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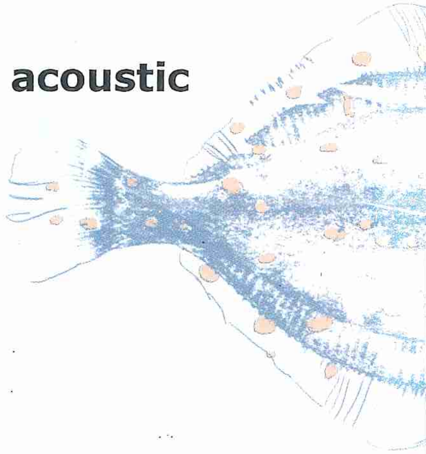


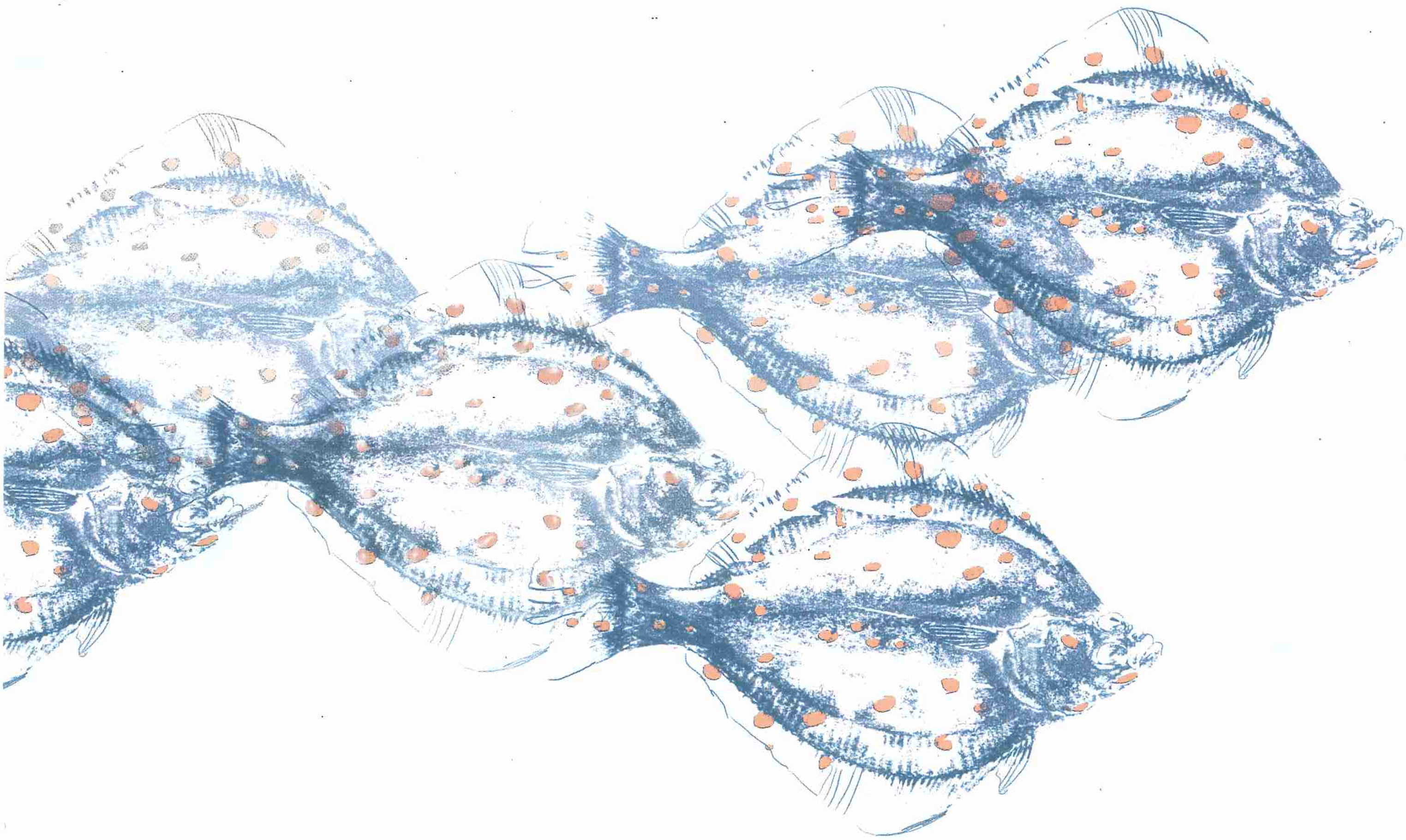
Stichting Wageningen Research
Centre for Fisheries Research (CVO)

Analysis of ancillary acoustic data during acoustic trawl surveys

B.J.P. Bergès, S. Sakinan

CVO Report 20.011

May 2020



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Analysis of ancillary acoustic data during acoustic trawl surveys

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Summary

Acoustic trawl surveys are routinely conducted around the world. They consist on following pre-defined transects, imaging the water column acoustically using downward active acoustic systems (so called scientific echosounders) and conducting regular trawling. This type of survey is used to assess the state of marine species (most often fish) at a specific point in time. Whilst echosounder data and trawling information are the base of an acoustic trawl survey, various types of ancillary data can be collected to complement the survey. An important part of the processing of data collected during a fish species acoustic survey is the scrutinisation process. It consists on the categorization and allocation of echo traces into species or species groups. Through expert judgement of the analyst, this relies on acoustic (frequency components, school morphology, time of day, depth etc) and biological (fishing) information. This information is usually specific to each survey and each species. For difficult scrutinisation cases, ancillary data (e.g. additional acoustic data, video data) can significantly aid this process.

In this report, the use of two type of ancillary acoustic data collected during the herring Acoustic Survey (HERAS) onboard Tridens II are investigated: the multi-beam echosounder data (MBES, ME70) and the multi-frequency data from the split-beam echosounders (EK60/EK80 Continuous Wave). First, MBES data from HERAS 2016 were analysed with the aim of: (1) building a database of 3D fish school descriptors for potential future use during HERAS survey scrutinisation, (2) comparing MBES data with single beam echosounder data (EK60) in the context of abundance estimation. The results of the comparison between the ME70 and the EK60 showed that results are in line though an increased coverage of the water column with the ME70 induces greater variability. Historical HERAS data were analysed in order to investigate acoustic fingerprints for herring during this survey. The HERAS surveys from 2015 to 2019 were reanalysed using LSSS (Large Scale Survey System) automatic routines for fish school detection. The fish school descriptors and acoustic fingerprints were then used for classification using a Neural Network (NN). The NN classifier yielded an accuracy for herring of ~70%.

1 Introduction

Acoustic trawl surveys are routinely conducted around the world. They consist of following pre-defined transects, imaging the water column acoustically using downward active acoustic systems, so called scientific echosounders (Simmonds and MacLennan 2005), and conducting regular trawling. This type of survey is used to assess the state of marine species (most often fish) at a specific point in time (Gunderson 1993; Fernandes et al. 2002). Whilst echosounder data and trawling information are the base of an acoustic trawl survey, various type of ancillary data can be collected to complement the survey.An important part of the processing of data collected during a fish species acoustic survey is the scrutinisation process. It consists on the categorization and allocation of echo traces into species or species groups. Through expert judgement of the analyst, this relies on acoustic (frequency components, school morphology, time of day, depth etc) and biological (fishing) information. This information is usually specific to each survey and each species. For difficult scrutinisation cases, ancillary data (e.g. additional acoustic data, video data) can significantly aid this process.

Onboard the Dutch Research Vessel (RV) Tridens II, three main acoustic pieces of equipment are available from SIMRAD[1]: the EK60/EK80, multi-frequency narrow beam split-beam echosounder (Figure 1-1(a)); the SU90 omnidirectional SONAR (Figure 1-1(b)); the ME70 multi-beam echosounder (Figure 1-1(c)). Both the EK60/EK80 and the ME70 are mounted on a drop keel (3 m maximum penetration depth). For the split-beam echosounder, both the EK60 and EK80 systems are fitted on the vessel because the EK80 superseded the EK60 in recent years. Until the herring Acoustic survey (HERAS) in 2018, the EK60 was routinely used for surveys. Since 2019, the EK80 in Continuous Wave mode (CW) is used instead. This was motivated by the fact that the EK60 was no longer manufactured but also by studies which showed that both systems yielded comparable measurements (Sakinan et al. 2018; Sakinan and Berges 2020; Macaulay et al. 2018; Demer et al. 2017). The omnidirectional SONAR is most commonly used during fishing operation for tracking fish schools and is only occasionally used for research or survey purposes. As for the ME70, it can be used alongside the EK60/EK80 for a range of applications (Trenkel, Mazauric, and Berger 2008).

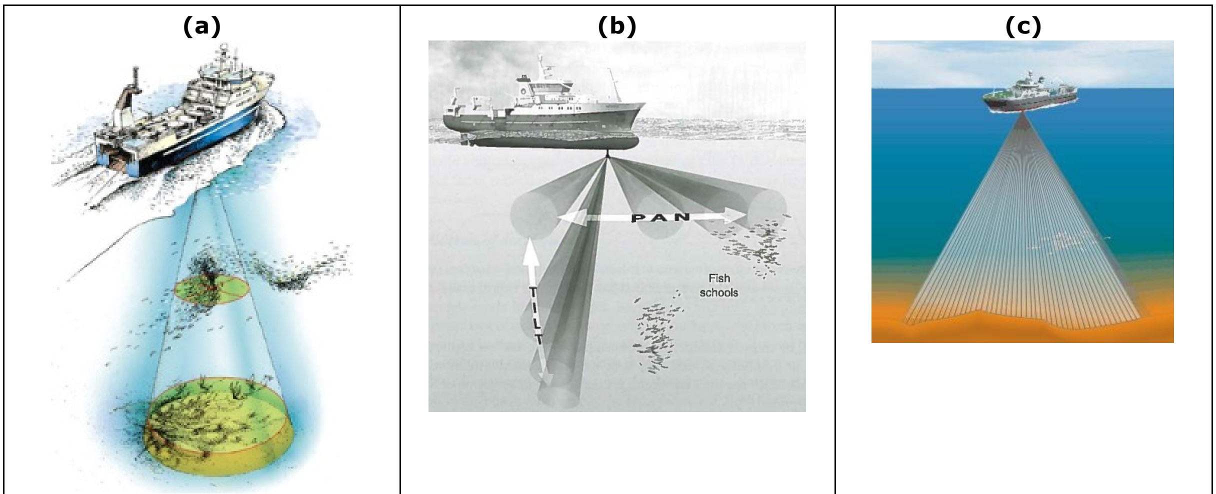


Figure 1-1: *schematics of working principles of acoustic equipment used onboard Tridens II. (a) Split beam echosounder (SIMRAD EK60 and EK80). (b) omnidirectional SONAR (SIMRAD SU90). (c) multi-beam echosounder (SIMRAD ME70).*

1 https://www.kongsberg.com/simrad

In this report, the use of two type of ancillary acoustic data collected during the HERAS survey (ICES 2018) are investigated: the multi-beam echosounder data (ME70) and the multi-frequency data from split-beam echosounders (EK60/EK80 CW) around fishing operations.

Narrow acoustic beams are useful to maintain the energy intensity at usable levels within the acoustic beam. These narrow beams provide very accurate measurement of scattering level in the water column as one sample per depth bin (with varying resolution). However, the subsequent coverage of the beam is limited. For example, the coverage of the EK80 CW echosounder at 38 kHz is ~12% of the water depth (7° beamwidth at 3 dB cut-off). In turn, this acoustic equipment only provides thin 2D slices of fish schools. Notably, the athwartships (Across the vessel direction) extend of the school cannot be determined accurately. In contrast, multi-beam echosounders such as the ME70 allow one to image the water column across a wide sector with a large sample area in the athwartships direction. This is achieved through a fan of acoustic beams orientated at different angles forming the swath of the multi-beam system (Figure 1-1(c)). The overall advantage of the ME70 is that it samples a larger volume while maintaining the range resolution and accuracy compatible with single beam echosounders. In this study, the use of the ME70 multi-beam echosounder data is twofold. First, the effect of increased water column coverage by the ME70 (compared to the EK60) is investigated in the context of abundance estimation. Second, the water column resolution offered by the ME70 is used to build a data base of volumetric fish school descriptors.

Acoustic surveys follow a random sampling design where a set of strata are arranged based on the assumption that the targeted fish within each stratum are distributed somewhat randomly. As a result of the survey design, the average abundance from many number of observations (fish school echo traces) along the transects within a stratum are considered to converge to the true abundance in that stratum. In the case of North Sea herring *Clupea harengus*, the distribution of fish school echo traces can be patchy. On specific strata (including the Dutch component of the survey), a large proportion of the biomass can be concentrated on very localized spots. Within these spots, fish can be further concentrated in large – dense schools. There are often very large and concentrated schools that contribute most to the abundance even though they are very few in number. The conventional single beam echo-sounder used as a standard tool for the survey uses a narrowly focused beam, therefore insonifying a very narrow cross-section from each encountered school. Because the sampled volume is limited, it may be important to asses: (1) from which portion of the school the cross-section is obtained, and (2) if the sampled sections are representative for the school. In the case of (2), an important bias may be introduced in either negative or positive way.

In order to deal with highly concentrated areas (to resolve the associated uncertainty), a solution would be to increase the survey effort. However, this solution is impractical because:

1. Fish are not stationary, therefore, grid resolution has to be to be arranged to prevent double counting
2. Survey needs to be synoptic and the time is limited
3. The main location of dense fish concentrations changes each year

An alternative solution would be using a different tool to enlarge the sampled volume. The ME70 system is suited to this task as a multi-beam echo-sounder used to sample the water column with high precision and accuracy. Its advantage relative to the conventional single beam is that larger part of the fish schools can be sampled. The sampled volume can be up to 15 fold compared to the regular single beam echosounders (EK60/EK80). This increased sample volume can be used to address the potential uncertainty of using single/narrow beam echosounders on the irregularly shaped fish schools.

Single beam echosounders such as the EK60 and EK80 CW are narrow beam systems using narrow frequency bandwidth. Onboard Tridens II, these echosounders are operated over six narrow band frequency channels: 18 kHz, 38 kHz, 70 kHz, 120 kHz, 200 kHz, 333 kHz. The collected data therefore consist of multi-frequency acoustic backscattering in the water column below the vessel. The multi-frequency aspect coupled with school morphology descriptors can be utilized (R. J. Korneliussen et al.

2008) and has applications for identification of fish species (R. J. Korneliussen et al. 2009; Rolf J. Korneliussen et al. 2016; R. J. Korneliussen 2010) (Figure 1-2). Though effective for discriminating biologically different species (with and without swimbladder, e.g. herring and mackerel *Scomber scombrus*), narrow band echosounders data have limitations when applied to biologically similar species (e.g. herring and horse mackerel *Trachurus trachurus*) (de Robertis, McKelvey, and Ressler 2010). This can potentially be overcome by the use of broadband transmit signals (EK80 in Frequency Modulated mode) (Berges et al. 2019). Though this solution comes with challenges (e.g. data size and data handling) and the methods are not mature yet in the context of acoustic surveys.

In this study, the use of multi-frequency echosounder data for fish species identification is investigated specifically for the Dutch component of the HERAS survey. This makes use of historical echosounder data to derive a classifier based on energetic and morphologic fish schools features.

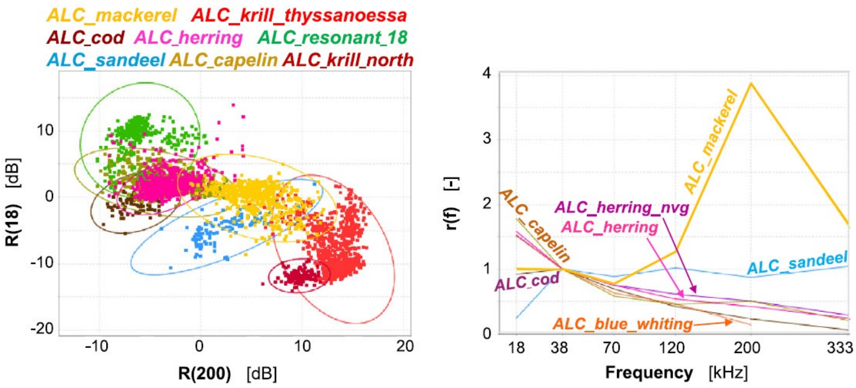


Figure 1-2: *categorization of fish species group based on their multi-frequency signatures. Figure extracted from Korneliussen et al 2016* (Rolf J. Korneliussen et al. 2016).

Data from the HERAS acoustic trawl survey used in this study are: 2015-2019 for the EK60/EK80 multi-frequency analysis and 2016 for the ME70 analysis. The HERAS survey is conducted across the North Sea in July every year to assess the North Sea herring stock (ICES 2018). It is also used to provide a survey index for sprat *(Sprattus sprattus)* in recent years. Specific guidelines for the analysis of this survey can be found in (ICES 2015). The stratification of the survey is shown in Figure 1-3(a). Historically, the Dutch component of the survey covers strata 101, 91 and 81. It covers the bulk of the SSB for the North Sea herring stock in the northern transects and part of the sprat stock in the southern transects. The coverage by the different countries for 2019 is presented in Figure 1-3(b).

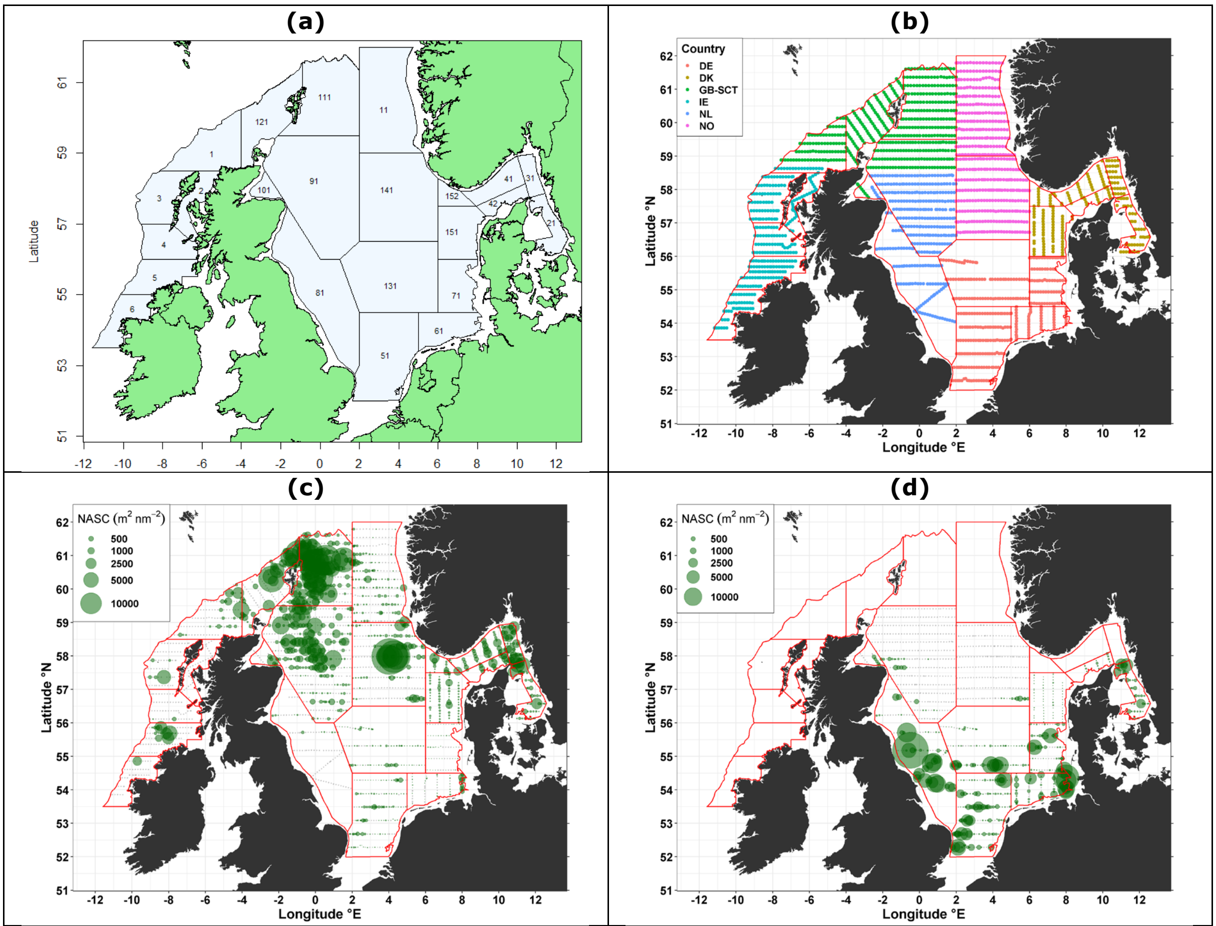


Figure 1-3: *coverage and herring distribution from the yearly conducted HERAS survey. (a) The survey area is divided into different strata (polygons) that are used for the computation of the index in the StoX software* (Johnsen et al. 2019). *(b) 2019 coverage during HERAS 2019 by the participating countries. (c) distribution of NASC (nautical area scattering coefficient)* (Maclennan, Fernandes, and Dalen 2002) *attributed to herring for the 2019 HERAS survey. (d) distribution of NASC attributed to sprat for the 2019 HERAS survey. NASC values are resampled at 5 nmi. intervals along the cruise track.*

2 Data overview

2.1 Utilisation of ME70 MBES data

The ME70 is a multi-beam system consisting of multiple beams (3-45) insonifying the water column at different steering angles (-45° to + 45° relative to centre beam) and frequencies (70-120 kHz). The ability of the system to perform split aperture processing in each beam is different from most multi-beam systems. Also of importance is the possibility to perform split aperture processing which allows one to calibrate the ME70 system using the standard sphere method (Foote et al. 1987; Demer et al. 2015) (applied to each beam), similarly to (Ona, Mazauric, and Andersen 2009). In turn, the ME70 provides calibrated (i.e. absolute) measurements of acoustic backscattering in the water column. It is also possible to detect and track single targets in the different beams and in turn estimate accurate target strengths. In addition, because of its beam configuration, the ME70 provides an imaging of the water column with a very high signal to noise ratio, especially for a multi-beam system. Whilst the beam width of the different beams is narrow, the ME70 has two reference beams with larger beam width. These reference beams allow comparison with single beam echosounders (EK60/EK80).

The ME70 system has two modes of operation: fisheries mode (FM) and bathymetric mode (BM). The main difference between these is the use of different frequencies in each beam in FM and the increased number of beams constructed in BM. The use of varying frequency in each beam in FM offers advantages in term of noise reduction in the water column. The difference in terms of data can be observed in Figure 2-1(a) (FM) and (b) (BM). While the echogram in FM exemplifies low noise, the echogram in BM has a non-useable zone in the outer beams due to the high contribution of side lobes. It has been shown that both the BM and the FM can be used for bathymetric purposes (Cutter, Berger, and Demer 2010). Though, the FM specifically requires custom code for converting the data in a format useable for specialised post-processing software (e.g. CARIS[2], fledermaus[3]). Overall, a downside to the ME70 in FM is the lack of software solutions for post-processing of both bathymetry and water column. For bathymetric purposes, it can be remedied by specific conversion. For water column studies, there are only few software packages available (e.g. Ifremer MOVIES3D) that allow data processing of all the beams combined. Echoview[4] is able to read and process ME70 data but the modules available at Wageningen Marine Research (WMR) limit the processing to each beam separately.

In this study, the ME70 is used in FM mode with nineteen beams creating the multi-beam swatch and two reference beams. Onboard Tridens II, the ME70 unit is mounted on a drop keel and the steering angle of the different beams is between -41° and 41°. A typical "V" shape configuration is used for the frequency of each beam (narrow band signal), as shown in Figure 2-2. The corresponding pulse length is 1.024 μs.

[2] https://www.teledynecaris.com/en/home/
[3] https://qps.nl/fledermaus/
[4] https://www.echoview.com/

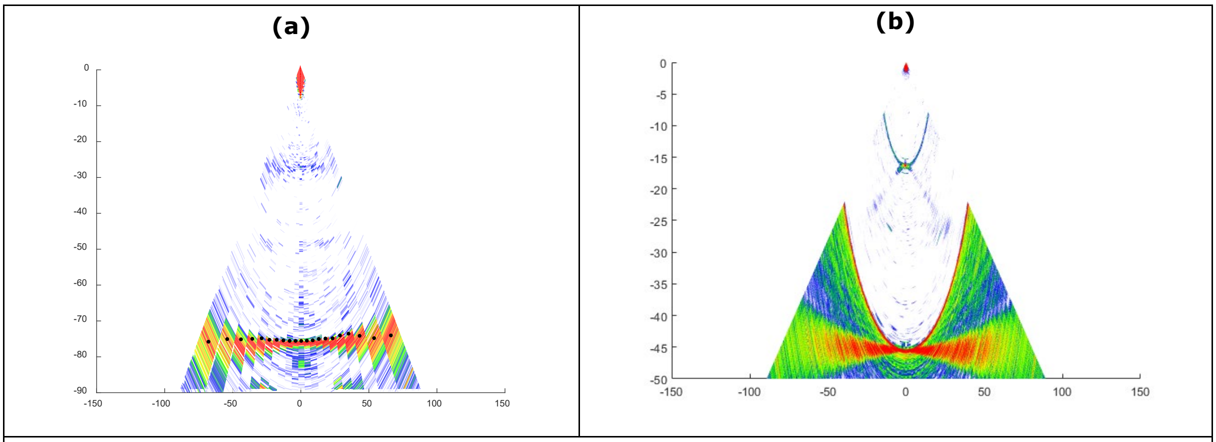


Figure 2-1: *example of ME70 watercolumn echogram in fisheries (a) and bathymetric modes (b). The main difference is the use of different frequencies for each beam in fisheries mode. This results in less noisy water column. In bathymetric mode, the frequency is the same in all beams and a low resolution zone appears in the outer beams because of the sidelobe effects from the middle beams.*

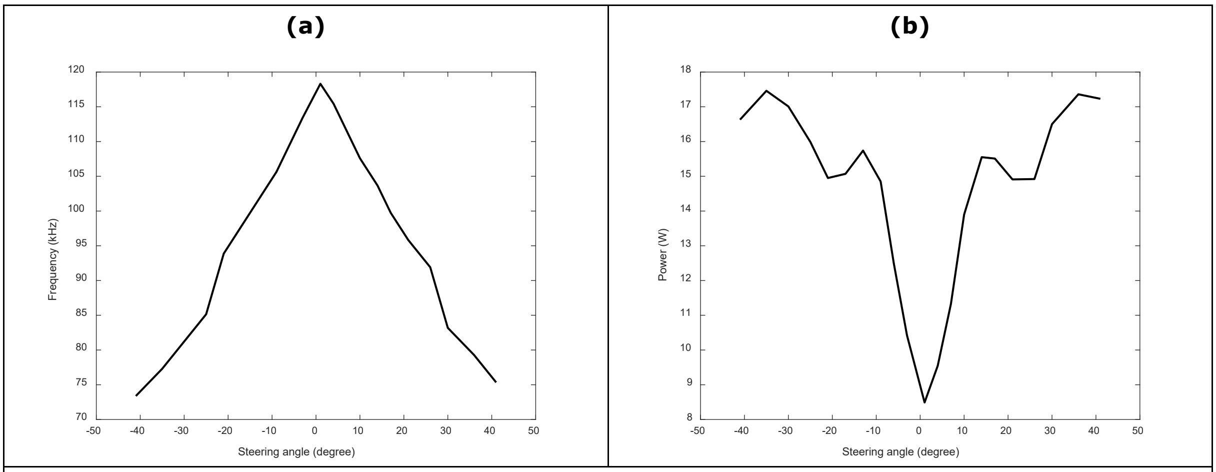


Figure 2-2: *ME70 frequency and power configuration used for this study.*

2.1.1 Calibration

The ME70 multi-beam echosounder is in effect a collection of narrowband split-beam echosounders using different frequencies. Each beam is calibrated similarly to classical echosounders (e.g. EK60/EK80 CW) using the standard sphere method (Demer et al. 2015; Foote et al. 1987). In practice, the calibration sphere is moved athwartships in each beam of the ME70. The calibration parameters for each beam are adjusted against the specific characteristics of the sphere in the water. It is common to use a tungsten carbide sphere of 38.1 mm or 25 mm. The main calibration parameters consist of: on-axis gain for each beam; S_{a} correction for each beam.

2.1.2 Data used for analysis

In FM, the ME70 provides a clean echogram of the water column. This is replicated across several pings. This allows one to obtain a spatial representation of targets (e.g. a fish school) in the water column, as shown in Figure 2-3. In addition, the calibration allows one to collect absolute backscattering measurements.

In this study, the data collected during the HERAS 2016 survey are used. Data were collected along transects and numerous herring schools were imaged. Approximately 200Gb of raw data was recorded as raw files 100 Mb each. The ME70 was used alongside the EK60 using a synchronisation unit (Kongsberg K-

Sync). For this study, the four northern most transects are focused upon as they exemplified the highest abundance of herring (fig. 2.3).

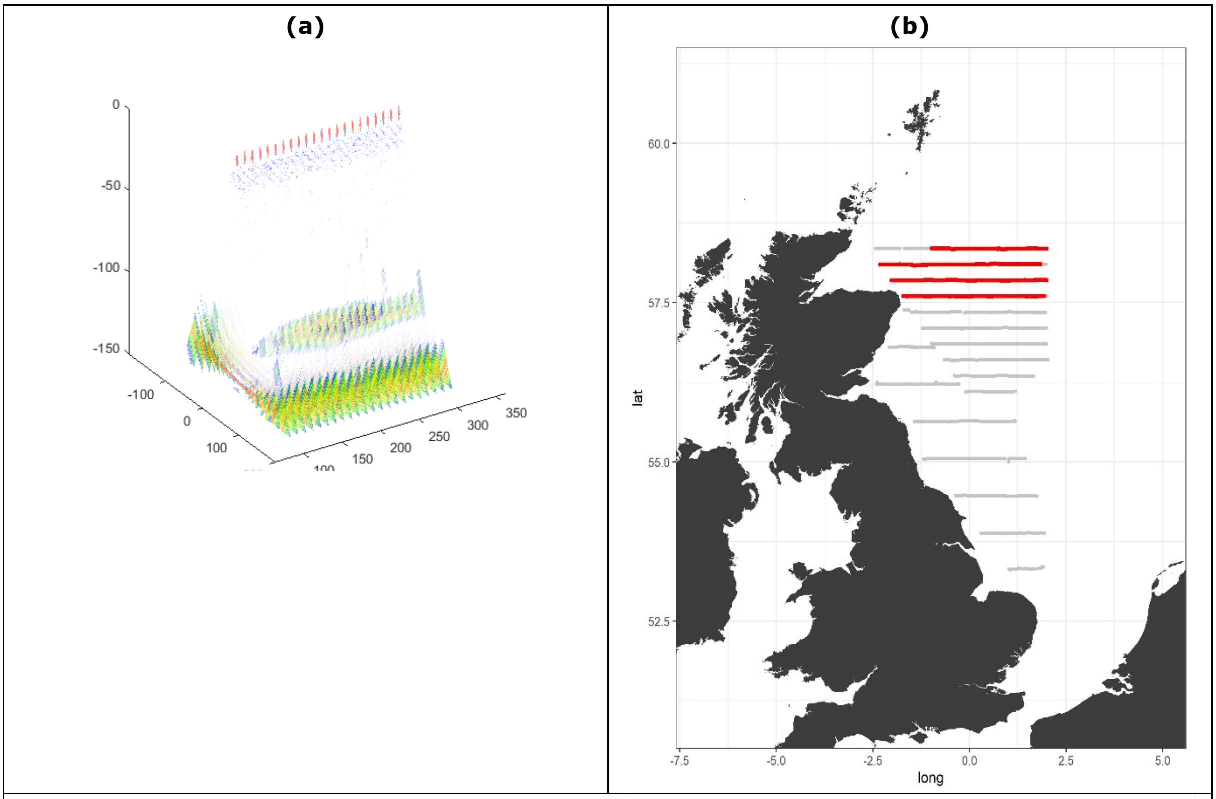


Figure 2-3: (a) example of data collected, it consists of 2D sector imaging along vessel tracks. This allows one to obtain a spatial representation of targets (e.g. a fish school) in the water column. (b) overview of the transects used for the analysis of the ME70 data.

2.2 Fish school classification using narrowband multi-frequency data

The split beam data (EK60/EK80 CW) collected during the HERAS survey from 2015 to 2019 are used here. The 2015-2019 period corresponds to the time after the refit of Tridens II, corresponding to enhanced acoustic capabilities. Of relevance for this study is having split-beam acoustic transducers mounted on a drop keel. The use of a drop keel enhances the signal to noise ratio and then the quality of the data as a result of lowering the equipment in the water column, in turn reducing noise due to surface bubbles (Dalen and Løvik 1981; Dalen, Nedreaas, and Pedersen 2003; Knudsen 2009). The data were collected using the EK60 during HERAS 2015 to HERAS 2018 with few transects where EK80 CW data were collected alongside using a multiplexer (Sakinan and Berges 2020). During HERAS 2019, only the EK80 CW (Continuous Wave mode) was used during survey time (i.e. along transects). As commonly used during acoustic surveys, the pulse length was 1.024 ms. The frequencies used are: 18 kHz, 38 kHz, 70 kHz, 120 kHz, 200 kHz. Whilst the 333 kHz frequency channel was available, it was too noisy to be used.

The EK80 CW superseded the EK60 which is no longer manufactured by the manufacturer SIMRAD. These two systems have been shown to yield comparable results in the context of abundance estimation (Sakinan and Berges 2020; Macaulay et al. 2018; Demer et al. 2017; Sakinan et al. 2018). Despite the malfunctioning of the 38 kHz frequency channel, Sakinan and Berges (Sakinan and Berges 2020) showed that the use of the EK60 and EK80 CW onboard Tridens II is comparable. The 38 kHz transceiver malfunctioning discovered in 2018 (Sakinan and Berges 2020) was fixed prior to the HERAS 2019 survey.

In this study, only the data around pelagic trawl hauls is selected and analysed. This is because one wanted to use an objective criterion for the allocation of acoustic traces to different fish species. The species allocation was done using the catch composition from each trawl (see Section 3.2). The HERAS survey is a dedicated survey on North Sea herring and the Dutch component of the survey covers the bulk of the herring stock (Figure 1-3(c)). The Dutch coverage since 2015 is shown in Figure 2-4. The fish species of interest are: herring (*Clupea harengus*), sprat (*Sprattus sprattus*), haddock (*Melanogrammus aeglefinus*), whiting (*Merlangius merlangus*), norway pout (*Trisopterus esmarkii*) and mackerel. The share of these different species for the surveys since 2015 is summarized in Table 2-1. Most of the catch is herring as the Dutch component of the HERAS survey is targeting to the bulk of the North Sea Autumn Spawners herring stock. However, the North Sea sprat stock is covered in the southern transects and this is reflected in the share of the catch (Table 2-1). In 2015, the share for sprat is particularly high due to the eastern extend of the coverage (Figure 2-4). In general, the presence of species with a swim bladder (sprat whiting, haddock and norway pout in Table 2-1) can be problematic during the scrutinisation of the acoustic data. For example, in 2019, norway pout was encountered in the northern transects.

Table 2-1: *summary of trawls conducted during the HERAS acoustic survey since 2015 and used in this study.*

		HERAS 2015	HERAS 2016	HERAS 2017	HERAS 2018	HERAS 2019
Herring	Total weight (t)	35.9	69.4	41.5	25.2	17.0
	% of total catch	76.1	98.3	89.9	83.2	77.8
Sprat	Total weight (t)	7.7	0.7	0.3	1.5	1.8
	% of total catch	16.4	1.1	0.7	4.9	8.1
Haddock	Total weight (t)	-	-	1.2	1.2	0.8
	% of total catch	-	-	2.6	3.9	3.4
Whiting	Total weight (t)	-	-	0.4	1.7	0.7
	% of total catch	-	-	0.8	5.7	3.3
Norway pout	Total weight (t)	0.1	-	-	0.3	1.4
	% of total catch	0.2	0.1	-	1.0	6.6
Mackerel	Total weight (t)	2.1	0.4	2.4	0.3	0.2
	% of total catch	4.5	0.6	5.2	1.1	0.8

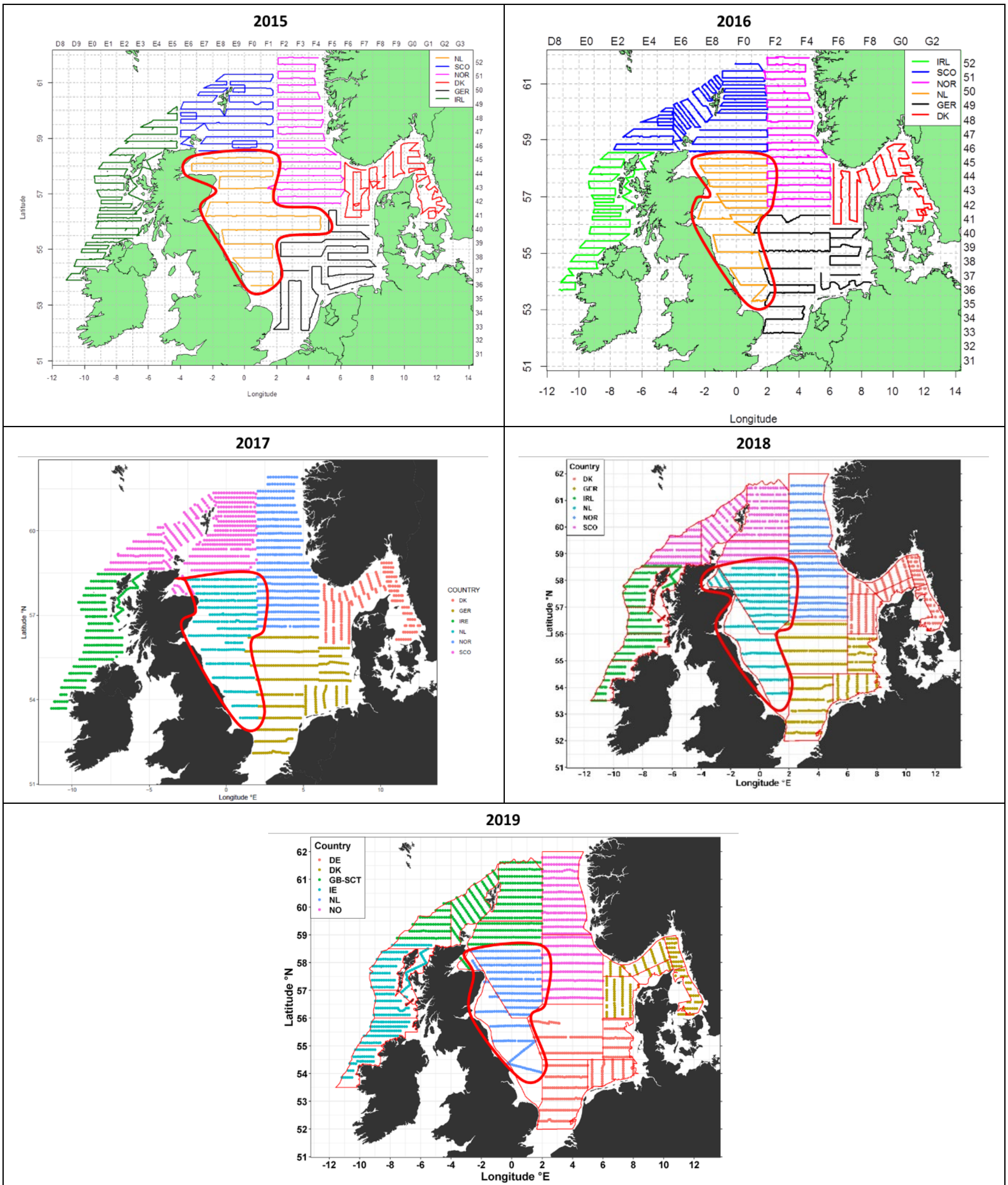


Figure 2-4: *historical coverage (2015 to 2019) of the HERAS survey. The Dutch component of the survey is located at the east of the UK/Scotland and is highlighted by the thick red line in each figure.*

3 Method

3.1 Utilisation of ME70 MBES data

3.1.1 Data processing

In this project, the ME70 data described in Section 2.1 were processed using Echoview. The aim of this study was twofold: (1) study the effect of increased water column coverage by the ME70 (compared to the EK60/EK80) in the context of abundance estimation; (2) extract volumetric descriptors of insonified fish schools for potential use during survey scrutinisation.

For the processing, Echoview with the following modules was used: fish school detection module, multibeam module, advanced operators module and automation module (to run scripts). Each beam of the ME70 was processed individually. The results from each beam were collated afterwards. This is different from ping based multi-beam data processing (Trygonis, Georgakarakos, and Simmonds 2009). This approach was chosen because of WMR software capabilities. The processing followed the following workflow:

A. 21 different echograms were created separately, each echogram corresponding to one of the beams. All the beams were used in the analysis, though the outermost beams were highly distorted.
B. The seabed was detected using a standard bottom detection algorithm for each echogram in an automated way (Figure 3-1(a)). Bottom depth information was exported for mapping the seabed and the echoes from the bottom were removed.
C. An upper separation line (from 7 m to 10 m depending on beam) was created to remove reverberations close to the surface. In the centre beam, the surface line was adjusted to a range of 7 m below transducer. In the outer beams, while the depth remaining the same, the range between transducer and the surface line increased up to 12m because of the steered angle of the beams.
D. Erosion – Dilation – Median Filtering and S_v thresholding was applied to create masks to help discerning the fish schools from other targets (using the Echoview advanced operators module).
E. Because the data set was large, not all the data is imported and analysed at once. To automate the processing, a template Echoview file (EV file) where all standard parameters were set (e.g. school detection criteria, echogram thresholds, bottom detection offset) and virtual variables were created (seabed smoothing mask, fish school mask).
F. Using the template file, new *.EV files were created automatically for every 10 raw files (1 GB of raw file per *.EV File) with a visual basic script (using the Echoview automation module). Bottom detection and school detection in each of these files were performed and bottom line and school files were also exported automatically.
G. For school detection, the automated Echoview algorithm was executed separately for each echogram (i.e. for each beam).
H. For further processing, data was reduced by averaging (1m vertical intervals) This was necessary to improve computation times while maintaining the resolution adequate for identification of the school shape.
I. Georeferenced data (X,Y,Z, Time and S_v) corresponding to each fish school at each beam were exported. Fish school parameters (such as length, height, mean S_v, mean depth) exported for each school separately also for each beam-echogram separately.
J. Each school assigned with unique reference id as ”Beam-No” and “School-No”. These unique school IDs and ping numbers were used at a later stage to detect and aggregate samples from each unique school.

(a)

(b)

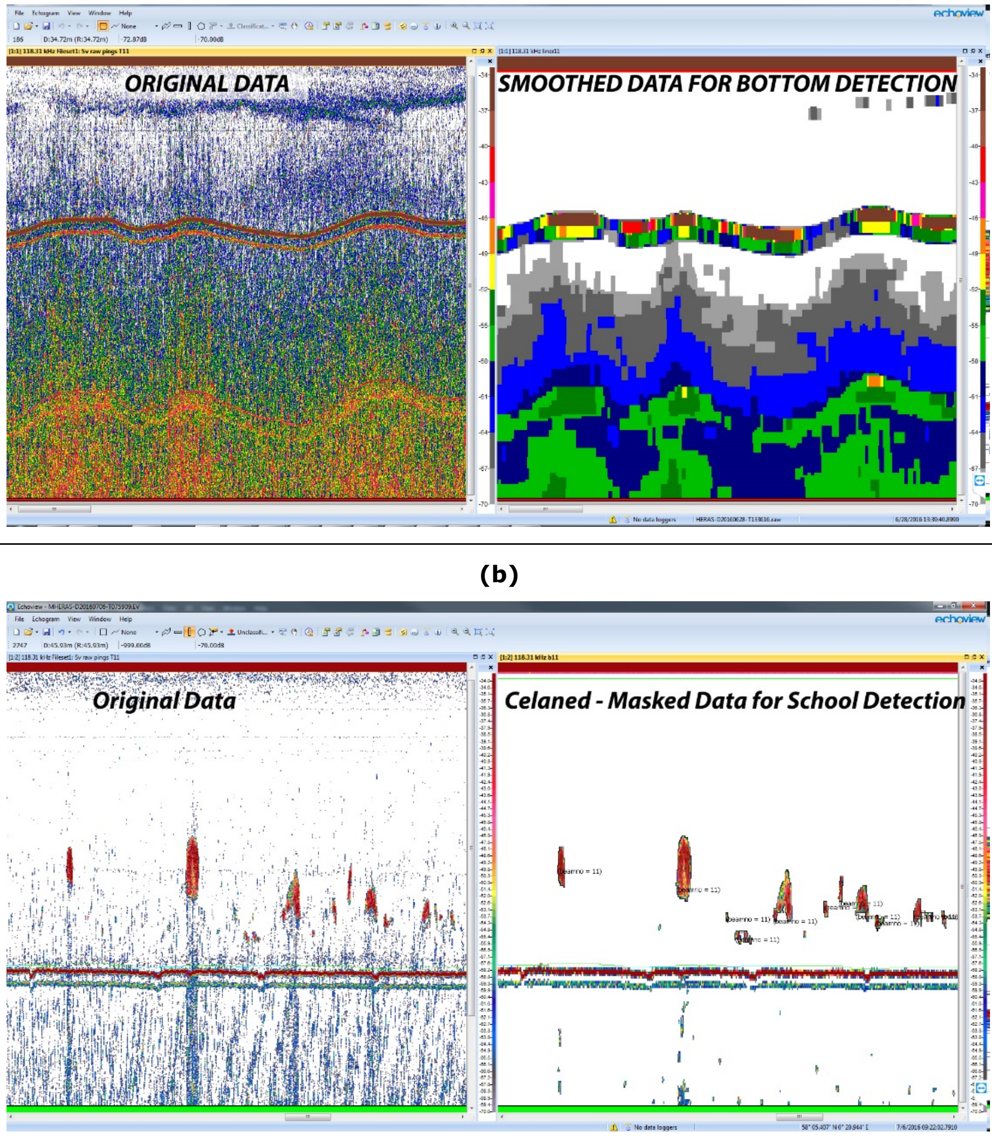


Figure 3-1: *processing workflow example of ME70 data (a) Smoothed echogram used for standard automated bottom detection (step B). (b) Masked – Cleaned echogram using noise removal – and filtering tools (Median, Erosion- Dilation) used to prepare the echograms for automatic school detection. The result is the detection and border tracing around of fish schools.*

3.1.2 EK60/ME70 comparison

Several potential problems that may have effect on the EK60 measurements were identified and investigated. The low sampling volume with the EK60 can be more problematic within the close range – close to surface (beam expands with increasing range). This may lead to misleading results for the schools that are close to surface. Whether or not the survey data is impacted by such an effect was investigated by a depth-wise comparison. In addition the effect of use of different processing thresholds, different frequency and different beam width coverage (from narrow to wide) were also investigated. For comparison of each scenario, both EK60 and ME70 were filtered for the seabed, surface and noise and integrated with 100 second intervals. For depth-wise comparison a vertical separation was performed for 10m depth intervals. For the other comparisons (processing threshold, frequency and beam width) the entire water column was integrated. The processing thresholds were (-42,-45,-48,-52,-58,-60,-62,-65 and -68 dB). The investigated beam width was changed from single centre beam to entire 21 beams increasing the swath by 2 beams at each comparison. In addition to the parameters from the fitted linear model such as slope and intercept, other parameters such as correlation coefficient, RMS (root mean square) error, mean and median S_v differences, t-test results (p value and t values) were calculated to be used for the comparisons and visualized by scatter plots. For the depth wise comparisons boxplots per each 10 m interval were visualized together with outliers by generating different plots for each different processing thresholds.

3.1.3 Fish school reconstruction

The fish schools detected in the previous stage are aggregated across the beams to form 3D schools. The challenge was to correctly pair the detected schools. Three different methods were tested and finally the three methods as described below were used for final school detection.

1) Visual scrutiny can be implemented by using a 3D maps and picking each school manually. Here, the 3D rendering capability of the Arcscene software[5] was used as a trial. Aggregating the schools in this way was straightforward and accurate. However going through the entire dataset would be time consuming, thus, not practical for a large data set.
2) An automated workflow:
    a) Each 2D fish school from different beam-echograms has a unique id and centroid with XYZ location. These schools were mapped according to their centroids in GIS.
    b) An independent reference centre line was created based on the GPS positions. This was used as a guide such that nearest GPS point was assigned to the each centroid.
    c) School were grouped together according to their centroids which match with the same nearest GPS points.
    d) A unique id was assigned to each grouped 3D school and mapped by assigning a different colour to each school. The accuracy of the grouping was assessed by visual inspection.
3) A third most accurate and generalised method was developed:
    a) Maximum intensity echogram with Echoview were generated by comparing the corresponding xyz pixels across the beams and retaining the maximum of each pixels (x = ping number, y= depth, z=beam number)
    b) Next, bottom detection, surface exclusion, noise filtering and school detection was performed on these maximum echograms
    c) Because maximum intensity operation in Echoview collapses all components of the same fish school across the beams onto one 2D echogram, these maximum echograms were used to detect schools. The schools detected at this step represented the maximum extent of each 3D school and was assigned with a unique ID.
    d) Subsequently, each beam echogram (of 21 beams) were masked to retain components corresponding only to the detected 3D pixels in previous step
    e) Then an additional school detection was performed on each of these 21 masked echograms to extract the 2D components of each 3D school and assigned with corresponding 3D unique ID's from the previous step based on their x,y extend.
    f) These 2D school components were then exported for their school descriptors such as school height, thickness, width, mean Sv, standard deviation, skewness, kurtosis, compactness etc.

[5] https://desktop.arcgis.com/en/arcmap/latest/extensions/3d-analyst/3d-analyst-and-arcscene.htm

3.2 Fish school classification using narrowband multi-frequency data

In this section, the method for the classification of fish school traces during the Dutch component of the HERAS survey is described. This utilizes the multi-frequency data from split-beam echosounders (EK60/EK80 CW). Using historical data from the HERAS survey (see Section 2.2), the accuracy of a classifier based on energetic and morphologic fish schools features is investigated with the aim to provide additional cues during the scrutinisation process.

3.2.1 Acoustic data processing

The acoustic data are processed using the LSSS (Large Scale Survey System) software (R. J. Korneliussen et al. 2006). As described in Section 2.2, the data consist of EK60 and EK80 CW acoustic data collected by Tridens II around trawl stations during the HERAS survey conducted in 2015, 2016, 2017, 2018 and 2019. On-board Tridens II, six frequency channels are used with either the EK60 or the EK80 systems: 18 kHz, 38 kHz, 70 kHz, 120 kHz, 200 kHz and 333 kHz. Because of the low signal to noise ratio for the 333 kHz channel, it is not used for the analysis presented here. An example echogram at different frequencies is shown in Figure 3-2.

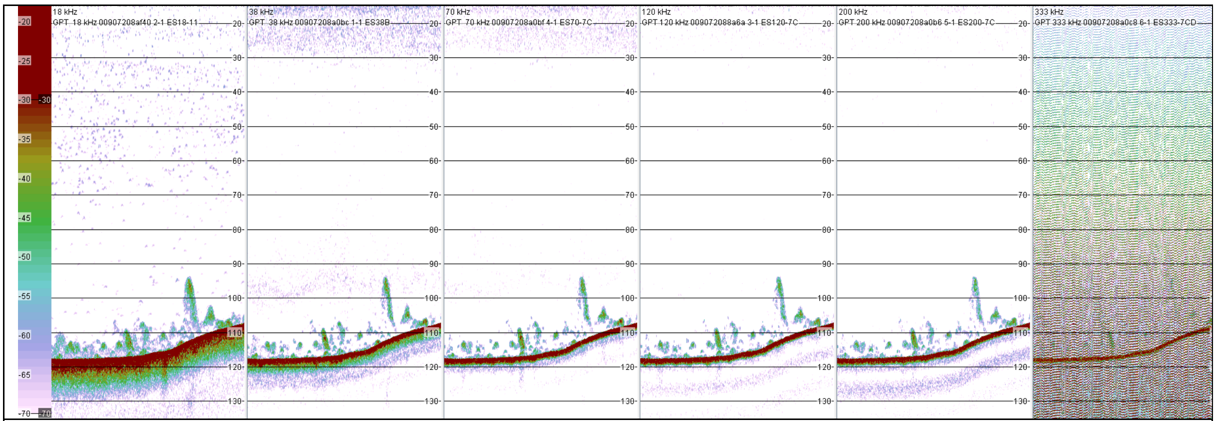


Figure 3-2: *example of acoustic data used here (extracted from the HERAS 2018 data set). It consists of EK60/EK80 CW data at five frequency channels: 18 kHz, 38 kHz, 70 kHz, 120 kHz and 200 kHz. Each panel shows a different frequency channel Though available for some data sets, the 333 kHz frequency channel is not used in this study.*

The processing workflow of the EK60/EK80 CW data is presented in Figure 3-3(a). Resulting echograms at different processing steps are shown in Figure 3-3(b). This processing is applied to each data set (Section 2.2). It specifically consists of the following steps:

A. Data pre-processing (steps 1to 6). This includes a spike filter (1) to remove impulsive noise and a smoothing filter (3) to smooth the data. Other operators are used to tidy up the process: cropping of data through data reduction (2), filling missing pings (4), remove the 333 kHz frequency channel (6).
B. Detect and crop seabed (steps 7 and 8). Bottom detection is done using the EK500 bottom detector (7). The data below 5 m from the detected bottom line is deleted (8).
C. Build combined echogram (steps 9 and 10, see Figure 3-3(b) left graph). The data from the different frequency channels are sampled at the same sampling rate and for each pixel, the mean across all the channels is used to combine the data into a single echogram. This is the base for further processing.
D. Thresholding (step 11) with a low threshold set to -55 dB.
E. Median filter (steps 12 to 14). A set of three 2D median filters is used to smooth the data.
F. Filtering echogram with one erosion filter and one dilation (15, 16, Figure 3-3(b) middle graph) filter. This sequence of filtering gets rid of the isolated acoustic traces while retaining the big marks.
G. Define school borders (step 17, see Figure 3-3(b) right graph). No specific filtering condition is set for the definition of schools.

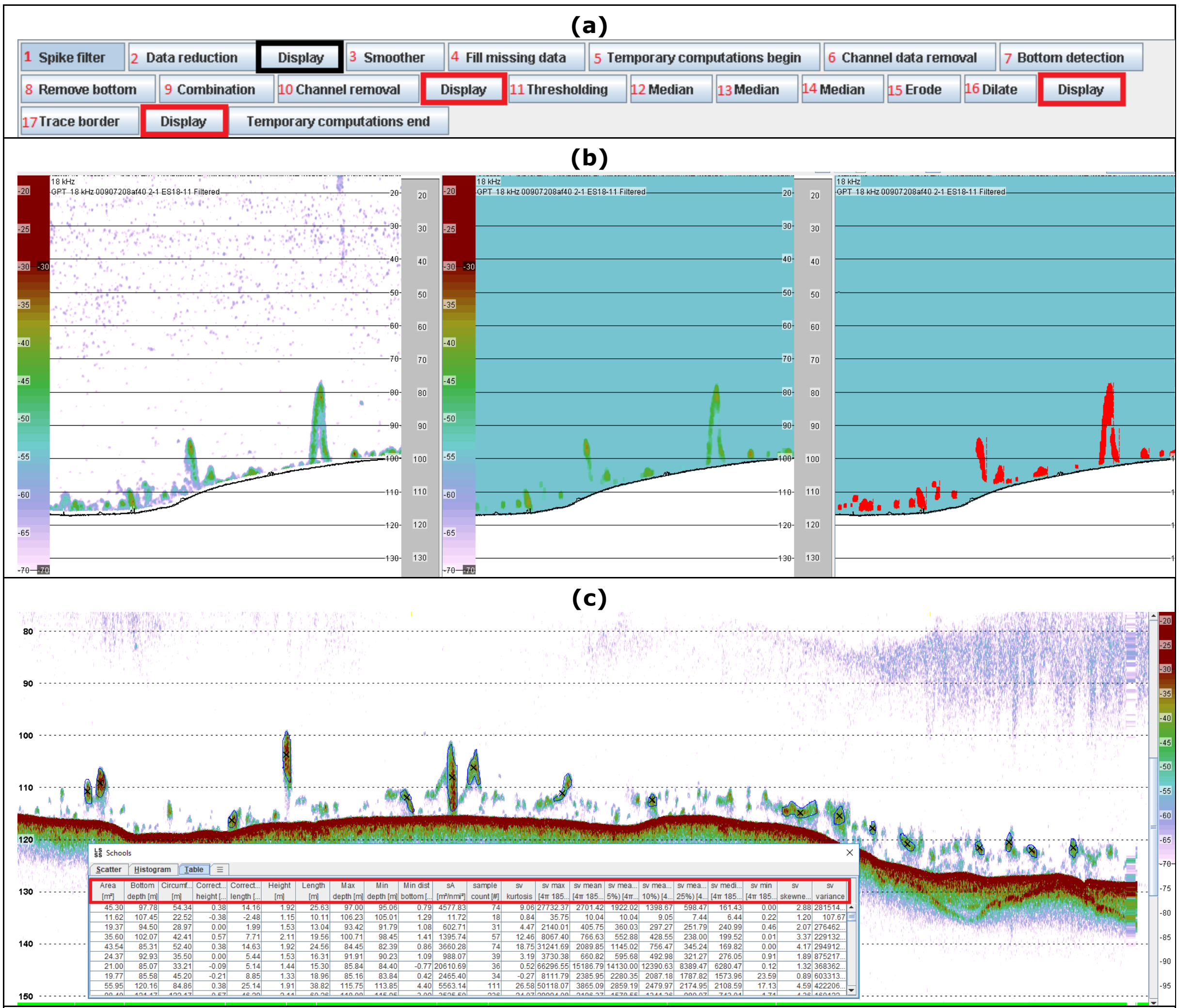


Figure 3-3: *(a) diagram of LSSS processing workflow used to process the acoustic data. Echogram displays are highlighted and are presented in Figure 3-2 (black rectangle) and in (b) (red rectangles). (b) resulting echograms at different processing steps (see (a)). The right most echogram shows the result of the processing, i.e. school detections (red areas). (c) echogram exemplifying detected fish schools and subsequent table of features (red rectangle).*

Following the automatic processing described above, all the detections were reviewed manually. In addition, manual edits were performed for false positives and true negatives. Then, features for each detected fish school was exported. This is done using the LSSS fish school feature capability. It is exemplified in Figure 3-3(c) where fish school boundaries can be observed together with the table with the different features. These can be divided in the following categories:

1. Descriptive features: bottom depth, maximum depth, minimum depth, sample count.
2. Morphologic features: area, circumference, height, length, height for pulse duration effect, length for beam width effect.
3. Energetic features: s_A, s_v distribution kurtosis, s_v distribution skewness, s_v variance, maximum s_v value, minimum s_v value, mean s_v, mean s_v truncated (5%, 10%, 25%), median s_v.

The quantity s_A is the area scattering coefficient and s_v is the volume backscattering coefficient (Maclennan, Fernandes, and Dalen 2002). It is important to note that these quantities (i.e. energetic features) are specific to each frequency channel. For example, there is five mean s_v features for a single fish schools. In order to define relative trends, the relative frequency response is computed relative to the 38 kHz frequency channels, i.e.:

$$R(f) = \frac{s_v^f}{s_v^{38\text{ kHz}}} \qquad (1)$$

With f the current frequency. The volume backscattering coefficient used at each frequency s_{v}^{f} is the mean with 25% truncation.

3.2.2 *Species allocation to acoustic traces*

The allocation of species for the various detected schools is done using the trawl information. It is assumed that a fish school is allocated a specific species if it fulfils the following conditions:

1. It is within the trawling time period or 30 minutes prior or after.
2. More than 80% of the catch composition of the trawl consists is a single species.
3. The total catch weight is greater than 500 kg (threshold based on analysis of data).

Though conditions 2 and 3 are rather restricting, especially for sparse species (e.g. norway pout, haddock, Table 2-1), it is important to reduce the trawls considered to those that exemplified a dominant catch (>80%) and a significant catch (>500 kg). Though "ground truthing" based on catch information can be flawed (e.g. missing acoustic marks, depth stratification), it is the best information available, especially when exemplifying a clear signal (large catch and non-mixed composition).

In addition, the selected fish schools are further filtered down to those having more than 100 sample points in order to avoid very small schools where statistics are only based on few pixels. It is important to have meaningful statistical features (mean, median, skewness, kurtosis). The resulting set of data is fish schools associated with species type. It is the input to the classifier described in the next section.

3.2.3 *Classification*

The classifier described here makes use of the features derived using the method described in the previous section. The features effectively are a reduction of data to make sure a classifier can derive boundaries to distinguish species. Hence, the features are derived such that data is reduced, while maintaining important signature information specific to a certain species. A machine learning approach is then used to derive an algorithm able to differentiate different species based on these features, more specifically a Neural Network (NN) (Hagan et al. 2014). This consists of interconnected processing elements that after appropriate training are able to solve a specific problem. Here, the problem consists of determining the fish species given a set of features.

A NN is typically constituted of several layers of neurons: input layers, hidden layers which undergo the classification process (through application of weights, biases and operators) and output layers, yielding the final scores for the classification.

Here, the input to the NN is a set of morphologic and energetic features for each fish school. Prior to entering the NN, these are normalized, a process that consists of bounding the maximum and minimum of each spectrum between -1 and 1 based on two threshold boundaries. The features are expected to vary between fish species, length classes and to a lesser extent with depth and area (Fassler et al. 2015; Fässler et al. 2007; Simmonds and MacLennan 2005). This is further fed into the various layers of the NN. For the purpose of pattern recognition, only one hidden layer is used with a number of neurons defined at two times the number of features. The design of the NN classifier is shown in Figure 3-4 and is typical of a pattern recognition NN.

For this study, two sets of features are tested:

1. A combination of morphologic and energetic features (11 features): $R(18)$, $R(70)$, $R(120)$, $R(200)$, s_{v} distribution kurtosis, s_{v} distribution skewness, s_{v} variance, mean of 25% truncated mean s_{v}, school corrected height, school corrected length, school circumference.
2. A set of energetic features (8 features): $R(18)$, $R(70)$, $R(120)$, $R(200)$, s_{v} distribution kurtosis, s_{v} distribution skewness, s_{v} variance, mean of 25% truncated mean s_{v}

Whilst the addition of morphologic features to the energetic features should yield a more accurate classifier, it is important to test the accuracy of a classifier based on energetics alone.

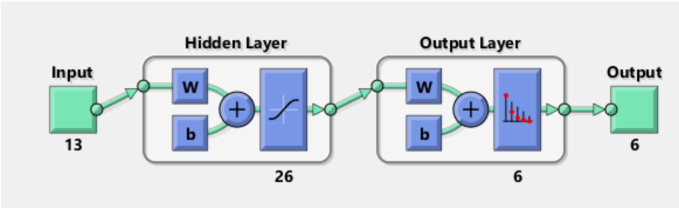


Figure 3-4: *schematic of NN architecture used here. This is composed of a hidden and an output layer. The number of neurons for the hidden layer is taken as twice the number of features.*

The species of interest for classification are those present in the catches (Table 2-1): herring, sprat, whiting, haddock, norway pout, mackerel. Different setups for the target species will be tested, mostly based on the number of samples available.

It consists of several sequences of: (1) training (2) validation and (3) testing the NN. This is done using a data set that consists of echosounder records of various fish schools of all three species. It is also associated with a robust ground truth in the form of catch samples.

The adjustment of the weights and biases is performed prior to the use of the NN in a real situation, during the training process. For this process, a training data set is drawn from the available data and is divided into three components:

- Training: these data are used to compute weights and biases through various iterations.
- Validation: these data are used to validate the NN and make sure it does not become too specialised with respect to the training data.
- Testing: these data are used to assess the performance of the NN after the training is completed.

An example of NN training is shown in Figure 3-5. A training data set is made of several inputs samples (features) together with associated outputs (fish species categories). The weight and biases are adjusted for each sample using a backpropagation algorithm (Hagan et al. 2014). This is repeated several times over the training data set and each iteration is called an "epoch" (x-axis in Figure 3-5). At the end of each epoch, an error index is calculated (y-axis in Figure 3-5, cross-entropy in this instance, (Hagan et al. 2014)) for the training data set and the validation data set. After 30 epochs, one can observe that the error index for the training data set drops rapidly while remaining constant for the validation data set. The set of weights and biases are becoming increasingly optimised for the training data set but not the validation data set. This is because the weights and biases are only updated using the training data set. Though, the validation data is here to ensure that the NN does not loose generality (i.e. is not too specialised to the training data set). Therefore, the optimal training is where the performance of the validation data set is maximized (i.e. minimized error).

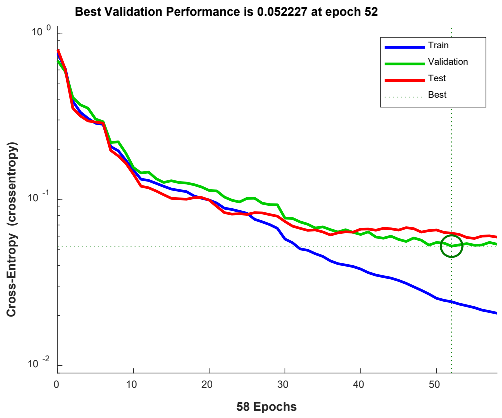


Figure 3-5: *results from Neural Network training. In this case, the training and validation data sets consist of equal number of samples of different fish species. Each sample consists on a selected number of features.*

4 Results and discussion

4.1 Utilisation of ME70 MBES data

4.1.1 Calibration

Prior to the comparison with the EK60, it is important to assess the consistency of the ME70 measurements for both the beams in the swath and the reference beams. Here, the data collected during the HERAS survey in 2016 is used and in order to assess the quality of the calibration on that year, the calibration results will be compared with other calibration trials performed since 2015. For example, the historical retrospective of the different EK80 calibration trials revealed a malfunctioning of the 38 kHz frequency channel (Sakinan and Berges 2020).

Onboard Tridens II and since 2015, the calibration of the ME70 system is most commonly done prior to the two yearly acoustic surveys: IBWSS (blue whiting, west of Ireland) and HERAS. However, because of rough weather conditions for the IBWSS survey, calibration for the ME70 was only performed in 2018 prior to this survey. In contrast, the equipment underwent calibration prior to each HERAS survey since 2015.

The results for the different beams in the swath is shown in Figure 4-1 (calibration gain, S_a correction, standard deviation in gain). It can be observed that overall the gain profile across the beams is consistent between the different calibration trials (Figure 4-1(a)). Only the results from the calibration trial prior to the 2018 IBWSS survey exemplify discrepancies in gain for the centre beams (Figure 4-1(a), green solid line). This might be due to rough weather conditions (common for the IBWSS survey). Regarding S_a correction, the different data sets are consistent (Figure 4-1(b)) apart from a 0.5 dB jump in a specific beam for the HERAS 2019 and 2017. These measurements are associated with high standard deviation (Figure 4-1(c)) which reflect a lack of measurements. Overall, these results suggest that the ME70 system onboard Tridens II is working effectively.

The historical results for the reference beams is shown in Figure 4-2 (calibration gain, S_a correction). For both reference beams, the result trends are consistent and the variation in both calibration and S_a correction is within acceptable range. This suggests that the reference beams are working as expected and could be compared to the EK60.

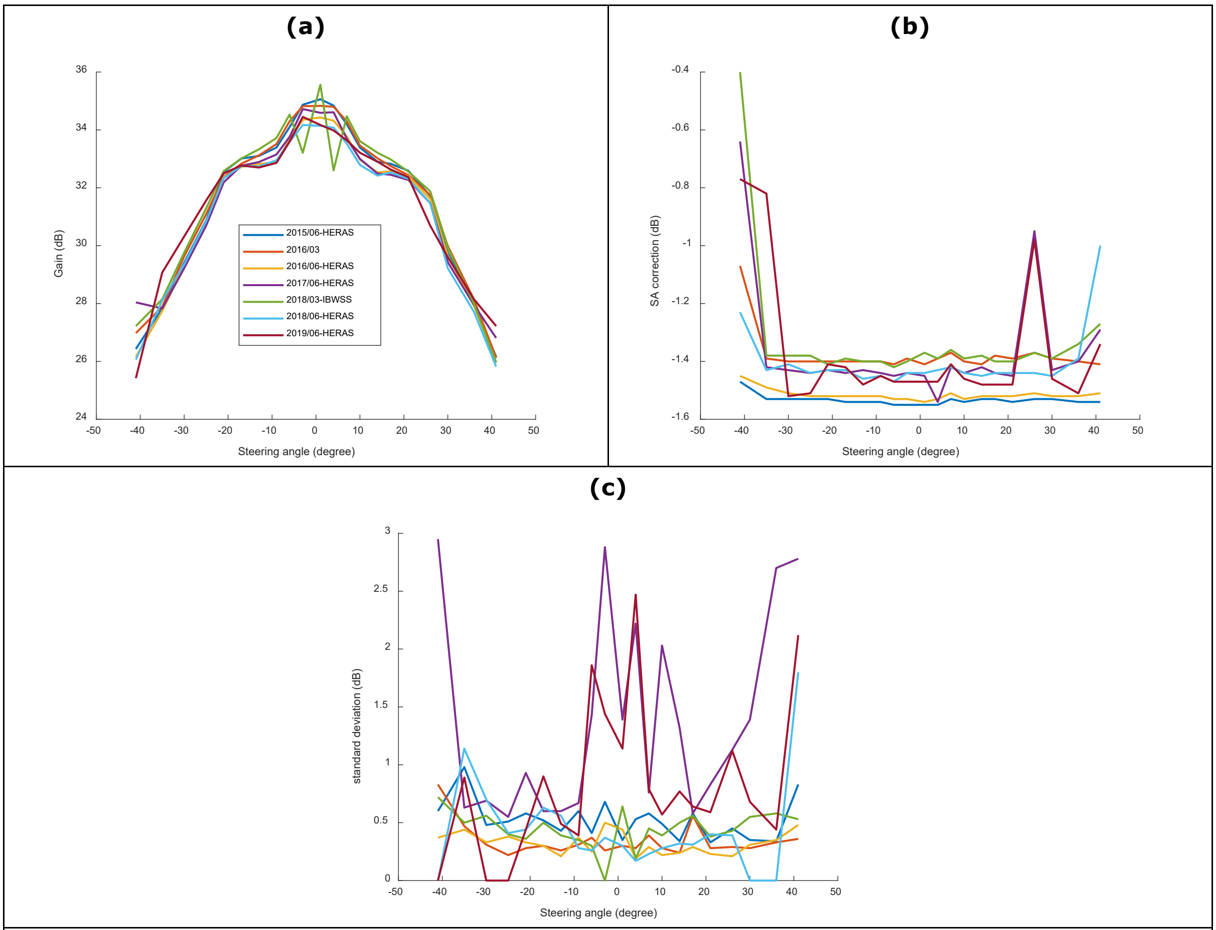


Figure 4-1: *historical results of the different ME70 calibration trials performed onboard Tridens II. (a) Resulting calibration gain. (b) Resulting S_A correction. (c) Standard deviation in gain associated with the results.*

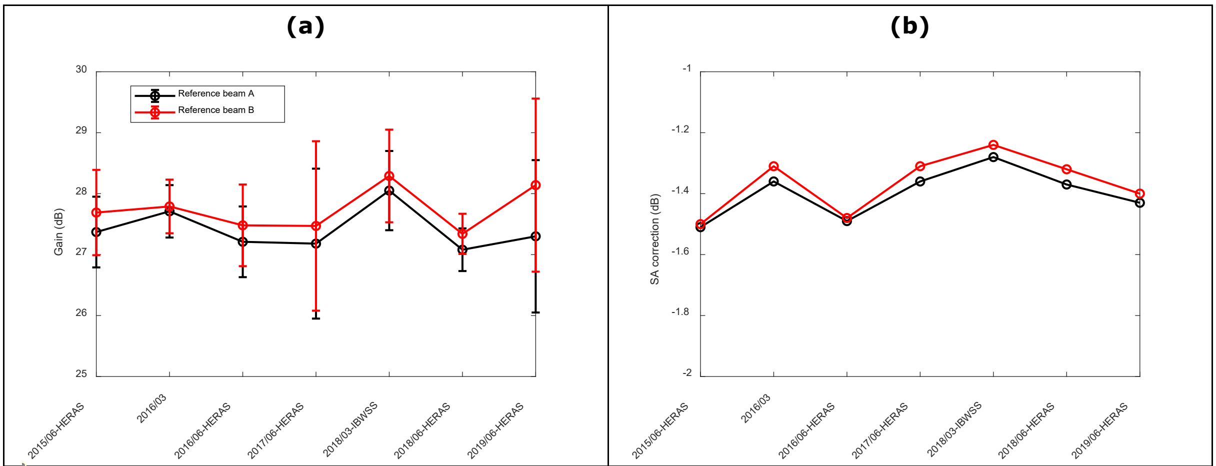


Figure 4-2: *historical results of the different ME70 calibration trials performed onboard Tridens II for the two reference beams. (a) Calibration gain with standard deviation in gain as error bars. (b) S_A correction.*

4.1.2 EK60/ME70 comparison

Figure 4-4 shows the depth-wise comparison between the ME 70 and EK60. The three plots on this figure show the same data processed with different thresholds. The first panel shows the processing results with the strongest threshold which ensures that what contributed to the signal is the fish schools. The second and third panels show the processing results for decreased thresholds. Results indicate that all data points are centred around 0 without systematic difference however outlier error increases with decreased threshold potentially due to increased effect of the random noise.

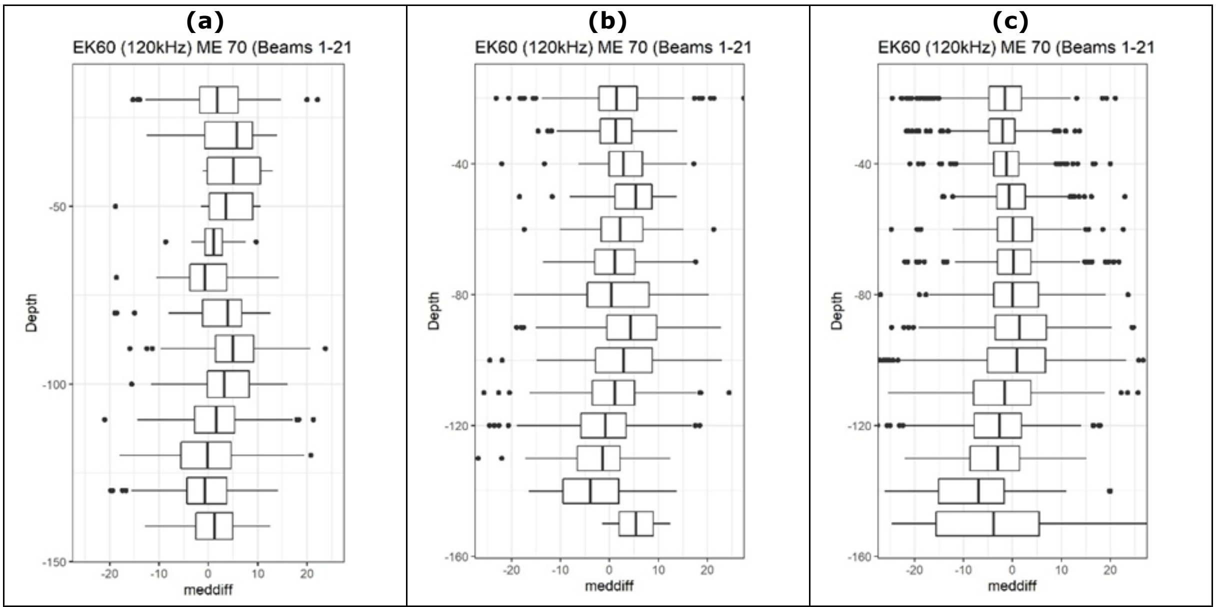


Figure 4-3: *The figures show depth-wise comparison between the ME 70 and EK60. These are the same data processed with different thresholds. The first one is processed with the strongest threshold which ensures that what contribute to the signal is the fish schools*.

The second group of questions addressed in this work were: is there a difference between the estimated abundance between the two systems? And would an increase in sampling volume cause a different abundance?

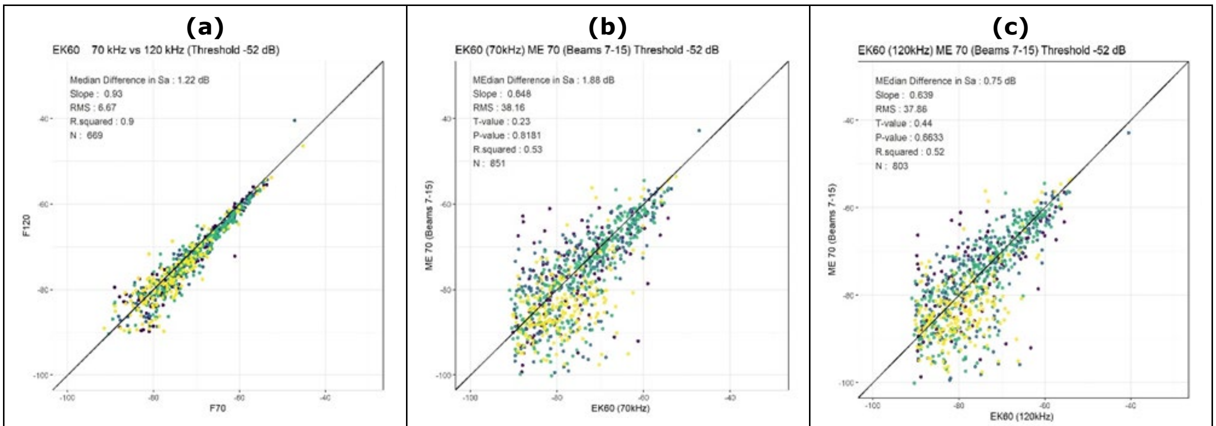


Figure 4-4: *differences between the compared sets for corresponding integrated time intervals (by 100 seconds).*

The scatter plots on Figure 4-4 compare the EK60 vs ME70 for each corresponding integrated time intervals (by 100 seconds). In this figure, the first panel shows a comparison within EK60 (between 70 and 120 kHz). Here, there is an increasing variability towards the lower values and overall 70 kHz is 1.2 dB greater than 120 kHz. Note that the each beam of the ME70 uses slightly different frequencies ranging between 70 kHz and 120 kHz. In the second and third panels, comparisons are done between EK60 and ME70. For this, a relatively narrower set of beams were used. Normally total beam opening is approximately 82 degrees across 21 beams. In EK60 this is only 7 degrees. But in this example for ME70, only 7 beams in the centre are used. This corresponds approximately 26 degree beam opening has a 4 time greater swath in athwart direction (starboard to portside of the ship). In this case the difference between ME70 and EK60 is 1.9 dB for 70 kHz and 0.8 dB in 120 kHz. Despite that the RMS values are substantially higher, the median differences are not. The effect of changing beam widths on the median differences are shown in Figure 4-5. In this figure, the lines with different colours show different processing thresholds, the left panel shows the differences relative to 70 kHz and right panel shows the difference relative to 120 kHz. The differences are relatively high when only the central beams are used, as the width of the beam coverage is expanded, a decrease is observed and then differences increase again as the width of the curtain is expanded further.

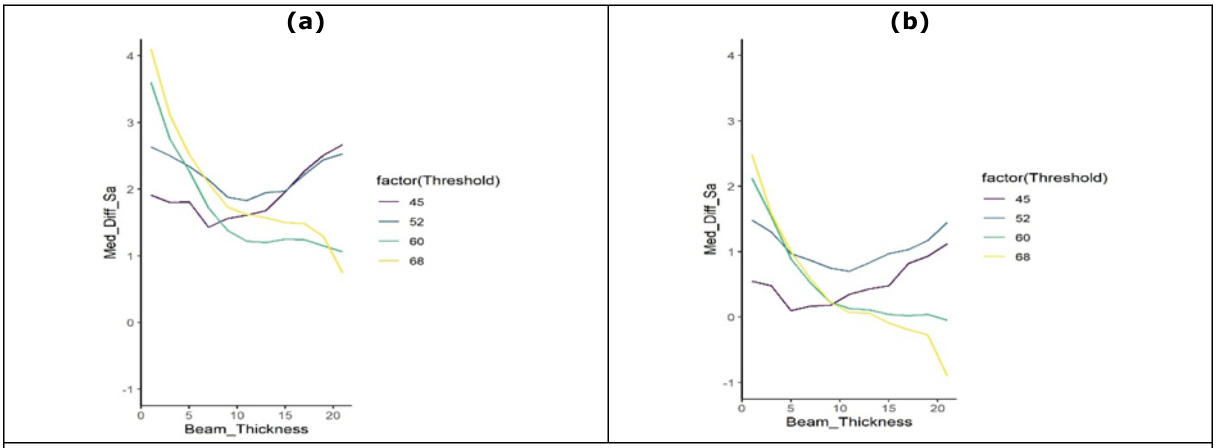


Figure 4-5: *Plots summarizing the effect of changing beam width and processing thereshold on the differences between the EK60 and ME70 at 70 kHzh (Left panel) and 120 kHz (right panel). Different colours show different processing threshold. Lower thresholds (greater numbers) includes some weaker targets such as small schools or few dispersed fish and other scattering layer such as microbubbles, plankton as well as noise. Higher threshold (lower numbers) are exclusively fish school.*

Results also indicated that as the size of the curtain expanded, the variability was increased. This can be caused by (1) as the beam width in ME70 expanded, the school coverage is enlarged, and portions of the school that are not visible to EK60 are being observed with the ME70. This leads to different results at different beam openings; (2) as the outer beams are tilted, the incident angles, therefore the target strength of the fish are also changing and (3) the noise sensitivity is different at different angles. And furthermore (4), even though the swath of the ME70 is much greater than the EK60, the individual beam opening angles are much narrower in ME70. Because of these reasons different beam openings give different results. Nevertheless the median difference overall are comparable between the systems

4.1.3 Fish school reconstruction

For demonstration purpose, a sample school detected on 7th July 2016 (9:21AM- 9:22AM) is chosen to exemplify the 3D school extraction. Figure 4-6 shows this school at different processing steps. Figure 4-6(a) exemplifies a single ping multi-beam swath image of the school (along ship direction). The numbers on the figure indicate the number of each separated beam. Beam no=11 corresponds to the central beam. Figure 4-6(b) shows EK60 multi-frequency echograms for the same school (18 kHz, 38 kHz, 70 kHz, 120 kHz, 200 kHz and 333 kHz). A comparison was also made between Multibeam (ME70) and multi-frequency (EK60) recordings of the school. Figure 4-6(c) illustrates different echograms of the school produced from the ME70 beams. Each window consists of approximately 80 consecutive pings. For each echogram, the corresponding beam number, the frequency of the beam and the beam angle are provided on the figure. Beam number 11 is the central beam with an almost vertical orientation (0.5°) and the beams at the two outer sides have the steepest steered angle (41.5°). Figure 4-6(d) shows the reconstructed 3D image of the school. The dense kernel inside the school has a different shape relative to the overall shape of the school. For a preliminary analysis, the extracted school parameters were compared. Figure 4-7 shows the mean S_v at different beams of ME70 and the overlaid points show the mean S_v at different frequencies for the EK60. The variability in this parameter is high both within the EK60 across the frequency spectrum and within the ME 70 across the beam angle spectrum. This variability is potentially due to several reasons such as: school geometry, acoustic tilt angle and frequency response. The fact that different beams of ME70 use slightly different frequencies makes the comparison difficult. In terms of the school shape, multi-beam echogram suggest that the school is composed of two lobes. The two peaks observable in Figure 4-7 exemplify these two different lobes. The beam numbers from 3 to 17 correspond to the main lobe. Within this main lobe there is a variation in the range of 8 dB. Within the 4-15 beams this variation is only of 4 dB. For the EK60, this variation is also about 3dB close to the across-beams variation of ME70.

ME70 data providing 3D school characteristics has potential to improve our understanding of the spatial variability of the fish schools and fish behaviour. In this particular exercise, a method was developed to process the data from the HERAS survey. Within school variation was analysed and compared with the corresponding multifrequency data in a sample case. Variation in the mean acoustic density (S_v) across the beams was important. This variation is potentially due to varying tilt angle of the fishes in the school as well as their density relative to their position. Even in the centre of the school the acoustic density varied approximately 2.5 fold. The multi-frequency variation in EK60 was also similar, approximately 2 fold.

The identified schools provide an interesting dataset to characterize herring schools in the area. A recent work by ifremer with ME70 in the bay of Biscay, France has revealed that there are substantial differences in 3D school forms between sardine and anchovy which had not been resolved previously with 2D echosounders. Because these two species are both with swim bladder and found in similar sizes, their frequency response characteristics can be very similar. There are similar cases in the North Sea where distribution of physically similar species overlap (such as herring, horse mackerel and sprat) in the surveyed area. Therefore improved understanding on school characteristics and fish behaviour with use of 3D may improve our interpretations from the 2D echograms.

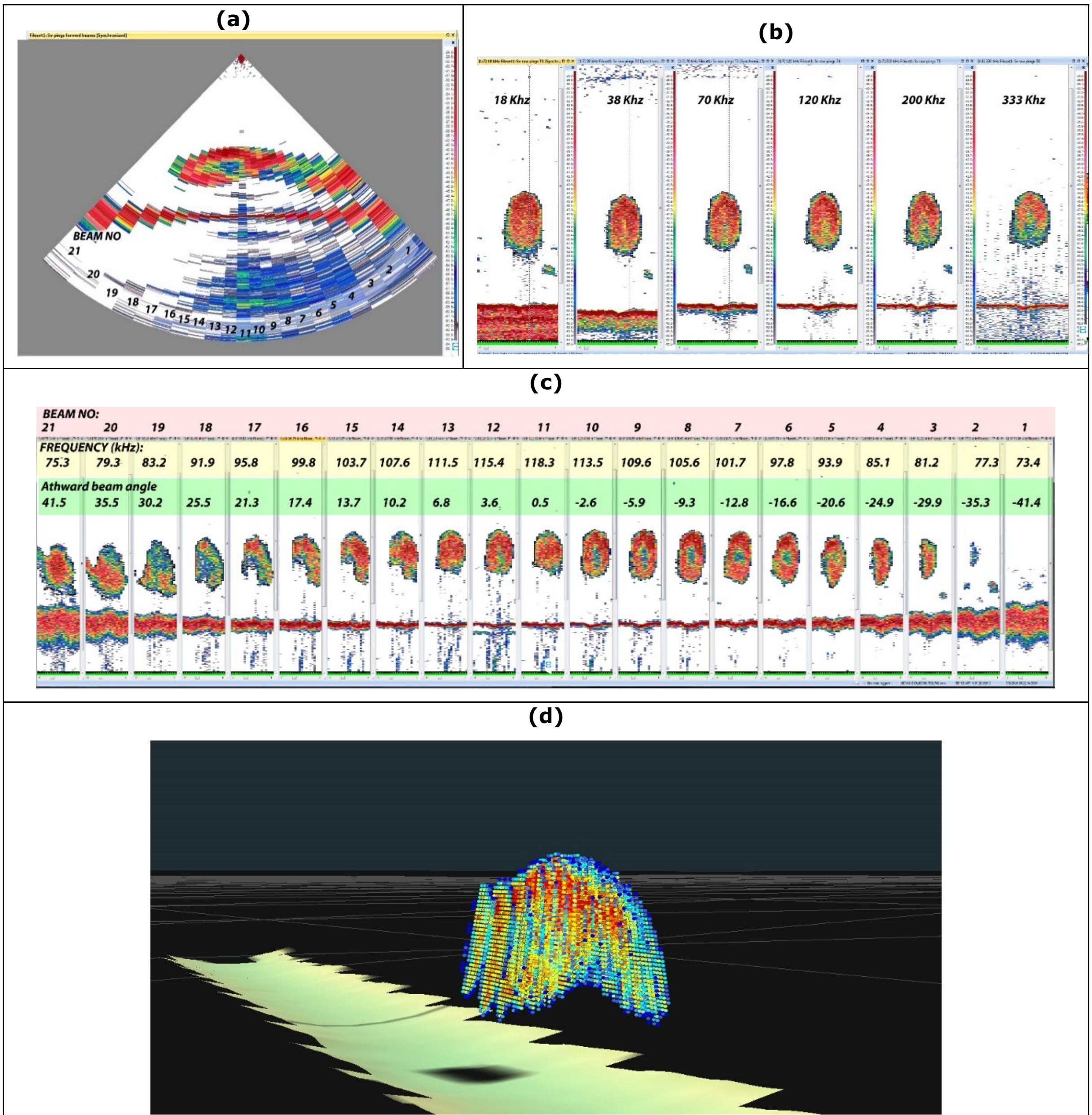


Figure 4-6: *(a) Swath image of an imaged school during Heras 2016 survey on July 7 9:21AM- 9:22AM. (b) The same fish school shown in (a) but imaged by the multi-frequency single beam EK60. (c) appearance of the same school in the 21 beams separately. This is a typical dense-compact-large herring school. The numbers on the upper side of the graph show the id number, frequency and angle for each beam. (d) Reconstruction of the 3D point cloud for the school. The acoustic density with red colours show the densest parts of the school. The layer underneath show the detected seabed.*

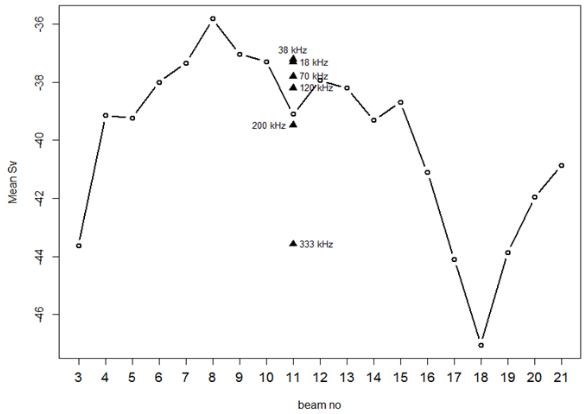


Figure 4-7: *Example comparison between EK60 (at different frequencies) and ME70 for the school shown on Figure 4-6.*

As a result of the processing described in Section 3.1.3, a database of detected fish schools is constructed. For each school, this consists of a 3D point cloud with the position of each pixel (ping, latitude, longitude, depth) and the associated backscattering coefficient S_v. The point clouds for all the schools detected along the four analysed transects were extracted and a volume reconstruction is undertaken using a convex hull. This is exemplified in Figure 4-8 with the 3D point cloud shown in Figure 4-8(a) and the reconstructed 3D surface shown in Figure 4-8(b). The reconstructed surface can be used to derive school shape descriptors such as: volume, vertical extend, horizontal extend, compactness, elongation, eccentricity, sphericity, orientation. These can be used alongside energetic descriptors such as: S_v distribution kurtosis, S_v distribution skewness, median S_v.

The calculation of the descriptors could not all be implemented due to the lack of time in the project. Only the volume and median S_v were calculated for each school. In a potential continuation of the project, the potential of the full range of morphological and energetic descriptors should be investigated for their ability to discriminate different species. This implies the gathering and analysis of more ME70 data (using the same framework described in Section 3.1.3) but also a method to allocate species. This could be done by correlating the catch composition of trawl hauls with ME70 records but this might result in a very low number of classified schools. A more practical solution would be to expanding the species allocation from the scrutiny of the EK60/EK80 data.

The two descriptors calculated here (median S_v and school volume) were explored. The histogram of school volumes is shown Figure 4-9(a). It is clear that the majority of the school exemplifies small volumes. When plotting school volume against median S_v (Figure 4-9(b)), it can be further observed that the small volume schools exemplify a wide range of S_v values. Larger schools exemplify a range of S_v values that is more limited.

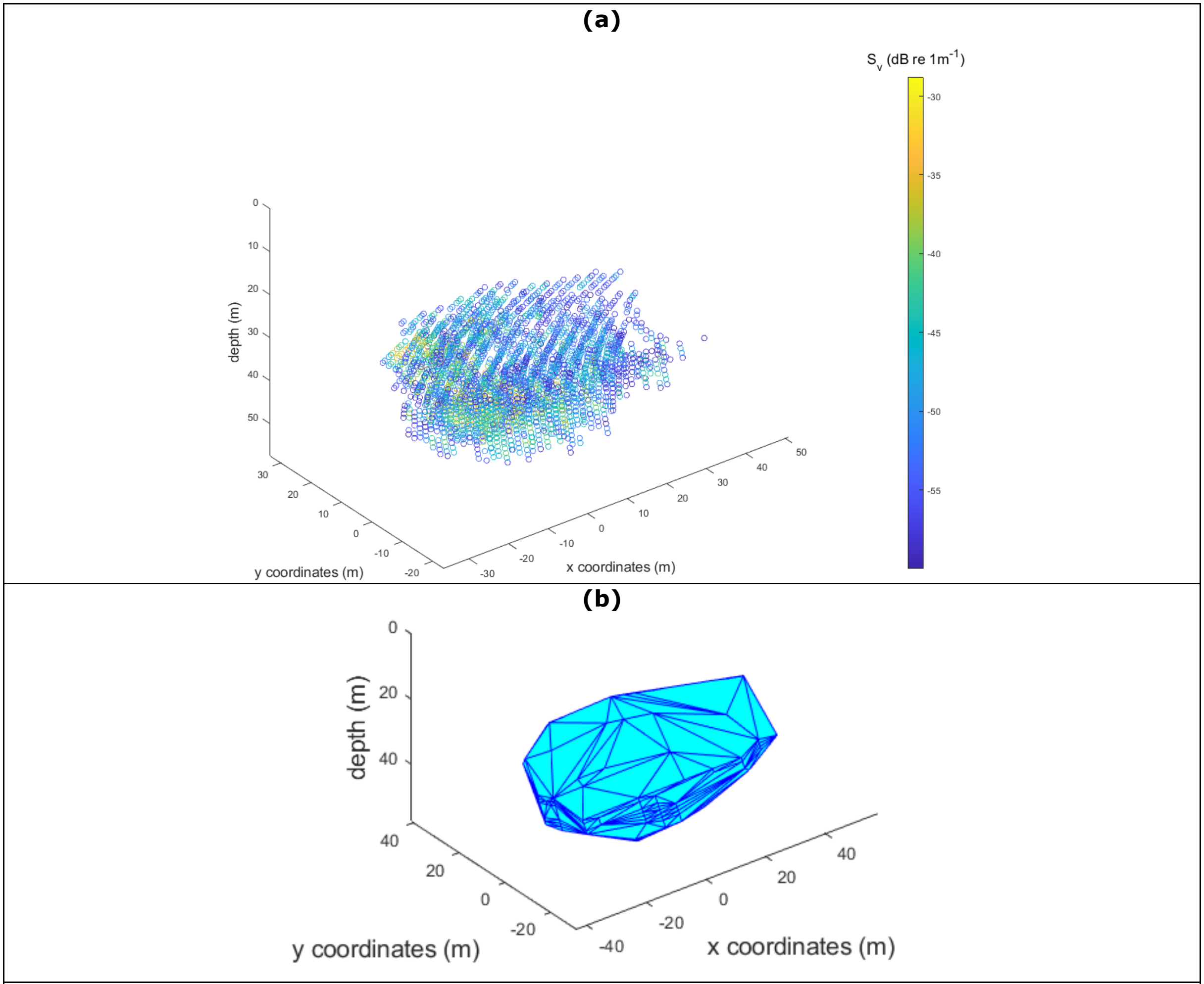


Figure 4-8: *3D point cloud reconstruction from the ME70 fish school database constructed. (a) 3D point cloud with S_v intensity. (b) corresponding 3D boundary of the school.*

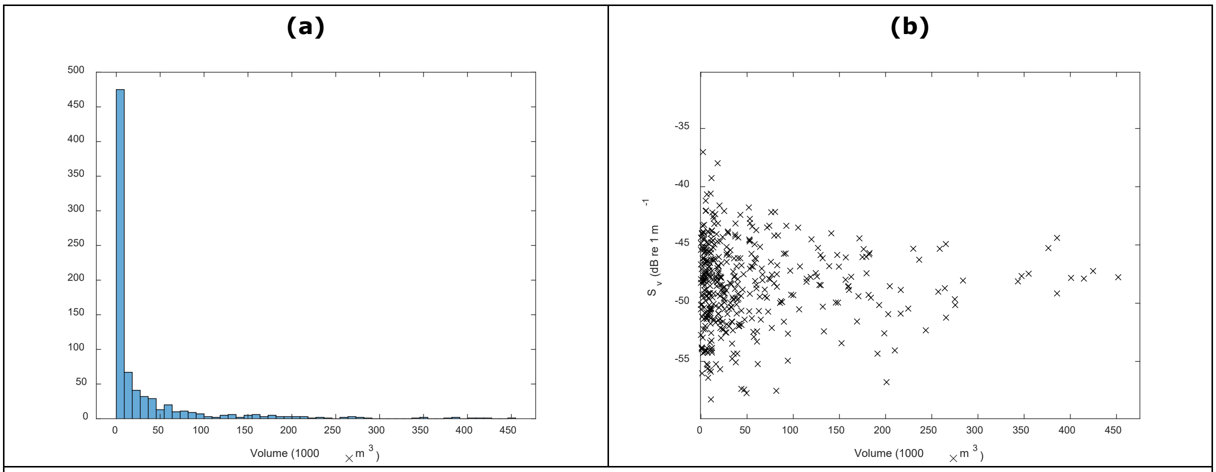


Figure 4-9: median S_v and school volume descriptors for the all the school extracted in this study. (a) histogram of school volumes. (b) median S_v against school volume.

4.2 Fish school classification using narrowband multi-frequency data

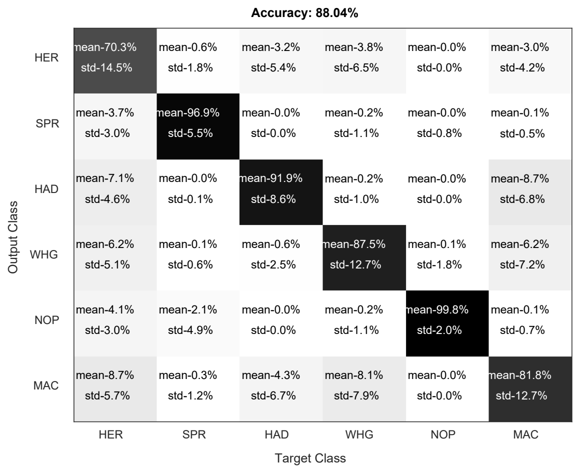
Each EK60/EK80 CW data set was processed using LSSS, following the procedure described in Section 3.2.1. The species allocation was further performed, matching the acoustic records with trawl timing. In addition, the trawls used are filtered down to those with a catch of at least 500 kg and a catch proportion for a single species of at least 80%. Because the Dutch component of the HERAS survey is located around the bulk of the North Sea herring stock, the subsequent catches are dominated by herring. This is shown in Table 2-1, with at least 76% (HERAS 2016) of the total catch being herring. For example, the catches during HERAS 2017 were fully dominated by herring (98%). As a result, a large majority of the acoustic marks detected are associated with herring. A summary of the species allocation process to the acoustic traces is presented in Table 4-1 for the different species and data sets. It is clear that the number of schools available for training for the different species is unbalanced with 574 for herring and only 4 for norway pout.

Table 4-1: *summary of acoustic fish school traces extracted from each survey per species. The allocation of fish species is based on fishing trawl information using: time, total catch weight and species proportions in the catch. These criteria are described in Section 3.2.2.*

	Herring (HER)	Sprat (SPR)	Haddock (HAD)	Whiting (WHG)	Norway Pout (NOP)	Mackerel (MAC)
HERAS 2015	123	15	0	0	0	0
HERAS 2016	210	0	0	0	0	0
HERAS 2017	148	0	9	0	0	22
HERAS 2018	53	0	0	19	0	0
HERAS 2019	40	4	0	0	4	0
Total	574	19	9	19	4	22

When training the NN, the cross-entropy index is used (Hagan et al. 2014) and this index is not weighted for the discrepancy in the number of samples for the different species (Table 4-1). Here, the approach of repeating the samples for species other than herring is used. In addition, the total number of samples used for training was limited to 50 samples per species in order to limit large repetition of samples. For example, in the case of the sprat, all the 19 samples where used and 31 additional samples were randomly drawn from these 19 samples. For norway pout and haddock, several repetitions of the same pool was performed because of the very low number of samples (9 for haddock, 4 for norway pout). For herring, 574 schools were available for training but only 50 samples were drawn for training. The accuracy of the NN was then assessed against the whole set of data for each species. However, in order to have the NN training representative of all the herring schools, 1000 replicates of the process (training of the NN, testing of the NN) were performed. The results are presented using confusion matrices with the mean and standard deviation over the 1000 replicates for each case.

(a)



(b)

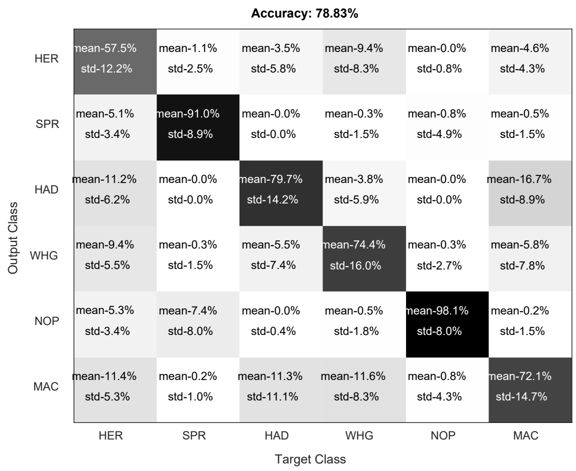


Figure 4-10: *classification results of the NN classifier for all the species allocated (Table 4-1). Results are a summary (mean and standard deviation) of the 1000 training and testing replicates. The two sets of features described in Section 3.2.3 are tested. (a) Classifier with feature set 1 (morphologic and energetic). (b) Classifier with feature set 2 (energetic features).*

The results of the NN classification are shown in Figure 4-10. The classification is done using the data from all the data sets and all species and are a summary of 1000 training and testing replicates. The two set of features, as describe in Section 3.2.3, are used. The first set of features (feature set 1, Section 3.2.3) uses both morphologic and energetic features (Figure 4-10(a)). It exemplifies classification scores for individual species between 70.3% (herring) and 96.9% (sprat). The classification results without morphological features (feature set 2, Section 3.2.3) is shown in Figure 4-10(b). A decrease in accuracy of ~10% can be observed. Solely based on energetic features, the classification score for herring is 57.5%. It is important to note that the effect of having a low number of samples for the species other than herring most likely influences the score for these species upward. This can only be remedied with a larger number of samples, i.e. additional data from future surveys. Moreover, the use of a classification method that is less affected by discrepancies in the number of samples would be advantageous.

Only nine haddock fish schools and four norway pout schools are useable for this study (HERAS 2017 and HERAS 2019, Table 4-1). This is limiting for these species and is driven by the filtering of the trawl hauls considered when allocating species to acoustic traces (Section 3.2.2). Because of this low number of samples, a classifier is derived without haddock and norway pout. The results are shown in Figure 4-11(a) for feature set 1 (morphologic and energetic features) and feature set 2 (energetic features only).

Classification accuracy is only slightly improved compared to the inclusion of all species though the use of target species with more numerous samples improves the reliability of the classifier. As observed in Figure 4-10, there is a ~10% decrease in classification accuracy when solely using energetic features. This is expected as morphological features are no longer used. These features provide further discrimination between species though they should be use with caution. Such a decrease in score reflects the difficulty to classify species based on their frequency response, especially using narrowband signals (i.e. continuous wave). It is well known that swimbladdered species exemplify similar acoustic fingerprints [4, Annex B], [14] and are therefore difficult to discriminate using narrowband acoustics. The use of broadband acoustic signals has shown to yield much higher classification scores between swimbladdered species using only energetic features at three frequencies (70 kHz, 120 kHz and 200 kHz) (Berges et al. 2019). In practice, this could be achieved during acoustic surveys with the EK80 running in mixed modes: 18 kHz and 38 kHz in Continuous Wave mode; 70 kHz, 120 kHz, 200 kHz in Frequency Modulated mode (i.e. broadband). It would probably require dedicated data collection over several surveys prior to practical use. In addition, the use of broadband acoustics is challenging with: (1) the amount of data it generates; (2) the processing of the data that is more complex.

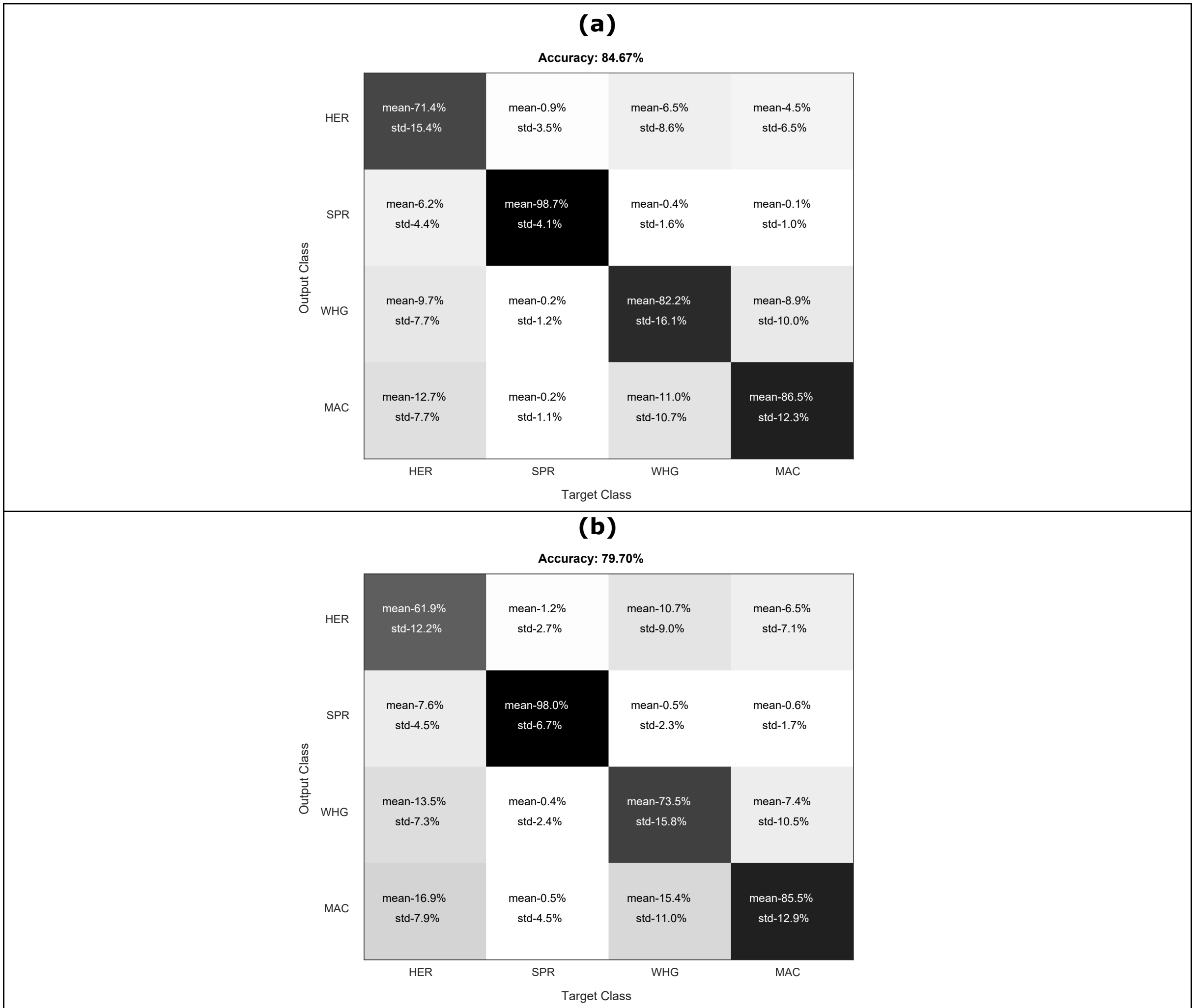


Figure 4-11: *classification results of the classifier with a reduced number of species. Results are a summary (mean and standard deviation) of the 1000 training and testing replicates. For each replicate, the NN is trained and tested with a number of species reduced to those exemplifying at least 15 samples (Table 4-1): herring (HER), sprat (SPR), whiting (WHG), mackerel (MAC). The two sets of features described in Section 3.2.3 are tested. (a) Classifier with feature set 1 (morphologic and energetic). (b) Classifier with feature set 2 (energetic features).*

5 Conclusion

From the ME70 data, the fish schools were detected and school parameters for each schools were extracted. Standard modules of the commercial post-processing software, Echoview has been customized for this specific data set and automatized. Different attempts were made to automatically group the slices from potentially the same fish school. From this analysis, many schools were successfully grouped together based on the maximum values at each corresponding pixel based on depth, ping number and beam number. A database was created from the outputs with desired details and ready for further analysis such as statistical comparisons and generating species specific school descriptors. Only two descriptors were derived in this study and the implementation of further descriptors will need to be carried out in a continuation of the project. The school detection in this work assumed each beam as an independent observation from the same area and time. For future applications alternative algorithms allowing processing the pings as a whole (rather than individual beams) and taking the school structure across the beams into account, can be used. An example of software having such capacities are MOVIES3D and HERMES[6]. The Echoview multibeam module also contains multiple 3D school detection algorithms.

In addition to 3D school structures, the effect of ME70 swath width, frequency and processing thresholds that may lead to differences between ME70 and EK60 were investigated. Rather high random variability between the EK60 and the ME70 was found especially with increased swath coverage. This increased variability could be due to the fact that more details on the fish schools are captured by ME70, but there is also the effect of tilt angle, differences in individual beam widths, differing sensitivity to noise and differing frequencies. However the mean integrated differences are comparable between the ME70 and the EK60. The observed small differences are acceptable given the other contributing factors such as different insonifying frequencies and tilt angles.

Historical echosounder data (EK60/EK80 CW) from the HERAS survey (2015-2019) have been revisited to extract features from fish school acoustic traces. The data processing was done using an automatic algorithm built in LSSS. Species allocation to these acoustic traces was done systematically using catch information from trawl hauls. A data base of descriptors for 647 fish schools was built and a classification using a neural network classifier was performed. The results yield classification accuracy >70% with morphological and energetic features and >60% with energetic features only. Overall, in the present data set, the lack of data for species other than herring hampered the performances of the Neural Network approach. Improved classification could be achieved as data expand with future surveys. Alternatively, as demonstrated in (Berges et al. 2019), the use of broadband acoustics could yield very accurate classification though the handling of such data sets is challenging. Integration of morphological school descriptors using the ME70 could also be beneficial (Trenkel, Mazauric, and Berger 2008).

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[6] https://www.flotteoceanographique.fr/en/Facilities/Shipboard-software/HERMES-and-MOVIES3D

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Justification

CVO Report: 20.011
Project number: 4311300067

The quality of this report has been peer reviewed by a colleague scientist and the head of CVO.

Approved by: C. van Damme
Colleague scientist

Signature:

Date: 20 May 2020

Approved by: B. Couperus
Colleague scientist

Signature:

Date: 20 May 2020

Approved by: Ing. S.W. Verver
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Date: 20 May 2020