local estimates i.e. calculating the volume of the map. The interpolation process is, therefore, fundamental and in geostatistics this is provided by a process called kriging. There are a number of kriging algorithms (Deutsch & Journel 1992) but all provide weights to sampled values which allow for a minimum error-variance estimate of any unsampled value.

Ordinary kriging is the most common form and this is often associated with the acronym BLUE (Best Linear Unbiased Estimator). It is ‘linear’ because its estimates are weighted linear combinations of the available data; ‘unbiased’ because it ensures that the average error is equal to zero (achieved by ensuring that the weights sum to one); and ‘best’ because it aims to minimise the variance of errors (calculated from the model variogram). Further details can be found in Isaaks and Strivastava (1989). The effect of changing the variogram parameters on kriging is nicely illustrated by Brooker (1991).

In kriging a neighbourhood must be chosen which defines an area within which the kriging weights will be assigned to samples. A unique or global neighbourhood can be used when the number of samples is not large (a few hundred at most). In the case of a moving local neighbourhood, the closest samples should be included as well as samples in various directions from the target point. Enough samples should be taken, including samples at a distance larger than the range (if this exists) if necessary.

Kriging is an exact interpolator: at a sample location, the kriged value equals the sample value. In the presence of a ‘pure’ nugget effect, the kriged map, obtained when using the same samples to krige each location, is continuous, except at sample locations. In the case of a regular or systematic grid, the arithmetic mean and the kriged mean are almost identical; therefore, kriging for global estimation is really only useful when samples are irregularly spaced. However, the best map (local estimation) is provided by kriging.

Estimation variance

The appropriate measure of precision of the global (abundance) estimate derived from a set of samples taken from a known domain is the global estimation variance (Matheron 1971). A detailed theoretical explanation in relation to fisheries data can be found in Petitgas and Lafont (1997). When computing the estimation variance the domain must first be discretised, which consists of defining a grid of nodes in the domain at a resolution greater than that of the samples. It is often necessary to refine the discretisation until convergence of the formula is practically observed. The convergence can also be speeded up through randomisation processes. Since the estimation variance is computed with a rather complex procedure, it is useful to check its order of magnitude by comparing it to the value which can be directly obtained ignoring the spatial dependence.

6.5.3 Fisheries acoustics applications

One of the first papers to utilise geostatistics in fisheries was actually from acoustic data (Laloe 1985). This and other prospective interests were followed up by the ICES community with a workshop on spatial statistical techniques (ICES, 1989) which in turn led to the setting up of a study group (ICES, 1990) and then another workshop (Anon 1993); fisheries acoustics data were considered at all of these meetings with the specific objective of producing abundance estimates with appropriate measures of precision from a systematic survey. These remain as the principal objectives of geostatistical analyses: see, in particular, the review by Petitgas (1993a) and the forthcoming book by Rivoirard et al. (in prep). Other notable contributions applied to fisheries acoustics data include: Conan et al. (1988); Foote and Rivoirard (1992); Guillard et al. (1990; 1992); Petitgas (1993b); Simard (1993); Simmonds and Fryer (1996); Warren (1992); and Williamson (1996).

These analyses, by virtue of their objectives, utilised estimates of mean fish density at sample locations which are points, but which represent the larger area over which
the data are averaged: the EDSU. ETC can provide for a more accurate scrutiny of acoustic data to obtain the selected fish species densities at the EDSU level. Subsequent geostatistical analysis may then derive estimates of abundance, variance and a map of the fish distribution. However, there are other useful pieces of information which are available at the structural analysis stage.

Application to the results of ETC

A structural analysis of the fish densities will reveal a variogram which describes the spatial structure. A linear variogram, for example, as stated above, is an indication of a trend whilst bounded variograms indicate a more patchy or clustered behaviour. In the latter case the range of the variogram is a measure of the maximum diameter of patches or clusters. As a result of ETC there are a number of options available in structural analysis which will enhance the information obtained. The most significant of these concerns a change in support. The support is the interval over which the data is averaged i.e. the EDSU, which in the case of acoustic data, is a adjustable quantity. Data collected at an EDSU of 2.5 n.m. can easily be postprocessed into EDSU’s of 0.5 n.m. or less. The ultimate extension of this is to use the highest resolution available - the ping data.

An analysis of ping data (Figure 6.5.2) from a single transect, taken from the North Sea herring acoustic survey, serves to illustrate the effect of support. The variogram of the ping data is clearly well structured and could be modelled with no nugget and a bounded variogram with a range of about 6 pings (18 m). This range corresponds to the maximum diameter of the schools (or echo traces). The variogram is then calculated using successively larger supports (10, 100 and 1500 pings). Increasing the support is termed regularisation because, as is evident from inspection of the y-axis labels in Figure 6.5.2, the variable becomes more regular (lower variance). However, regularisation at a support of 10 pings immediately loses the school based structures (range of 6 pings), as it is absorbed into the nugget’s micro scale component. The next most evident structure occurs at a support of 1500 pings with a range of about 5000 pings (15 km): this corresponds to the ‘shoal group’ or cluster of schools. This structure was not evident in the variograms using lower supports because it was absorbed into the high variability. Capturing a particular type of spatial structure is, therefore, often dependent on the support chosen in addition to factors such as the type of variogram estimator.

Capturing the structure of clusters is probably the most significant result of a geostatistical analysis on classified echo traces. There is good evidence to suggest that fish stocks have a strong spatial structural component beyond that of the school (Cram & Hampton 1976; Horwood & Cushing 1978; Blaxter & Hunter 1982). In Atlantic herring for example, clusters have been observed by various methods to be of the order of 10 n.m. which is very similar to the mean value of the range from variograms calculated from 6 years of North Sea herring acoustic data (Fernandes and Simmonds 1997). More significantly, Warren (1997) calculated variograms from northern cod trawl data, taken from 1985–1992. He observed a trend from a population with strong spatial structure (range of about 60 n.m.) in the mid 1980s, to one with little or no structure in 1992. This trend was coincident with the collapse of the stock and indicates that variography may be used as an additional tool for stock monitoring purposes. Barange and Hampton (1997) also used variography to examine school groups in sardine and anchovy; however, in this case the objective was to determine the spatial structure in order to improve the survey design.

There are variations on the basic variographic technique which may be useful at the structural analysis level. One such technique is the indicator approach where each datum z(x) is transformed into an indicator variable defined as 1, if z(x) is greater or equal to a cut-off value of z, and as 0 otherwise. Indicator variograms are then calculated for varying cut-off values so that the influence of various quantiles of the distribution can be examined. Using this method, one could, for example, look at the distribution of the extreme values which are common in acoustic surveys. Another derivative is the cross-variogram which examines the spatial covariation between two variables (see Rossi et al., 1992). This can be combined with disjunctive variograms to examine transitions between low and high density regions; examples are given in Petitgas (1993b) and Barange and Hampton (1997).

There are many other outputs from ETC in addition to fish density (Reid et al., in press). These include: morphometric parameters such as width, height and perimeter; energetic parameters such as acoustic energy; and environmental parameters such as school depth. It is certainly useful to map many of these features and in such cases a kriged map is the best method. The variography of such features should be more robust because unlike density estimates they do not contain zero values which are often responsible for masking spatial structure. Guiblin and Rivoirard (1996), for example, used geostatistics to analyse herring length and age from acoustic survey trawl data with the objective of mapping age proportions.

6.5.4 Limitations

Geostatistics is quite specific in its objectives: it is primarily an interpolation and estimation technique. In one particular respect it differs greatly from other branches of statistics: there are no tests of statistical significance. One can not, therefore, use it to make absolute comparative statements about differences in, for example, spatial structure between variables.

There are certain stationary assumptions which are specific to the particular type of geostatistical theory employed. For the methods outlined above (which rely on the intrinsic hypothesis), the process Z(x) is assumed to have stationary increments between any two points x and x+h (i.e. Z(x+h)-Z(x) have a mean 0 and variance depending only on the distance h between points, not on x). This hypothesis is implicit when modelling the variogram and in subsequent applications. It is more general than assuming the process itself is stationary, where the expected mean and variance are independent of x. This latter assumption is required for some of the alternative
Figure 6.5.2. Variograms of acoustic density on (from top to bottom) 1, 10, 100, and 1500 ping support (distances in pings, where 1 ping is approximately 3 m).
variogram estimators such as the non-centred covariance and the log backtransform. If the process is non-stationary, then stratification of the domain can be used, when the spatial structure is believed to be different in the different strata. Further details about stationary assumptions are described in Rivoirard et al., (in press).

Geostatistics can sometimes be an arduous process which can only be carried out by computer using specific software or custom made routines. It is tempting to use ‘black-box’ software packages which have convenient default settings; kriging is often implemented in this way. For example, in the old version of the popular mapping software ‘Surfer’ a linear variogram was always inferred without options to change it; and in the new version this remains as the default although a different model can be chosen. Surfer does not however, provide means for calculating the variogram. Variographic analysis of any variable is an essential requirement and must therefore be carried out using appropriate software.

One of the main limitations regarding fisheries acoustic data is the poor stability of the experimental variogram which makes the modelling process difficult. Although there are methods which may cope with this problem (see above) they may not be satisfactory in all cases. In such cases it is useful to have some knowledge of the expected spatial structure a priori so that justifications for model parameters can be made.

6.5.5 Future developments

The discipline that is geostatistics is in fact extremely large and the methods outlined in this brief review are but a fraction of what is available; however, these methods have, until now, been those that have been applied to fisheries data. In the future, more complex techniques (which by their complex nature require more stringent assumptions) may become available. These include the various other forms of kriging, and, in particular, incorporating secondary or soft information (such as sea temperature or depth) in kriging with external drift (e.g. Guiblin & Rivoirard 1996) and/or co-kriging. Conditional simulation is a common technique in mining geology which provides a more realistic global map of the variable, one that is not as smooth as the kriged map. This technique has been restricted in fisheries data due to problems associated with transforming the probability density function, but is an avenue worth exploring.

These are techniques which are commonly applied elsewhere. In addition to these are those techniques being developed within the geostatistics community itself. These include: some direct applications to fisheries (e.g. the development of weighted variograms in Rivoirard 1998) which are self evident in their applicability; developments which have the potential to be useful, such as extreme value theory which specifically considers highly skewed distributions; as well as various other cross-disciplinary movements (e.g. Bayesian fuzzy kriging), which although daunting and perhaps irrelevant today, may prove useful in the future.

6.5.6 Overview

In summary, geostatistics is a self contained discipline with the primary objective of estimating a quantity of a natural population with a measure of precision. In so doing it also provides an explicit description of the spatial structure of the population, which in itself is a useful outcome. The methodology is somewhat intricate and requires some computing power and appropriate software; an appreciation of the assumptions involved is also advantageous. Despite these limitations the technique provides the best map to describe a distribution of a variable and it is this function alone which makes it very popular.

6.5.7 References


6.6 Generalized Additive Models

6.6.1 About Generalized Additive Models

General Introduction Generalized additive models (GAM) are a generalization of generalized linear models (GLM; Nelder and Wedderburn 1990). They are both generalisations of multiple linear regression. GAMs are non-parametric regression methods which model the dependent variable as an additive sum of unspecified functions of covariates and, if desired, their interactions. The underlying probability distribution, rather than being assumed to be normal, may come from any member of the exponential family of probability distributions, which include the Bernoulli, binomial, Poisson, gamma, and inverse Gaussian distributions as well as the normal distribution. Least squares and maximum likelihood methods used in multiple linear regression and GLM are replaced by quasi-likelihood methods which rely on local scatter plot smoothing methods (such as loess or spline smoothers).

The following discussion is paraphrased from a webpage by Hastie and Tibshirani (who developed GAM; http://www-stat.stanford.edu/gam/paper/paper.html) and an article by Beck and Jackman (http://wizard.ucr.edu/polmeth/working.papers96/beck96.html). In the latter article Beck and Jackman show how GAM relates to other methods such as neural networks, GLM, ACE and projection pursuit regression. There is also a good, basic introduction to Gam by Bassett and Bishop (http://www.bioss.sari.ac.uk/smart/unix/mgam/slides/fra mes.htm).

The building block of the generalised additive model algorithm is the scatter plot smoother. Suppose that we have a scatter plot of points like that shown in Figure 6.6.1.

Here y is a response or outcome variable, and x is a prognostic factor. We wish to fit a smooth curve f(x) that summarises the dependence of y on x. If we were to find the curve that simply minimises, \( \sum (y_i - f(x_i))^2 \), the result would be an interpolating curve that would not be smooth at all.

The cubic spline smoother imposes smoothness on f(x). We seek the function f(x) that minimises:

\[
\sum (y_i - f(x_i))^2 + \lambda \int f''(x)^2 \, dx
\]

(1)

Notice that \( \int f''(x)^2 \) measures the "wiggliness" of the function f:

Linear fs have \( \int f''(x)^2 = 0 \), while non-linear fs produce values bigger than zero. \( \lambda \) is a non-negative smoothing parameter that must be chosen by the data analyst. It governs the tradeoff between the goodness of fit to the data and (as measured by \( \sum (y_i - f(x_i))^2 \)) and the wiggliness of the function. Larger values of \( \lambda \) force f to be smoother.

For any value of \( \lambda \), the solution to (1) is a cubic spline, i.e., a piecewise cubic polynomial with pieces joined at the unique observed values of x in the data set. Fast and stable numerical procedures are available for computation of the fitted curve. The right panel of figure I shows a cubic spline fit to the data.

The above discussion tells how to fit a curve to a single prognostic factor. With multiple prognostic factors, if \( x_{ij} \) denotes the value of the jth prognostic factor for the ith observation, we fit the additive model:

Figure 6.6.1. Left panel shows a fictitious scatter plot of an outcome measure y plotted against a prognostic factor x (covariate). In the right panel, a scatter plot smooth has been added to describe the trend of y on x.
\[ y_i \approx \sum_j f_j(x_{ij}) \]  

A criterion like (1) can be specified for this problem, and a simple iterative procedure exists for estimating the \( f_j \)'s. We apply a cubic spline smoother \( y_i - \sum_{j \neq k} f_j(x_{ij}) \) to the outcome \( x_{ik} \) as a function of \( f_j \) for each prognostic factor in turn. The process is continued until the estimates stabilise. This procedure is known as "back-fitting" and the resulting fit is analogous to a multiple regression for linear models.

When generalised additive models are fit to binary response data (and in many other settings), the appropriate error criterion is a penalised log likelihood or a penalised log partial-likelihood. To maximise it, the back-fitting procedure is used in conjunction with a maximum likelihood or maximum partial likelihood algorithm. The usual Newton-Raphson routine for maximising log-likelihoods in these models can be cast in an IRLS (iteratively reweighted least squares) form. This involves a repeated weighted linear regression of a constructed response variable on the covariates: each regression yields a new value of the parameter estimates which give a new constructed variable, and the process is iterated. In the generalised additive model, the weighted regression is simply replaced by a weighted back-fitting algorithm.

6.6.2 Other sources of GAM information

There is a nice introduction and tutorial written by Stefan Sperling on the use of GAM within a statistical language called XploRe. The tutorial includes some theory (http://www.xplore-stat.de/x4intro/). The most complete software development for GAM is in Splus (http://www.uni-muenster.de/URZ/Mitarbeiter/Benno-Sueselbeck/s-html/helpfiles/gam.html).

6.6.3 Potential application to acoustic data analysis

It is important to recognise that what is modelled in GAMs is the MEAN of the dependent variable. As such, the estimate for a variable at a measured point need not equal the value of the variable at that point. In fact, because GAM uses a scatter-plot smoother for its fitting it is unlikely that the estimate at any measured point would be equal to the GAM estimate. Also, confidence limits shown around the best fitting estimate are confidence bounds for the mean. From simple statistics we know that a direct estimate of the mean has a lower standard error than the variance of the estimate (by a factor of square root of sample size \( n \)). We mention this up front because several applications, which fit the spatial distribution of some variable of interest in a survey (like egg or larval abundance in an egg or larval survey), with GAM, then use the confidence limits as error bounds on the estimate. Since they obtain substantially reduced error bounds than by classical methods (random or stratified sampling) the resulting abundance appears to be more accurately known. Given what is being estimated (mean abundance and not absolute abundance) this is not surprising. But the results are commonly misinterpreted to apply to absolute abundance. These results are particularly dangerous for surveys where the biota of interest are highly clustered. In these cases adaptive sampling methods (Thompson 1992) should be considered to improve estimation accuracy, and NOT GAM.

However, if the primary interest of the investigator is in abundance trends and how they are related to spatial and environmental conditions, GAM is totally appropriate, because, after all it is the trend in the mean abundance we are concerned with (but trends and spatial autocorrelation can be related). Unlike various classification methods (which GAM is not) GAM cannot be applied directly to the question of fish school classification, but rather can be used after classification to relate different species distributions to spatial, temporal and environmental factors as well as to each other (i.e. species associations in space). They bear a major advantage over correlation and linear regression methods of not assuming a specific functional form for the relationship, and therefore allowing for general associations (e.g. temperature preferenda or acceptable salinity or depth ranges for a species).

6.6.4 Applications in fisheries and wildlife

GAM is becoming more commonly used in looking at trends over space and time of surveyed populations. Examples include:

- using bird survey data to relate trends in bird abundance over time to environmental factors Fewster, 1997; http://www-rwpa.cs.stand.ac.uk/~rachel/bto3.html
- plant abundance to temperature conditions (Petr Smilauer)
- fish abundance (including fish data collected through acoustic surveys; Swartzman 1992, 1994, 1997
- the movement of fishing vessels relative to previous catch (Dorn, 1997).

6.6.5 Technical References


Brian Ripley software (http://www.stats.ox.ac.uk/pub/5

Hastie and Tibshirani gamfit fortran routines to do GAM (ftp://lib.stat.cmu.edu/general/gamfit)

GAIM software by Hastie and Tibshirani (http://phase.etl.go.jp/netlib/a/gaim)

GAM is also available in the Genstat package developed at the Rothamstead Experiment Station and available through the Numerical Algorithm Group (NAG; http://www.nag.co.uk/stats/TT.html).
6.6.6 References


7 Current state of the art of sonar techniques

7.1 Introduction

There are several syntheses of studies with sonars, where the sonar is a part or the totality of the subject, including Simrad (1965), Forbes and Nakken (1972), Mitson (1983), MacLennan and Simmonds (1992), Diner and Marchand (1995) and Misund (1997), among others. The objective of this chapter is not to describe again the theory and techniques used for sonar research, but rather to present a little of the past, a review of the present and to look speculatively into the future on how these tools are and may be used for fisheries research. For questions on the underlying theory and technical implementation, you should consult the references above.

The term SONAR (acronym for Sound Navigation and Ranging) is nowadays rather confusing, and a redefinition could be proposed for this report. We will consider that a Sonar is the proper name for any underwater active acoustic device which is not a vertical echo sounder (i.e. one beam deployed on a vertical axis). Using such a definition, a sonar can be one of the following acoustic devices:

- Single-beam directed in a non vertical direction;
- multi-beam, whatever their main direction (considering that a multi-beam cannot be directed exclusively along a single vertical axis).

Inside this family of methods we will consider only the tools used for fisheries investigations. We will not review equipment which is designed for studying plankton at high frequencies, although this might fit in the above definition, nor will we consider in detail the state-of-the-art or unconventional tools, such as Continuous Transmission Frequency Modulated Sonar (CTFM) Acoustic Doppler Profilers (ADCP), the use of non linear acoustics or acoustic tags.

As in the case of the echo sounder, the sonar was not specifically designed for scientific research, but for industrial applications such as fisheries, oil extraction and harbour management, etc. The potential use of the sonar for research was only considered once fishermen were already using it. It is only very recently that the specific “scientific fisheries sonar” was launched, in contrast to the scientific echo sounder which has been available for 30 years. As far as research is concerned, the history of sonar is therefore linked to those used for the fishing industry.

The first sonars were single-beam horizontal systems. These began with the use of military sonars after the second world war. Simrad (1965) provides an historical insight: “Einar Lea, consultant to the Norwegian State Department of Fisheries (...) contacted the first allied naval vessel which arrived at Bergen, Norway, in May 1945. The corvette Eglantine was placed at E. Lea’s disposal during the winter herring fisheries of 1947”.

These single-beam tools were used in fisheries research, and the most important work in developing the use of sonar was carried out by a US team in California, in the late 1970s (Smith 1970, 1977 and Hewitt et al. 1976) and an FAO team in Morocco (Lamboeuf et al. 1983). Other studies over much greater distances aimed at seabed investigations, including GLORIA, (Rusby et al., 1973) and long range transmission (Weston and Revie, 1971) indicated interesting results for fish school observation with sonar. Sadly these systems were never developed further for fisheries purposes. This was probably mainly because of the problem that the sea is a strongly refracting environment (i.e. it is often stratified) and thus it is often difficult to predictably insonify targets at any reasonable range. The use of bottom bounce or the excitation of modal transmission provides a good way of achieving propagation and ensonification of schools at greater ranges. In this case there is reduction in the predictability of the signal and thus the quantitative evaluation of schools but very useful information about presence or absence may be obtained. In fact it seems that single-beam horizontal sonar did not give all the results that were required, for fisheries development concentrated mostly on the vertical sounder.

After development of the single-beam sonar, the multi-beam horizontal sonar became available. This tool is first mentioned in the fisheries research literature by Cushing (1977) who described the horizontal shape of herring schools. This system could be deployed horizontally to give a sector across a school or vertically to give the plane through the school. The sonar was also used to track the movement of fish in front of fishing gears, acoustically tagged plaice could be tracked and their gear avoidance studied. In one of the few studies on real whole gear efficiency Harden Jones et al. (1977) described the catch efficiency of a demersal trawl using these methods. A major problem at this time was the huge effort required to maintain the system and to process the data, and thus the multi-beam horizontal sonar was not considered as applicable to main stream fisheries research another decade or more.

The next improvement in equipment was the use of omni-directional horizontal sonars, which were designed primarily for fishermen. These tools used similar techniques to the multi-beam, but with the difference that they gave a complete view of the 360° around the vessel. These systems were designed first through the use of a multi-beam sonar observing successively larger sectors e.g. 6 beams of 6°, see Bodholt and Olsen (1977), then full omni-directional, with simultaneous 360° observation. These latter tools are much more recent and there use followed their appearance during the mid 1980s in commercial fisheries. They were used in fisheries research but gave limited results at the beginning (Diner and Masse, 1987; Misund, 1987a & b), and their use did not become as widespread as might have been expected, until the interest of such a tool for research on fish be-

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4 In this definition, the split-beam and dual beam transducers are considered as one beam.
haviour and stock abundance estimates was developed in Norway at the end of the 1980s (Misund et al., 1996).

Another use of sonar was the development of side-scan sonars particularly long range systems. Harden Jones and McCartney (1962) describe such a tool. The first one applied on fish schools was the GLORIA system designed in UK in the early 1970s (Rusby et al., 1973). This kind of tool was originally designed for bottom mapping. The small scale mechanical scanning sonar was subsequently developed in the late 1980’s and used in a vertical plan perpendicular to the vessel by Gunder sen et al (1982). Its value was clearly demonstrated by Ona and Eger (1987) who deployed the underwater unit near a net and observed both the mouth of the net and the fish traces. At this time multi-beam scanning systems were also being developed, though primarily for seabed mapping as swath systems as they provided precise three-dimension relief of the seabed. The first application of multi-beam side scanning sonar for fisheries acoustics was carried out in 1993 (Ger lotto et al., 1994).

Another use of multi-beam sonar is as a “multi-beam echosounder”. In this case the sonar is deployed on a vertical plan as in the case of side scanning sonar, but with the main axis of the sonar plan maintained vertical. The main difference is that this sonar does not provide necessarily a wider beam than some of the single-beam echo sounders (i.e. up to around 30°), but it does provide detailed description of the fish location below the vessel and improved information very close to the bottom (Allais and Person, 1990; Diner and Marchand, 1995).

This paper will describe each type of tool and its application in the field of fisheries research, its limitation and future use.

7.2 Single-beam sonar

7.2.1 Application in fisheries research

7.2.1.1 School counting

The main use of the single-beam horizontal sonar (SBS.) was to count fish schools over an area to one the side of the vessel. The method is described by Vestnes (1964) and Forbes and Namken (1972) and more detailed information is provided by Smith (1970). The general principle is to set the sonar horizontally on the side of the vessel and to scan the lateral area of the transect (Figure 7.1).

Then an optimal zone is defined within which the fish schools are counted and measured. This zone is limited firstly close to the vessel corresponding approximately to the distance where the water column is supposed to be exhaustively ensonified, and where the effect of the vessel on the fish behaviour is assumed null (Figure 7.2).

The second limit corresponds either to the maximum range of the sonar or to the efficient range, where discrimination between the school echo and background reverberation of bottom echoes is still possible. The most usual range is from 200 to 500 meters (Smith, 1970). The use of this type of school mapping has been infrequent. Lamboeuf et al. (1983) presented studies on distributions of sardine from surveys off Morocco, and O’Driscoll and McCatchie presented studies of sprat, baracouta, jack mackerel and tuna using sidescan off New Zealand to observe schools up to 100 m on both sides of the vessel.

Figure 7.1. Sampling strategy with single beam horizontal sonar (from Forbes and Nakken, 1972).
7.2.1.2 School behaviour

This kind of research was not the most important, but gave some pioneer results on school avoidance. The best example is the work of Neproshin (1978), who described the measurement of school avoidance in relation to the hour of the day, the noise of the vessel (speed), etc. (Figure 7.3).

7.2.1.3 Individual fish studies

Another application of single-beam horizontal sonar was to install it at a fixed location in order to evaluate the abundance of migrating fish. This method was first used for salmon counting. More recently the use has been extended to applications in shallow waters and also mobile small boat mounted systems (Trevorrow, 1997; Thorne, 1996; Duncan and Kubecka, 1996; Kubecka, 1994; Guillard, 1996; Gonzalez and Gerlotto, 1998). The main difference between this approach and earlier ones is that the fixed horizontal method is usually used for shorter range and is directed at single fish studies rather than schools.

7.2.2 Limitations

7.2.2.1 Sampling variability

There are a number of sources of error which are found with all acoustic methods which also apply in the case of sonars (Simmonds et al., 1992) these will not be discussed here. Hewitt et al. (1976) list the main sources of variability, among which the target size (i.e. the horizontal dimension of the school) is likely the most important. The source of school size measurement error is similar to that from an echo sounder when observing a school vertically, but is greater because the range and beam angles are often larger. The case of small schools is documented by Hewitt et al. (1976), who conclude that there is a general underestimation of the size of small schools. Another source of variability is the TS of a single fish or of schools. This point is critical, for the following main reasons:

- single fish: the side aspect of the target and its huge variability makes the TS measurement extremely variable. Some measurements were presented by Duncan and Kubecka (1996). Differences of more than 30 dB can be observed according to the position of the fish in the beam (Kubecka, 1994) (Figure 7.4).
Figure 7.3. Description of avoidance reactions of fish to a vessel (from Neproshin, 1978).

Figure 7.4. Target strength of a 190 mm rudd at different orientations in an horizontal plane. The points represent calculated TS values for individual hits. Curves A and B represent respectively theoretical and observed TS at different angles (from Kubecka, 1994).
single fish and schools: the correct TS of the target single fish and schools; the correct TS of the target is distorted by the multiple paths, via the surface and the bottom for both incident and reflected waves. In some favourable cases, the distance between the target and the surface and the bottom allows the clear extraction of the multi path echoes from the direct echo (Trevorrow, 1997), but when the target is far from the transducer and close to the surface or the bottom, such discrimination is impossible (Figure 7.5).

- schools: the school is not often completely included inside the beam, and the total TS of the school has to be reconstructed.

7.2.2.2 Sampling volume

Calculation of the sampling volume in the case of horizontal single-beam sonar is practically impossible, due to multiple reflection both on the bottom and the surface, and to the changes in the beam directivity due to hydrography. The usual method is to consider that due to the long distances the water column is exhaustively sampled at some distance from the transducer.

7.2.2.3 Effect of hydrographic variation

The hydrographic characteristics of the sea are usually highly anisotropic, with strong vertical stratification. This fact is of little importance for vertical echo sounders where the sound propagates normal to the stratification, but is very important in horizontal acoustics and may result in blind areas at large distances from the vessel (Figure 7.6).

A good illustration of this process is given by Rusby et al. (1973). Moreover the changes in hydrographic conditions may have a rather important effect on the sound absorption and thus the correction for this variable may be in error. Finally the hydrographic stratification may produce echoes which can be mixed with school echoes (Forbes and Nakken, 1972).

7.2.2.4 Effect of bottom echoes

The sonar range is usually much longer than the depth, and echoes from the bottom are often observed on the sonar echogram. When the bottom is flat this gives a continuous line followed by an increase in reverberation, which easy to recognise. When the bottom is rough, some discrete echoes may appear and are practically identical in characteristics to school echoes. The other problem for echoes far from the vessel is the multi-path reflections via bottom and surface discussed above.

7.2.2.5 Choice of settings

Considering that single-beam horizontal sonar is used mainly for fish schools, the TVG requirements are similar to those for a vertical sounder. A 20logR TVG will give the correct density, averaged over the beam. Thus with a knowledge of school size this could provide a measure of within school density. If the school is larger than the beam in one dimension but smaller in the other, which is often the case for single-beam sonars, it may not be possible to estimate the true within school density. If the schools are smaller than the beam, they could be regarded as point targets and thus with 40logR would give a measure of school Target Strength. There is no simple TVG to cope with all situations.

7.2.3 Future of single-beam sonar

Single-beam horizontal sonar was used for school counting during the 1970s, and the correlation between
the abundance estimates from vertical echosounding and sonar was often extremely poor for the reasons detailed above. Currently single-beam horizontal sonar is not used for school observation. Moreover technology has dramatically improved with the introduction of multi-beam sonar making SBS methods for school counting obsolete. Nevertheless this method has reappeared recently for shallow water observation of scattered fish.

A conference was held in London in 1995 and a special issue of Fisheries Research on this theme has been published (Fish. Res., 1998). The availability of elliptic transducers with low side-lobes provide a more suitable sample volume with no, or low, incidence of surface or bottom reflection. For the future some areas remain to be studied:

- the mean TS values for side aspect of fish;
- the removal of the effect of reflections from surface and bottom;
- the removal of side lobe related reflections;
- the interpretation of echoes from fish at short distance or close to the near-field. This point is not specific to horizontal single-beam sonar, but is particularly critical to this application.

7.3 Multi-beam horizontal sonar

7.3.1 Application in fisheries research

This section covers both mechanically scanned and within pulse scanning sonars. The difference is primarily the time taken to update a sector, the former may take minutes compared with one or two seconds for the latter.

Multi-beam horizontal sonars (MHS) came into major use with the implementation of contemporary computer technology to underwater acoustic instruments in the beginning of the 1980s (Mitson, 1983). Earlier work reported by Bodholt and Olsen (1977) used a 36° (six beam of 6°) scanning sonar and by Cushing (1977) on the use of multi-beam for describing the internal structure of fish schools (Figure 7.7) was followed by the first omni multi-beam sonar, for a fisheries application, the Simrad SM600 (Bodholdt, 1982).

This sonar working at 30 kHz could receive on nine adjacent horizontally oriented partly overlapping multiple beams of 12° width (-3dB points), covering a total sector of 90 in one ping. The transducer could then be trained to cover another sector, emitting one to four pings, then trained further to new sectors, and thus covering the whole 360° sector if desired. More recently developed multi-beams as the Simrad SR240 can cover the whole 360 sector in one ping (Figure 7.8).

The multi-beam sonars developed for fisheries applications have been designed for use onboard commercial fishing vessels with the sonar display updated ping by ping without a mode for presentation of past records. This presents a difficulty for scientific applications in which collection and storage of records are vital for post-processing and later analysis. The first applications of multi-beam sonars for fisheries research were therefore based on in situ measurements directly on the sonar display, or by video recording of the sonar display, and subsequent analysis of the video images.

7.3.1.1 Measurement of school behaviour

Diner and Masse (1987) used a multi-beam Furuno sonar to record schools during a survey of pelagic species off France. Subsequent analysis of the video recordings showed substantial horizontal avoidance of the schools as the vessel approached. A similar approach (Figure 7.9) has been used to quantify the avoidance of herring schools during surveys in the North Sea (Misund and Aglen 1989, Misund et al., 1997) (Figure 7.10), avoid-
ance of schools in the Mediterranean Soria et al. (1997), and swimming behaviour during purse seining (Misund 1988, 1993a) (Figure 7.11). The same device was used to map the shape and size of herring schools (Misund et al., 1993), and to establish relationships between the school geometry and biomass of schools (Misund et al., 1992). Models of fish school behaviour have been described by several authors including Pitcher et al. (1996) (Figure 7.12) and Soria et al. (1996).

Figure 7.7. Three large schools observed with multi-beam horizontal sonar; ranges in intervals of 10 m shown on the centre line (from Cushing, 1977).

Figure 7.8. Photograph of underwater situations of school and purse seine as observed on sonar data display. 1 ship symbol; 2 ship path; 3 school centre; 4 school path 5 echoes from fish school; 6 echoes from sea bottom (from Bodholt and Olsen, 1977).
Figure 7.9. Analysis of horizontal multi-beam sonar display (from Misund, 1991).

\[ CW_n = c w_n s - 2R_n \tan B/2 \text{ (m)} \]  
\[ LW = l w_n s - c v/2 \text{ (m)} \]  
\[ A_n = (LW_n CW_n/4) \pi \text{ (m}^2\text{)} \]  
\[ V_h_n = Y_n s/t \text{ (m/s)} \]  
\[ V_v_n = -(D_n - D_{n-1})/t \text{ (m/s)} \]  
\[ \alpha_n \text{ (°)} \]  
\[ V_h t = Y_n \cos \alpha_n s/t \text{ (m/s)} \]  
\[ \beta_n \text{ (°)} \]  

Index of horizontal movement \[ IHM = HD/ \sum_{j=1}^{n} Y_n \]  

- Crosswise extent
- Lengthwise extent
- School area
- Horizontal swimming speed
- Vertical swimming speed
- Radial swimming direction
- Radial hor. swimming speed
- Direction of bearing

\[ a: \text{ Calculated for encircled schools only;} \]
\[ s: \text{ Scaling factor (sonar dist./dist. on monitor screen);} \]
\[ B: \text{ Width of single sound beam (5° on transmitter);} \]
\[ c: \text{ Speed of sound (~1500 m/s);} \]
\[ t: \text{ Pulse length (4 ms with sonar range = 250 m);} \]
\[ HD: \text{ Horiz. distance between first and last school position.} \]
Figure 7.10. Distribution of radial swimming directions and a diagram of presumed noise directivity of the vessel (from Misund and Aglen, 1991).

Figure 7.11. Two examples of mackerel school behaviour during a fishing operation. Numbers refer to simultaneous position of school and vessel (from Misund, 1988).
7.3.1.2 Distributions of schools

By taking measurements directly from the display of a multi-beam Furuno sonar, Misund (1987) mapped the size distribution of anchovy schools off Mozambique. Similarly, a high-frequency multi-beam Furuno sonar was used to record mackerel schools in the North Sea, measuring their size in situ by the sonar’s estimation function, and thus assess the total abundance of schooling mackerel in the area surveyed (Misund, 1993b). The variability of measurements of school biomass was found to be substantial in these studies (Figure 7.13). Freon et al. (1992) may have explained some of this variability by showing that school density is highly heterogeneous and subject to rapid change, with a school changing its horizontal surface by a factor of four within 10 minutes.

More recent multi-beam sonars such as the Simrad SR240 were equipped with serial line output for export of data generated by the target tracking function of the sonar. Misund et al. (1993) used this method to assess the reliability of observations on fish schools during acoustic surveys. This method of logging data from the sonar has also been used during studies of the reactions of herring schools to the approach of a survey vessel (Misund et al., 1996).

To be used regularly during acoustic surveys to record, count and measure the biomass of fish schooling close to surface, horizontal guided, multi-beam sonars must be connected to software capable of detecting and measuring schools in situ, and storing of the recording for subsequent postprocessing. Such a system was developed for a single-beam sonar as early as the mid 1970s (Hewitt et al., 1976). By using the same principles for school detection, Misund et al., (1994) developed a system for computerised, automatic detection and measurement of schools by a multi-beam sonar. The basis of the school detection algorithm is to search for successive pixels along the beams above a certain threshold, defining an echoline if they extend beyond a minimum length, then to search for adjacent echolines in neighbouring beams constituting an echoblock and finally for school candidates which are persistent echoblocks. Such a system implemented on an HP workstation and connected to a Simrad SA950 sonar has been used regularly by Norwegian vessels to improve the mapping of schooling fish near surface since 1993 (Misund et al., 1996). Similarly Soria (1996) used mapping techniques to provide information on school clustering.

Figure 7.12. Mean frequency intervals (columns) and 95% confidence limits (bars) for 15 recorded behavioural events scored for four tracked herring schools (from Pitcher et al., 1996).
7.3.2 Limitations

The great advantage of multi-beam sonars compared to single-beam sonars is the greater volume coverage which give a more effective search, and the ability to insonify complete schools in a single ping. This last function is nearly a prerequisite for reliable measurements of horizontal area and estimation of echo abundance of single schools. A fundamental limiting characteristics of multi-beam sonars is resolution for reliable measurement of school dimensions. The resolution is determined by the horizontal beam width and the pulse length, though the latter is nearly negligible when the pulse length is <3 ms. Simulations have shown that reliable measurements of school dimensions require that the beam width does not exceed about 2° (Misund, 1991). Usually, low frequency fisheries sonars for the commercial fleet have beam widths of about 10°, the high frequency alternatives have beam widths of about 5°. However, more advanced sonars designed for military applications such as the Simrad SA950 has a horizontal beam width of 1.7° and the short range multi-beam Reson Seabat has 1.5° beams. In addition it is important to include stabilisation of the sonar using either mechanical or electronic correction for heave, pitch and roll.

Due to the great variability in target strength of fish in the side aspect, multi-beam sonar measurements of school dimensions and echo abundance are associated with substantial variability. The effective search volume and detection distance may also be difficult to assess, especially in areas with a stratified water column. Rough weather also limits the applicability of horizontal multi-beam sonar to detect schools near surface because reflections from air plumes and reverberation from surface may mask school echoes. Similarly, rough or hard bottom may induce bottom reverberation that masks or creates false school echoes in shallow water.

7.3.3 Future of multi-beam sonars

High resolution multi-beam horizontal sonars have undoubtedly been useful tools for studies of swimming and avoidance behaviour (Soria et al., 1996), schooling behaviour (Pitcher et al., 1996), fish migrations (Misund et al., 1997) and for mapping and abundance estimation of fish near surface (Gerlotto et al., 1994). However, further development of computer based school detection and school measurement in situ is still required. The development towards measurement of absolute school biomass based on quantification of back scattered echo intensity from schools is also to be encouraged. This will be a demanding process which will require measurement of target strength of fish on side aspect, modelling of school target strength, and methods to determine the aspect angle of fish in schools when recorded in situ. It will also require multi-beam sonars that provide a calibrated output of volume back scattering strength compensated for the gain and filter settings of the sonar.
As detailed above, Multi-beam scanning sonar (MSS) specifically its use vertically, is the most recent tool introduced in fisheries acoustic research, although its potential use was described a long time ago (Gunderson et al., 1984). Currently two teams are working on the development of this methodology, in Europe inside E.C. FAIR Project AVITIS (Gerlotto et al., 1999; Fernandes et al., 1998) using a Reson Seabat and in Canada (Mayer et al., 1998; Melvin et al., 1998) using a Simrad. The Reson sonar operating at 455kHz has a 90° sector with 60 beams of 1.5° each and 15° in the perpendicular direction with a range of 100m. The Simrad system operating at 200kHz covers 180°, with approximately the same characteristics for the beams and a range of 200m. The sonars are deployed with the fan of beams normal to the passage of the vessel, giving two dimensions normal to the track and a third dimension along the track in a manner similar to a conventional echosounder (Figure 7.14).

The conventional output consists of video images, reconstructed from the beams to produce a real time observation slice (Figure 7.15). These are recorded during the survey on videotapes or screen captured by computer for post-processing in the laboratory. In this case, the post-processing is either by eye, to produce a database containing the main geometric data; or by digitisation using an image analysis software.

A second type of output is digital data provided by the sonar at full frame rate. For the Reson Seabat on each ping a matrix of 60 columns (representing the 60 beams) and 2040 lines (i.e. 122400 pixels) is generated, producing approximately 45 MB per min. Once these raw digital data are extracted, it becomes possible to reconstruct the 2D and then 3D images of fish schools, with a much better definition than when using the video image. Processing beyond this point is similar for both the digital and digitised data sets. The sonar scans the side of the vessel route, and exhaustively explores the water volume (Figure 7.15). When used as profiling sonar (90° starboard or full 180°), the third dimension is obtained through the succession of pings along a transect, as in conventional vertical echo sounding (Gerlotto et al., 1994, Soria et al., 1996).
7.4.1 Application in fisheries research

7.4.1.1 School counting

This application is not fundamentally different from the school counting method developed for single-beam. Fish schools are counted all along the vessel track, from the vessel up to the maximum “efficient” range (in case of European MSS, 80 meters in a total range of 100). The main differences are that there is no risk of confounding pelagic school echoes with bottom echoes, as the bottom is continuously observed on the images and there is no loss of close range observations as the full water column is covered. Therefore counting is normally unbiased, as the water volume is exhaustively observed and schools are clearly identified. These two characteristics resolve the most critical points that were stressed in SBS, and we may thus assume that school counting is now a viable proposition.

7.4.1.2 School dimensions

The MSS allows the vertical and horizontal dimensions and position of the schools to be measured (Figure 7.16a,b). This gives the possibility to reconstruct precisely the 3D school shape, with the usual corrections for pulse length and beam width, but now without the need for assumptions about how the school is cut by the echosounder beam.
7.4.1.3 School behaviour

3D acoustics, by the way of observation at different horizontal distances from the boat, allows for the calculation of a correction factor for vertical echo sounding, as in the case of MHS; but the fact that the vertical dimension is also exhaustively observed allows a more detailed analysis. Soria et al. (1996) show that the effect of the vessel on school distribution can be demonstrated and evaluated. They proposed a general avoidance model. We present here the results obtained during five surveys.

Figure 7.16a. A view at different angles of the 3D reconstruction of a herring school from a multi-beam scanning sonar (from Fernandes et al., 1998).

Figure 7.16b. A 3D reconstruction of a number of herring schools from a multi-beam scanning sonar (from Fernandes et al., 1998).

Figure 7.17 shows the spatial distribution of all the fish schools along the side of the vessel, which demonstrate the existence of an avoidance reaction. Unlike the MHS, these behaviour studies are not dynamic (it is impossible to measure the speed and individual reaction of the schools), but statistical. This shows that the two tools are complementary: MHS describes the instantaneous reaction of a given school, while MSS describes the effect of school behaviour on survey data.
7.4.1.4 Biomass estimate

Simmonds et al. (1992) showed that the accuracy of the biomass estimates depended on sampling errors and on a series of methodological biases. The 3D sonar method is able to improve the precision of the biomass estimate in both these aspects: it increases the sampled volume, which could improve the precision of the estimate, and it gives a count of schools far from the boat, which quantifies the bias due to lateral avoidance. The echo energy of the school is theoretically measured too. However, two problems remain:

- not all the schools can be measured cleanly, due to the high background reverberation generated by side lobes at distances beyond the vertical distance to the bottom, the background reverberation can be as strong as the school echo;
- and lateral target strength must be known and orientation may be important. If school avoidance is indicated by school counting, it is hard to be sure that fish orientation is independent of the observer.

7.4.1.5 Shallow water observation

We described above the recent development of SBS for shallow water. This tool presents one important drawback in the case of shallow water; reflectivity from the bottom and surface may have a strong influence on the results, firstly because a single fish echo may not be clearly recorded independent of multi-path echoes, and secondly because it is difficult to discriminate between the bottom or surface echo and fish echoes. MSS provides a good solution to this problem, as the bottom and surface are more precisely located and fish echoes can be more easily discriminated (Gerlotto et al., 1999) (Figure 7.18). Distribution of schools and single fish can be recorded, and fish biomass evaluated with less bias than when using SBS.

7.4.1.6 Multi-beam vertical echo sounder

We described at the beginning of this chapter the possibility of using multi-beam sonar as vertical echo sounders. This method is rather similar to the use of MSS as described above, with the difference that the axis of the observed plane is vertical. This tool dramatically reduces the problems related to the beam angle: fish close to the bottom can be observed with a good precision, as well as fish at greater depths (Diner and Marchand, 1995).

7.4.2 Limitations

Most of the limitations of MSS are rather similar to those of MHS. Some others are detailed below.

7.4.2.1 Technical limitations

The most important limitation in MSS is the effect of side lobes. The bottom echo is extremely strong compared to school echoes, and thus produces reverberation on all the beams. This limitation has two consequences. The first one is that the information at distances greater than the depth is contaminated by background reverberation. Thus echo energy cannot be measured directly.
Figure 7.18. Application of multi-beam scanning sonar in shallow waters (2m). The successive cross sections of a fish school can be seen in the centre of each image. The solid sloping line is the seabed. The low quality of the image is due to the video acquisition process. (from Gerlotto et al., 1996).
Fortunately this phenomenon does not affect seriously the school image, as far as geometry and shape are concerned. This implies that we cannot measure school biomass for the schools at distances beyond the distance to the bottom. The second point is that currently due to dynamic range limitations it is practically impossible to consider the use of MSS for scattered fish, except under unusual conditions. This may have an impact on shallow water developments.

7.4.2.2 Calibration

This point is not very different from the case of MHS. The calibration procedure for the MSS is more complex but not fundamentally different from the standard echo sounder calibration (MacLennan and Simmonds, 1992; Simmonds et al., 1999).

7.4.2.3 Data management

The huge amount of data collected by MSS makes an acquisition and storage procedure indispensable. Currently the volume of data to be recorded is around 45 MB per minute. While this may be approaching critical limits at present, one may assume that the improvements in data processing and storage capabilities of the PC will provide a solution to this problem soon.

7.4.2.4 Significance of sonar images

Another limitation is the representativity of the frames, due to hydrographic stratification. As in the case of horizontal sonar, as long as the range is not too great this point can be neglected. It will however, always limit the application of multi-beam at long ranges.

7.4.3 Future of multi-beam scanning sonar used vertically

There is no doubt that MSS will be an important tool in the future of fisheries acoustics, as it solves several problems present in other tools. We may imagine that the future MSS will observe the complete plane of 180°, from one side of the vessel to the other, with 120 to 180 beams of 1.5° or 1.0°. The beams around the vertical axis (e.g. the 10 or 20 beams closest to the vertical axis) would give echo integration output, as in this water volume fish are observed in a standard position, for this part of the instrument separation of bottom is relatively easy and the side lobes have no real impact. The lateral beams would give information on the school number and shape, and allow better extrapolation of the echo sounder results. Thus this tool will overcome any avoidance factors, increase sampling volume while retaining all the advantages of the conventional sounder.

7.5 Future technological development of sonar systems

7.5.1 Technology of multi-beam sonars

Two major points require still some extensive research and development: the effect of side lobes in MSS, and the school recognition in MHS.

7.5.1.1 Side lobe effect

We have detailed above the effect of side lobes and shown its limiting effect on range. As long as this problem is not resolved, MSS will not allow biomass estimates to be extended over 100s of metres to the side of the vessel. The ideal equipment would present at least a difference of 40 dB between main lobes and side lobes, which is far from the current case of 20–25 dB. Once such a tool has been developed, we may assume that MSS would be in condition to substitute the vertical single-beam echo sounder for fish stock assessment, considering all the advantages MSS presents compared to echo sounder.

7.5.1.2 School echo recognition

At present the algorithms are developed for fishermen. Most of the small schools are not resolved. The school images are suited to commercial value, and, except on more recent sonars, do not necessarily represent the full range of schools. A proper algorithm for school recognition should be developed. Once this “scientific algorithm” has been developed, MHS will provide evaluation of individual school movement, school clustering behaviour and avoidance reaction.

7.5.2 Processing

7.5.2.1 Data acquisition and storage

There is usually no way to access the signal itself (either analog or digital), and the main output for most sonars is still the video image. This is not satisfactory for scientific purposes, as the scientist cannot determine the effects of the different settings, and calibrating the beams is difficult. Moreover there is considerable degradation in the precision of the data. Some specific methods for acquisition and data storage have to be developed.

7.5.2.2 Visualisation and image analysis

Sonars generally give 2D or 3D images. It is clear that image analysis will be the most likely processing method for these data. Some preliminary studies have been carried out. Nevertheless there is there a wide field of technical research to be developed in order to make sonar image analysis routinely possible. It is likely that true 3D observation of fish schools will be greatly improved in the future, including 3D stereo visualisation. This kind of output will serve to assist decision making for fishermen and the development of in situ behavioural research.
7.5.2.3 Data analysis

The research using multi-beam sonars are still preliminary, and the actual capability of those tools are not yet completely explored. It seems clear, for instance, that spatial analysis tools could be applied to sonar data to give 2D maps of school structures and their distribution. The use of geostatistics inside cluster images, or even school images, should be considered. School classification could be much enhanced by the use of 3D reconstruction of schools.

7.6 The future tool

One may imagine the ideal future acoustic tool for fish stock research; it would have a multi-beam architecture, not very different from that already proposed by several designers, with the following features:

- a 360° multi-beam head for the horizontal plane, rather low frequency to give long range, beams as narrow as possible (3°) for horizontal observation of schools dynamics and distribution;
- a 180° multi-beam head for the vertical plane, deployed perpendicularly to the vessel track, observing exhaustively the water column from one side of the vessel to the other. Very narrow beams (around 1°) in any direction, rather higher frequency for good short range definition;
- Inside the 180° beams, a portion (around 30°) centred on the vertical line below the vessel processed as vertical echo sounder, giving echo integration and TS information on the scattered fish and schools.

This tool would overcome most of the current problems: fish avoidance, fish observed close to the surface and the bottom, school structure and shape, full 3D fish and school distribution, unbiased echo integration, etc.

7.7 Bibliography on the use of sonar (including all papers refereed to in the text)


8  Review of multi-frequency and wide-band systems

8.1  Introduction

It is well known that extending the frequency range of radar or sonar allows more information about remote targets to be extracted from the observed echoes. Conventional sonars have a bandwidth which is only a few percent of the operating frequency. It is technically difficult to overcome this limitation, however, there are two approaches to the problem. Firstly, several narrow-band transmissions centred at different frequencies might be used in combination. This is the multi-frequency concept. Secondly, if the bandwidth of one instrument can be extended sufficiently, the useful frequency range is continuous. This is the wide-band method which term we will adopt for instruments having a bandwidth more than 50% of the centre frequency.

The ICES Study Group on Echo Trace Classification (SGETC) recognised at an early stage that many organisations have or are developing wide-band and multi-frequency systems. Such instruments provide additional information which could assist with ETC. Furthermore, there may be other acoustic or non-acoustic techniques which could be useful in this type of study.

In order to collect background information on this topic, and to see how effective or otherwise wide-band/multi-frequency methods are for ETC, we circulated a questionnaire in January 1998. A copy of this questionnaire is attached as Annex 2. The aim has been to cover both (a) development work, where the equipment is the end product, and (b) applications, where the equipment is used in a specific fishery and/or plankton research project.

The initial survey resulted in 14 returned questionnaires. Later on we sought to fill in gaps through correspondence with a few researchers who had not returned a questionnaire but were known to be active in the field. A list of the contributors who provided the information compiled in this review is given at Annex 1.

Here we present a summary of the main findings, and we consider the extent to which existing equipment is capable of meeting scientific requirements for ETC, or whether continued development of wide-band/multi-frequency techniques is necessary. Our review is unlikely to have achieved a complete coverage of relevant work in the field, however we believe the range of equipment and methodologies reported here do give a reasonably complete picture of techniques now in use or which may yield exciting new prospects from further development.

The following numbered paragraphs refer to the information given in the corresponding section of the questionnaire (Annex 2).

8.2  Sources of information

The number of replies by country is shown in Table 8.1. All respondents were reporting personal research experience, except for two replies concerning “activities at my institute”.

8.3  Equipment specification

8.3.1  Introduction

The responses generally fell into three categories: 1) the use of two frequencies; 2) use of more than two frequencies; and 3) the use of wide-band acoustical systems. Only one respondent is working with a single frequency EK500. Each of these methods has advantages and disadvantages, with cost and availability driving the investigators to use existing gear, trying to extract as much information as possible from what they have. While this is clearly not optimal from a theoretical point of view, it is a practical approach and offers a good deal of promise in some environments.

8.3.2  The Two-Frequency Method

Theoretically, the two-frequency approach is particularly promising for locations in which the acoustical scattering is dominated by physically separate schools, layers or aggregations, each of which is characterised by a single species with a narrow size range. Several investigators report success with this approach while working with a variety of taxa. The basic theory is well established, but models are lacking for all but the simplest shapes. Several investigators are approaching the problem of classification with the two-frequency method from an empirical, rather than a theory-based direction.

8.3.3  Multi-frequency methods

Multi-frequency systems, meaning those which use two or more frequencies, are summarised in Table 8.2.

Table 8.1. Number of replies by country to the questionnaire.

<table>
<thead>
<tr>
<th>Country</th>
<th>Australia</th>
<th>Canada</th>
<th>France</th>
<th>Iceland</th>
<th>Norway</th>
<th>UK</th>
<th>USA</th>
</tr>
</thead>
<tbody>
<tr>
<td>Replies</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>1</td>
<td>1</td>
<td>3</td>
<td>4</td>
</tr>
</tbody>
</table>
8.3.4 Wide-band methods

For the purposes of the present review, we use the term “wide-band” to mean sonar which has an operating bandwidth more than 50% of the centre frequency. Transducers capable of such a broadband performance are usually limited in power, depth rating, or some other performance factor compared to conventional devices. Nevertheless, wide-band systems have the advantage of allowing one to extract essentially continuous spectral shape and amplitude information from the echoes. One also has the choice of processing for high range discrimination (resolution) without necessarily obtaining spectral information. Some combinations of pulse waveform and processing can give both good range discrimination and doppler (target motion) information.

The primary disadvantage is that bandwidth is generally a percentage of the centre frequency of the transducer. As the percentage goes up, so does the cost, especially for high power transducers. An early approach was the so-called parametric sonar (Westervelt 1963; Smith 1971). This uses the non-linearity of acoustic propagation in water to generate a low-frequency signal by mixing two high-power transmissions at higher frequencies. Unfortunately, the method is energy inefficient and the achievable signal power is rather weak.

In the case of transducers constructed from conventional ceramic materials, an important requirement (at least for abundance estimation) is the need to sample the same volumes of water (i.e., the same animals) over the entire band of frequencies with a wide-band system. This can be challenging, as the beam-width usually changes with frequency within the band. There are sophisticated ways to overcome this problem, for example the spherical cap transducer which uses beam shading to achieve a beam-width which is almost independent of frequency (Simmonds et al. 1996). However, none of these advanced concepts are known to be in use within the fisheries assessment community, beyond the experimental stage.

It should be noted that added bandwidth can carry more information about an object or animal that scatters sound, but there are choices in how one processes the echoes. The choice of the processing method ultimately determines the kind and amount of information that one can extract and use in a broader classification scheme. One must be careful to examine the signal-to-noise per unit bandwidth in such systems because opening the receiver bandwidth to more signal frequencies also opens the system to more noise. These considerations usually require the use of more complex waveforms and more complex signal processing. Furthermore, it can be useful to obtain sets of discrete measures from the continuous spectral signature, as a basis for quantifying differences between signals in numerical terms. Techniques for this have been adapted from research on speech recognition, in particular the use of “cepstral coefficients” to compute a “spectral distance” between two signals (Zacharia et al., 1996).

Investigations with five wide-band sonars were reported in the replies to our questionnaire. A summary of the principal features of these systems reviewed in this study is shown in Table 8.3.

<table>
<thead>
<tr>
<th>Lowest Frequency (kHz)</th>
<th>Highest Frequency (kHz)</th>
<th>Waveform</th>
<th>Status</th>
</tr>
</thead>
<tbody>
<tr>
<td>20</td>
<td>80</td>
<td>Modulated pulse and chirp (FM)</td>
<td>Experimental</td>
</tr>
<tr>
<td>27</td>
<td>54</td>
<td>Chirp</td>
<td>Experimental</td>
</tr>
<tr>
<td>150</td>
<td>350</td>
<td>Chirp or gated sine wave</td>
<td>Laboratory</td>
</tr>
<tr>
<td>230</td>
<td>384</td>
<td>Coded pulse</td>
<td>Experimental</td>
</tr>
<tr>
<td>300</td>
<td>700</td>
<td>Chirp or gated sine wave</td>
<td>Laboratory</td>
</tr>
</tbody>
</table>

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What is the equipment used for?

Multi-frequency acoustic techniques have been employed in many of the world’s oceans and seas over a variety of water depths, and to a lesser extent in freshwater lakes. They have been used as an aid to species identification, to improve accuracy of biomass estimates, and for behavioural studies. Responses to this questionnaire suggest that a desire for information on the identification of acoustic targets is the motivation behind the greatest number of ongoing multi-frequency studies, see Table 8.4.

Equipment used for multi-frequency studies ranges from purpose-built instruments developed in response to knowledge of particular scattering properties of target organisms (e.g. TAPS), through specifically modified commercially available instruments (including ADCP), to standard, off-the-shelf hardware (e.g. EK500). The equipment has been deployed from dedicated research vessels, from ships of opportunity, and on buoys: studies have also been conducted on caged animals.

Multi-frequency techniques have been used for studies of fish, micronekton and zooplankton. They have been used to discriminate within and between these groups, and for discrimination of biological targets from physical phenomena such as bubbles.

Zooplankton/Micronekton: Multi-frequency techniques have been used to discriminate between and identify zooplankton/micronekton species/size classes, to estimate zooplankton abundance, and to draw inferences on zooplankton abundance and distribution relative to prevailing oceanographic conditions and environmental variability.

Fish: Multi-frequency techniques have been used to characterise aggregation patterns of several pelagic fish species, to identify fish species, and to discriminate between fish species. Resulting knowledge of the identity of acoustic targets, and target behaviour, has in some instances been used to improve accuracy/precision of biomass estimates.

Data analysis

Use of standard packages or special software

A variety of general-purpose packages were mentioned in the questionnaires, ranging from common spreadsheets like MS Excel to the more sophisticated Matlab (4 cases), SPSS and Oracle (1 case each). Three respondents said they had developed their own software. We note that in the case of Matlab, in-house software in the form of Matlab procedures (written in a language similar to C) would still be required. It is likely that such routines would be designed for the specific application and may not be useful to other users unless the application was the same. The replies did not generally say whether the in-house software was just that, as opposed to being fully developed and commercially available. Presumably the latter would apply to companies selling the software as part of an integrated system.

There are several packages which have been or are being developed specifically for the analysis of acoustic data, which may be considered “standard” in the sense of being generally available and useful in a range of applications.

Four of the respondents were using the Simrad B1500 which is well established as a commercially available package. This has to be run on a Workstation with the Unix operating system which is technically complicated and not very user friendly.

More recent developments have aimed at PC-based solutions which should in principle be simpler to operate. One report from Canada described an integrated software package called CH1 which is under development. This uses a standard data format known as HAC and combines several data analysis approaches.

The Australian company SonarData is marketing the “EchoView” proprietary software for acoustic data analysis. Although still under development, this package is already being used by several research institutes. It is intended that “EchoView” will soon include a capability for the analysis of multi-frequency data.

General approach and methods

This question really covered three different aspects: (a) Selection of records for archiving; (b) analysis methods and (c) display of data and/or results.

1. Most respondents gave comprehensive details of the collected data. These might include SV by depth bin at various frequencies, either as the raw values or as summary statistics, and supporting information such as environmental observations. In this type of work there is the potential for collecting very large quantities of data and some degree of selection or summarising is normally essential.

2. There are several examples of discriminant analysis and neural networks being used for school identification. These appear to be the most promising approaches at present. Time/frequency analysis was mentioned but it does not seem to have produced
useful results so far. In the case of plankton studies, models are often used to interpret the acoustic data in terms of size distributions. The “truncated fluid sphere” and the Holliday-Greenlaw algorithm are particular examples of the modelling approach.

3. In some cases the display of data is part of the analysis procedure when, for example, the user has to control the selection of schools for processing. Apart from echograms, there is also the problem of how to present statistical results in an informative way. Some form of picture presentation is an obvious way to show a mass of data so that the important features are apparent. GIS (Geographic Information Systems) have been mentioned as a useful approach in this connection.

8.6 Reports and publications

The references quoted in the questionnaires have been extracted to produce the comprehensive bibliography given at the end of this report.

8.7 Potential for further development

There is a unanimous view from respondents that new methods for ETC are needed in support of fisheries assessment efforts, and that the exploitation of the frequency domain by using multiple discrete frequencies or increased bandwidth around a single frequency are attractive candidate approaches to the ETC problem. These responses are consistent with the theory of signal processing which relates the bandwidth and the amount of information that can be transferred over a communications channel. While the details differ, both large bandwidth systems centred at a single frequency and multiple, discrete frequency instruments may exploit the consequences of increased bandwidth.

Multi-frequency and wide-band methods are relatively well developed for plankton and may now be considered a routine technique in studies of biological oceanography. The principal results achieved by these developments have been measurement of biomass by size in relation to the physical, food and chemical environment. However, unless size is a unique discriminant within a particular environment, these methods cannot yet be used alone for species identification. Additional approaches such as multi-frequency, multi-static methods are under investigation and seem to have some potential for extraction of shape and several physical characteristics such as compressibility and density contrast of the animals compared to sea water.

In the opinion of the respondents, the exploitation of multiple frequency and wide-band acoustical signals for classification and identification of fish is a promising avenue for future investigation. Multi-frequency methods are currently being applied to nektom in a variety of locations and for a variety of taxa. However, the application of the technology for fisheries assessment is in its infancy, with a need for application to additional species at different depths, in different seasons, and in a diversity of geographical locations. The need to examine aggregations of mixed populations or assemblages, especially in situ, was explicitly noted.

Several responses directed attention to the need to include all available information in classification processing, not just acoustical data. This means including such parameters as location; season; time of day; depth of the target; characteristics associated with its aggregation (e.g., layering, schooled, size, shape); the environmental or ecosystem characterisation (e.g., association with food and the physical environment); historical catch data; bottom characteristics (e.g., topography, vegetation, bottom type), etc. It is thought that the inclusion of as many factors as is possible might enhance the power of future discriminant or other analyses leading to species identification. The need for mathematical models that are useful for a wider variety of species, optimisation of the frequency bands to be utilised for particular species and the spacing or resolution (number of frequencies) within those bands were also mentioned.

One respondent summed it up rather well with the comment that "Multi-frequency is definitely the way to go ... imagine looking at the world through sunglasses that allowed us to see in only ONE colour ...".

8.8 Any other comments or views on echo classification problems

Use of multi-frequency acoustic techniques, and associated statistical analyses, have proved to be moderately successful at target identification, achieving between 70 and 90% correct species classification in some instances. However, more successful results have been obtained in the controlled conditions of cages than in the open ocean, and particular difficulties have been experienced when trying to classify mixed species aggregations.

Technical problems associated with multi-frequency studies include:

- The short target range associated with high frequencies;
- Variation of the beam width and sampling volume with frequency;
- The change in noise level (and thus signal threshold) with frequency.

Although there have been some notable successes, the general application of multi-frequency techniques to fisheries and plankton acoustics is in the early stages of development, and much remains to be done before autonomous acoustic classification of species can become routine. However, it seems likely that many of the associated problems can and will be overcome, and multi-frequency data will be used increasingly as target identifiers, augmenting the probably biased information on species composition which is obtained from net catches.

The more lines of information (discriminating characters) one has available, the greater the likelihood of correct target identification. The multi-frequency and wide-band methods have shown promise and they have potential for further improvement. But there are other possi-
bilities for future work leading to improved target identification methods. These might include the integration of conventional sonar observations with other kinds of information, such as optical sampling (OPC) and Doppler signals which show the speed of targets. Another approach is the matching of observed signals with predictions of what is expected from likely targets. There is need for new theoretical studies of acoustic scattering by live plankton and fish, to predict the acoustic signature and especially its frequency dependence, for a range of species more accurately than is possible at present.

8.9 Bibliography

In addition to the citations listed below, a number of others will be found in Vol 3 of the proceedings of the 16th International conference on acoustics which was held jointly with the 135th meeting of the Acoustical Society of America, in Seattle USA 22–26 June 1998. The proceedings were edited by Kuhl and Crum.


Socha, D. G., Watkins, J. L., and Brierley, A. S. 1996. A visualisation-based post-processing system for analy-


## 8.10 Correspondents

List of correspondents who contributed information compiled in this report

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