CCAMLR Science, Vol. 23 (2016): 17–30

A post-processing method to remove interference noise from acoustic data collected from Antarctic krill fishing vessels

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Abstract

The use of fishing-vessel-based acoustic data has been recognised as an important way to estimate the distribution and relative abundance of Antarctic krill (*Euphausia superba*), yet the quality and even the utility of the data may be seriously degraded by interference noise due to the lack of synchronisation of the acoustic instruments found on some of the vessels. A simple method to remove significant interference noise was introduced based on relevant virtual variable operators in the existing acoustic data post-processing software. The utility of the method was demonstrated by applying it to the acoustic data at 38, 70 and 120 kHz collected from a Chinese krill fishing vessel. Results show that the interference noise was effectively reduced while structure and echo strength of the krill swarms were retained. The method may provide opportunity to improve the utility of fishing-vessel-based acoustic data for a range of objectives.

Introduction

Acoustic sampling has long been used as an important tool for mapping the distribution and estimating the abundance of Antarctic krill (*Euphausia superba*) in the Southern Ocean (Greene et al., 1991). To date, only two large-scale multiship scientific acoustic surveys, the FIBEX (Trathan et al., 1995) and the CCAMLR-2000 krill synoptic survey of Area 48 (Watkins et al., 2004), have been undertaken across the main distribution centres of krill. The estimated standing stock of krill (B_0) derived from the CCAMLR-2000 Survey is still used by the Commission for the Conservation of Antarctic Marine Living Resources (CCAMLR) to set the precautionary catch limit for the krill fishery in the southwest Atlantic (Hewitt et al., 2004; CCAMLR, 2015). To improve the management of the krill fishery, an updated estimate of the current status of krill stock and its distribution at small-scale management units is required (CCAMLR, 2015).

Compared with typical scientific surveys for krill, commercial fishing vessels usually operate at a more extensive spatial–temporal scale. In addition, some of these vessels have already installed, or intend to install, scientific echosounders that are the same or similar to those used by research vessels. For example, three Chinese krill fishing vessels have Simrad EK60 scientific echosounder systems operating at 38, 70 and 120 kHz. It has been shown that various objectives, such as estimating krill abundance in a defined region or obtaining data on the spatial organisation of krill, can be achieved using acoustic data collected by fishing vessels (ICES, 2007; Skaret et al., 2012; Wang et al., 2014; Watkins et al., 2015).

Owing to the design of fishing vessels, including the lack of noise-reduction measures, acoustic data collected from them are more likely to be degraded by noise, including interference noise or impulsive noise (Ryan et al., 2015) and background noise, as well the attenuation of acoustic signal (Mitson, 1995; Simmonds and MacLennan, 2005; ICES, 2007). If the acoustic data is going to be used for krill abundance estimation or swarm structure analysis, then the effect of such interference noise needs to be removed. Background noise can be estimated, and subsequently removed, using multiple post-processing methods (Watkins and Brierley, 1996; Korneliussen, 2000; De Robertis and Higginbottom, 2007). The effect of an attenuated signal may be compensated for by using the strength of the seabed return signal (Dalen and Lovik, 1981; Cox et al., 2006; Honkalehto et al., 2011) or the deep-sea sound scattering layer as a reference (Ryan et al., 2015). Acoustic instruments, such as echosounders, fish finding or net monitoring sonars that are likely to cause interference due to the lack of synchronisation, are widely used simultaneously during fishing operations (ICES, 2007). The duration of the interference is less than one transmit–receive period (one 'ping') and for small datasets, a practical way to remove it is simply by manually defining these signals as bad data via visual inspection of the echogram during post-processing (Dorn et al., 2002; Parker-Stetter et al., 2009). However, such an approach would become very time-consuming, variable or even impractical if significant interference noise occurred widely throughout large datasets. Hence, there is a need for the development and consistent application of semi- or fully-automated post-processing methods (Cox et al., 2006). Based on a two-sided comparison method, an interference noise filter was described by Anderson et al. (2005) and was further applied to process the open-sea echo integration data by Kloser et al. (2009) and Ryan et al. (2015).

Currently, CCAMLR's Subgroup on Acoustic Survey and Analysis Methods (SG-ASAM) is developing the protocols for the collection and analysis of krill fishing-vessel-based acoustic data (CCAMLR, 2015). As part of this activity, this paper presents a post-processing method to remove significant interference noise from acoustic data collected from krill fishing vessels. The main processing procedures are illustrated based on the existing virtual variables built into the Echoview acoustic data post-processing software (V4.90, Myriax, Pty Ltd., Australia, 2010; Higginbottom et al., 2008). The potential effects of applying this new method on echo integration and swarm structure analysis of krill are also assessed.

Materials and methods

Raw acoustic data collection

Acoustic data were collected using a SIMRAD EK60 echosounder system working at 38, 70 and 120 kHz. The echosounder system was installed on board the Chinese krill fishing vessel *Fu Rong Hai* in December 2012 and was subsequently calibrated using the standard sphere method (Foote et al.,

1987) at the anchorage outside Valparaiso, Chile. The vessel then fished for Antarctic krill (*Euphausia superba*) in CCAMLR Statistical Subareas 48.1, 48.2 and 48.3. Acoustic data were continuously logged throughout the cruise. Echosounder system configuration and parameter settings for acoustic data collection are shown in Table 1.

In addition to the EK60 system, the vessel was also equipped with a 38 kHz SIMRAD ES60 echosounder, a 32 kHz KAIJO sonar, a three-frequency (24, 75, 200 kHz) KAIJO MEMO-2000 sonar and a 28 kHz JRC JFS-3380 sonar. All these devices were operational during normal fishing activities; however, none of them were synchronised with the EK60 echosounder due to the lack of suitable synchronisation devices.

Interference noise removal

The interference noise removal method presented here treats the volume backscattering strength (S_v, dB re 1 m^{-1}) echogram as an array of values. Main processing procedures, as shown in Figure 1, are based on relevant virtual variable operators built in the Echoview software (V4.90, Myriax, Pty Ltd., Australia, 2010; Higginbottom et al., 2008).

The specific operations in each step are described as follows, with operators indicated in Figure 2.

(i) Weak and strong interference thresholding

In order to remove the background noise and very strong interference signals, a minimum threshold (T_{min}, dB re 1 m^{-1}) and a maximum threshold (T_{max}, dB re 1 m^{-1}) were determined and applied to the S_v echogram respectively. The T_{min} can either be determined as the level that visually seems to give good discrimination of 'target' from 'background' scattering on the echogram (Lascara et al., 1999) or biologically based on the measurements of krill visual acuity (Lawson et al., 2008). The T_{max} applied here is defined as the maximum S_v of krill samples in the treated dataset, which can be determined by gradually increasing the minimum display color to the level while the target, such as krill swarms, are visually absent on the echogram.

By thresholding, noise, including background noise and interference noise with the strength falling outside the thresholds [T_{min}, T_{max}], can be removed. Meanwhile, the removed S_v values were set as 'vacant' (–999 dB re 1 m, approximation of zero in the linear domain). However, noise with the strength falling within the range of [T_{min}, T_{max}] would remain intact in this stage.

(ii) General removal of interference noise

To further remove the remaining interference and background noise, an '*erosion*' filter was applied to the thresholded data. The filtering process was done via a sliding window, $w_{p,s}$, defined as

$$w_{p,s} = \begin{pmatrix} S_{v_{p-m,s-m}} & \cdots & S_{v_{p-1,s-m}} & S_{v_{p,s-m}} & S_{v_{p+1,s-m}} & \cdots & S_{v_{p+m,s-m}} \\ \vdots & \ddots & \vdots & \vdots & \vdots & \iddots & \vdots \\ S_{v_{p-m,s-1}} & \cdots & S_{v_{p-1,s-1}} & S_{v_{p,s-1}} & S_{v_{p+1,s-1}} & \cdots & S_{v_{p+m,s-1}} \\ S_{v_{p-m,s}} & \cdots & S_{v_{p-1,s}} & S_{v_{p,s}} & S_{v_{p+1,s}} & \cdots & S_{v_{p+m,s}} \\ S_{v_{p-m,s+1}} & \cdots & S_{v_{p-1,s+1}} & S_{v_{p,s+1}} & S_{v_{p+1,s+1}} & \cdots & S_{v_{p+m,s+1}} \\ \vdots & \iddots & \vdots & \vdots & \vdots & \vdots & \vdots \\ S_{v_{p-m,s+m}} & \cdots & S_{v_{p-1,s+m}} & S_{v_{p,s+m}} & S_{v_{p+1,s+m}} & \cdots & S_{v_{p+m,s+m}} \end{pmatrix} \quad (1)$$

Where $w_{p,s}$ is comprised of $N \times N$ samples of S_v values, N should be an odd number and $m = (N-1)/2$; the subscripts p and s denote the ping number and the sample number in the ping respectively.

During *erosion* filtering, the value, $S_{v_{p,s}}$ at the centre sample is replaced by the minimum value of the $N \times N$ samples in window $w_{p,s}$ while moving across each sample. As a result, if the centre sample is interference noise occurred outside the krill swarm, it will be set as vacant based on the assumption that most of its neighbouring samples are vacant.

Simultaneously, if there is any vacant sample inside the krill swarm (i.e. due to previous thresholding processing), the $S_{v_{p,s}}$ in the sliding window will also be set as vacant, resulting in an 'empty hole' on the swarm echogram.

(iii) Refilling the vacant samples inside swarms

To refill the empty hole in the swarm, a '*dilation*' filter was successively applied to the erosion-filtered data (Figure 2, step iii). The *dilation* filter is also based on the sliding window method, however, it replaced the value, $S_{v_{p,s}}$ of the centre sample with the maximum value of the samples in

Table 1: Parameter settings for the EK60 echosounder system during acoustic data collection.

Parameters	38 kHz	70 kHz	120 kHz
Transducer type	ES38B	ES70-7C	ES120-7
Transmitted power (W)	2000	750	250
Pulse length (ms)	1.024	1.024	1.024
Ping interval (s)	2	2	2
Sample interval (m)	0.187	0.187	0.187
Receiver bandwidth (kHz)	2.43	2.86	3.03
Sound speed (m s^{-1})	1462	1462	1462
Absorption coefficient (dB km^{-1})	10.4	19.2	27.8
Two-way beam angle (dB)	–20.6	–21.0	–21.0
Transducer gain (dB)	23.75	26.65	26.87
Angle sensitivity alongship (°)	21.9	23.0	23.0
Angle sensitivity athwarthship (°)	21.9	23.0	23.0
3 dB beamwidth alongship (°)	7.09	7.13	7.13
3 dB beamwidth athwarthship (°)	7.40	6.90	7.07
Data collection range (m)	400	400	400

window $w_{p,s}$. The dimension ($N^1 \times N^1$) of the sliding window applied in the *dilation* filter should be larger than that applied in the *erosion* filter.

(iv) Swarm signal correction

During the *erosion* and *dilation* filtering, the S_v values of the resulting krill swarm signals were modified. In addition, the krill swarm signals with values above the maximum S_v threshold were removed as vacant due to thresholding. These errors must be corrected if the filtered data were used for echo integration purpose.

To correct these errors, firstly, all the values of non-vacant samples in the dilation-filtered data were replaced by S_v at corresponding positions in the thresholded echogram. This is done via a combined application of '*data range bitmap^1*' and '*mask*' operators. The minimum and maximum values for *data range bitmap^1* were T_{min} and T_{max} respectively. Secondly, the krill signals which has strength above the maximum S_v threshold were compensated with an intermediate S_v level of its surrounding samples. This is done via a series of operators, including '*data range bitmap^2*', '*median*' filter and '*select*' (Figure 2, step iv). The minimum value for *data range bitmap^2* was set as T_{max}, as a result, the values above the maximum threshold were subsequently set as 'true' while the others as 'false'. The *median* filter is also based on the sliding window method as above. Specifically, it replaced the centre sample with the median S_v in the window. Finally, by applying the *select* operator, the samples with true and false in the *data range bitmap^2* were attributed with the median-filtered data and the raw S_v at corresponding positions in the thresholded data.

Application of the method

To evaluate the performance of the method, it was applied to about 24 hours of acoustic data collected during normal fishing activities in waters around the island of South Georgia on 24 August 2013 (Figure 3). Typical trawling and cruising speeds were about 3 and 10 knots respectively. The swarm echoes mainly consisted of Antarctic krill based on simultaneous biological sampling using a commercial mid-water trawl with codend mesh size of 15 mm.

To determine the maximum threshold (T_{max}), the echograms of the treated dataset were visually scrutinised while varying the minimum display colour. For 38 kHz, the echoes of krill swarms were absent on the echogram with a minimum display colour of –50 dB. Similarly, the maximum thresholds for 70 and 120 kHz were determined as –45 and –40 dB respectively. The minimum thresholds (T_{min}) were set as –70 dB for 120 kHz as advised by Lawson et al. (2008) and –80 dB for both 38 and 70 kHz by visual inspection of the echograms.

Based on the available operators in the software, the sizes (N) of the sliding window in the *erosion*, *dilation* and *median* filters were set as 3 × 3, 7 × 7 and 7 × 7 respectively.

Table 2: Specification of parameter settings applied in the swarm detection algorithm for 120 kHz data.

Parameters	Settings
Maximum permitted data range (m)	400 or sea bottom
Minimum S_v threshold (dB)	–70
Min. horizontal candidate (m)	10
Min. vertical candidate (m)	0.5
Max. horizontal linking distance (m)	15
Max. vertical linking distance (m)	5
Min. total swarm length (m)	15
Min. total swarm height (m)	2

To assess the performance of the method, a series of descriptors of swarm structure, including mean volume backscattering strength (MVBS, dB re 1 m^{-1}), perimeter, area, mean depth and thickness of krill swarms, were obtained by applying the '*school detection*' module (Higginbottom et al., 2008; Diner, 2001) to the 120 kHz data. Parameters used for detecting krill swarms are shown in Table 2 based on the specification in Klevjer et al. (2010). Subsequently, a two-sample *t-test* (hypothesising that the 'means are equal' at 5% significance level) was applied to compare the statistical difference of the descriptors of krill swarms between the results obtained from the raw and interference noise removed data.

Potential effect on echo integration was firstly investigated by comparing the difference of mean S_v over a random selected region. Mean S_v was defined as the arithmetic mean of the S_v samples over a 1 m depth bin performed in the linear domain. The effect was further evaluated based on the dB differences analysis (ΔMVBS – Madureira et al., 1993; Watkins and Brierley, 2002) between 38, 70 and 120 kHz. The dB differences in the dataset were calculated over the regions of krill swarm identified using the interference noise removed data at 120 kHz. The grid size for calculating the dB difference were 50 pings horizontally by 5 m vertically as advised by SC-CAMLR (2010).

Results

Application of the method

Due to the lack of synchronisation of various acoustic instruments on board the vessel, substantial 'spike-like' interference was detected at all three frequencies in the EK60 data, but were most pronounced at 38 kHz (Figures 4a to 4c). The vertical location and strength of the interference noise was frequency dependent (Figure 5). The background noise amplified by the time-varied gain (TVG) compensation increased with depth and were highest at 120 kHz. After removing the interference noise, the echograms of all the three frequencies were visibly improved (Figures 4d to 4f). The interference and background noise outside the krill swarms were effectively removed, although some interference was still evident at depths below 200 m at 38 kHz. Furthermore, the geometrical shape and echo strength of the krill swarm seemed to be retained compared to the original echogram.

Effect on krill swarm structure

To further investigate the effect on krill swarm structure, the *school detection* module was applied to the 120 kHz raw and interference noise removed data. A total of 51 krill swarms were subsequently identified from the dataset analysed. The swarm properties examined did not differ significantly between the raw and the processed data ($p > 0.2$, see Table 3 and Figure 6).

Effect on echo integration

The mean S_v values of 1 m depth bin of the raw samples, with background noise and strong interference included, showed skewed distribution with a long right tail for the three frequencies (Figure 7(a), black lines). Taking 38 kHz for example, about 80% and 1.3% of the total raw samples have an S_v value falling below the T_{min} (–80 dB) or above the T_{max} (–50 dB) respectively, while contributing about 0.45% and 97% to the total backscattering coefficient (s_a, m^2 m^{-2}). By removing the interference noise, unimodal distributions (Figure 7(a), red lines) mainly consisting of krill swarm

Table 3: Summary statistics and difference (p-values in t-test) of the properties for the 51 krill swarms obtained from the raw and interference noise removed data at 120 kHz. Statistical values are represented by 25% quartile/**median**/75% quartile.

	Swarm properties					
	MVBS (dB)	Thickness (m)	Depth (m)	Log_{10} length (m)	Log_{10} perimeter (m)	Log_{10} area (m^2)
Raw	−59.0/**−54.8**/−52.6	27.5/**52.6**/105.8	164/**217**/253	2.22/**2.67**/3.23	3.03/**3.53**/4.15	3.30/**3.88**/4.88
Processed	−58.9/**−56.3**/−53.8	23.9/**37.8**/103.5	164/**217**/253	2.22/**2.67**/3.23	2.96/**3.40**/4.07	3.29/**3.87**/4.87
p-value	0.2058	0.6864	0.9986	0.9761	0.4983	0.9374

echoes were obtained. Subsequently, echo intensity (MVBS) over each ping in the defined region were significantly reduced (Figure 7b).

The distribution of $\Delta MVBS_{120–38\ kHz}$ obtained from the raw data of 51 swarms were obviously skewed (Figure 8a), with a mean (±s.d.) of 2.8 ± 10.0. By removing the interference noise, the $\Delta MVBS_{120–38\ kHz}$ showed a much narrowed distribution with a mean of 10.2 ± 3.2 re 1 m^{-1} (Figure 8c). The mean (±s.d.) of $\Delta MVBS_{120–70\ kHz}$ were estimated as 4.8 ± 2.4 and 4.8 ± 1.6 dB re 1 m^{-1} for the raw (Figure 8b) and interference noise removed data (Figure 8d) respectively.

Discussion

Recently, an increase in the number of krill fishing vessels and the rising cost of undertaking large-scale scientific research in the Antarctic have drawn attention to potential use of fishing vessels to collect extensive scientific data (Watkins et al., 2015). The concept that krill fishing vessels could contribute acoustic data was evaluated with example datasets from several vessels (SC-CAMLR, 2014). Preliminary investigation of this fishing-vessel-based data has shown the potential to provide qualitative and quantitative information on the distribution and relative abundance of Antarctic krill and other pelagic species (SC-CAMLR, 2015; IMOS www.imos.org.au/basoop.html). However, one of the impediments that restricts the utility of such data is the high level of noise, typically due to the configuration of vessels for commercial, rather than scientific survey, purposes (ICES, 2007). In addition to the frequent occurrence of background noise, interference noise arising from other acoustic instruments may also contaminate the acoustic data collected by fishing vessels. For example, the Chinese krill fishing vessel *Fu Rong Hai* was found to have two other echosounders besides the Simrad EK60, as well as two sonars, working at the same time during normal fishing operations. Due to the lack of any synchronisation of these acoustic instruments, significant 'spike-like' interference noise occurred widely because the EK60 data were corrupted by the krill swarm echoes. The interferences were most pronounced at 38 kHz because of other acoustic instruments having the same or a similar frequency, while the level of background noise was frequency-dependent and the highest at 120 kHz.

It is reasonable to assume that similar situations of interference noise might also be present in the acoustic data collected from other krill fishing vessels. Two post-processing methods have been described to filter out interference noise. One method is based on a 7 × 7 convolution filter, which was subsequently used for investigating the krill swarm characteristics (Klevjer et al., 2010); the other method was based on a two-sided comparison filter, which was applied to acoustic data collected both from fishing and research vessels (Anderson et al., 2005; Ryan et al., 2015). In both of the methods, an empirical threshold value needs to be determined and applied to differentiate interference noise from 'target' echoes. As a result, there will be instances where target echoes are removed or interference noise is retained if the threshold criteria are violated (Ryan et al., 2015). Moreover, both of these methods are designated to treat datasets where there is a low occurrence of interference, therefore, with particularly poor-quality data where significant interference occurred, the residual error in the processed data might still be significant.

Compared with the above techniques, the post-processing technique presented in the paper is aimed at reducing significant interference noise from contaminated acoustic data. It can be simply utilised based on the existing virtual variable operators in the Echoview post-processing software. Its utility was demonstrated by applying to the data collected from a Chinese krill fishing vessel. The resulting echograms showed that most of the significant interferences were effectively removed and there was no evident change to the swarm structure. Only the mean acoustic density, thickness and perimeter seemed to be reduced which were likely to be caused by removing strong interference noise within, or affiliated with, the krill swarms.

Echo integration over an example region showed that although the majority (80%) of the samples are contaminated with background noise, the strong interference noise is likely to dominate the total backscattering. Without appropriate elimination, this strong interference noise will cause significant positive bias if the data are used for krill density estimation.

The dB-differencing (ΔMVBS) technique is widely used for identifying Antarctic krill from other acoustic scatters (Madureira et al., 1993; Watkins and Brierley, 2002; Fielding et al., 2014). For krill with length ranging from 30 to 60 mm, the target identification window is estimated as 0.4 to 12.0 and –0.6 to 13.8 based on the simplified and full SDWBA model for $\Delta MVBS_{120-38\ kHz}$ respectively (McGehee et al., 1998; Demer and Conti, 2003; Conti and Demer, 2006; SC-CAMLR, 2010; Calise and Skaret, 2011). For the krill swarms examined in this study, only 53% and 65% of the $\Delta MVBS_{120-38\ kHz}$ obtained from the raw data were located within the above theoretical windows; by removing the interference noise, the proportions increased to 79% and 93% respectively. There was no evident change to the mean value of $\Delta MVBS_{120-70\ kHz}$, while the standard deviation was reduced by 0.8 dB by applying the method, indicating the application of the method would benefit krill identification utilising the dB difference technique.

Although the results are encouraging for the examination of krill swarm structure and echo integration, other sources of bias and error may still remain in the retained data. Firstly, a major bias may arise from removing the background noise and strong interference by S_v thresholding (step i). In the present study, the minimum and maximum thresholds were determined either as empirical values or by visual inspection of the echogram when good discrimination between noise and krill echoes are observed. Inevitably, there will be instances where echo strength of krill overlaps with background or interference noise. If this occurs, negative bias may arise from thresholding because valid echo from krill may be mistaken as noise. This bias is likely to increase when the variance of krill swarm echoes is significant, therefore, reducing the size of treated dataset and determining thresholds for each dataset may reduce the bias. Secondly, an error may arise from the potential ineffectiveness of erosion filtering for general removal of interference noise (step ii). The source of error is that the $N \times N$ erosion filter will be invalid if there are $N \times N$ or more samples of noise retained within one sliding window after thresholding. For example, some interference noise was still evident at depths below 200 m at 38 kHz, an error may become more significant when the data quality is extremely poor or at long range where the signal-to-noise ratio (SNR) is low. A pre-estimation and removal of background noise (Takao and Furusawa, 1995; Watkins and Brierley, 1996; Korneliussen, 2000; De Robertis and Higginbottom, 2007) is likely to improve the performance of the present method.

Finally, it should be noted that the method presented here does provide an opportunity to improve the utility of acoustic data contaminated by significant interference, however, exact estimation of the residual bias in the processed data is still unknown. It is important to stress that, while post-processing can alleviate the potential problems of interference noise, measures to avoid the situation occurring, such as turning off other acoustic instruments or proper synchronisation, should always be the first priority if the data are collected for krill biomass estimation.

Acknowledgement

We sincerely thank the crewmembers on board the *Fu Rong Hai* for helping with the data collection during the cruise. We also thank Dr Martin Cox, Dr Keith Reid and two anonymous reviewers for their efforts in improving the manuscript. This work was supported by a Chinese National key Science & Technology Program (2013BAD13B03). The lead author (X. Wang) would also like to thank CCAMLR for granting him its scientific scholarship (2013–2014).

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Raw S_v data

$\downarrow$

(i) Weak noise and strong interference thresholding

$\downarrow$

(ii) General removal of interference noise

$\downarrow$

(iii) Refill the vacant samples inside swarms

$\downarrow$

(iv) Swarm signal correction

$\downarrow$

Interference noise removed S_v data

Figure 1: Conceptual flow diagram of the main procedures in the interference noise removal method. The operations applied, indicated in *italics*, follow the terminology defined in Echoview.

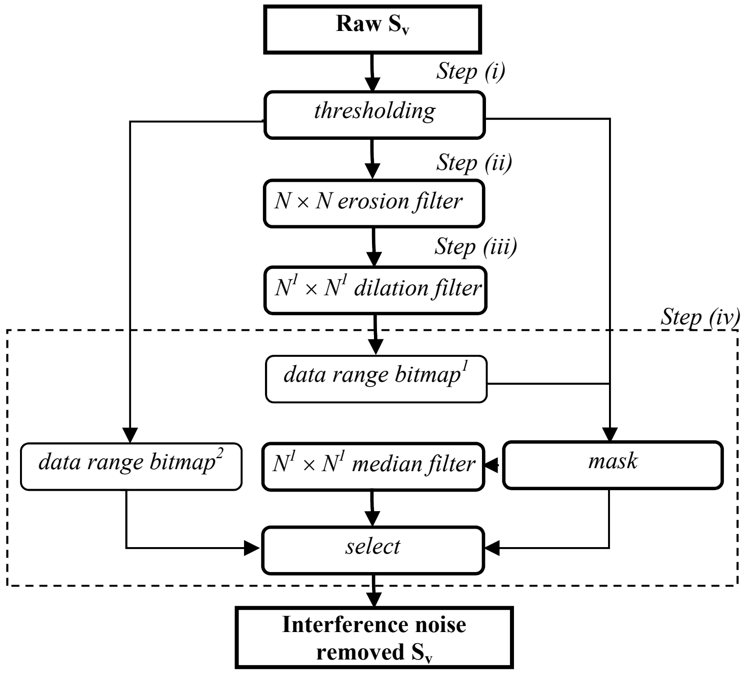

Figure 2: Operational flow diagram of the interference noise removal method based on the virtual variable operators in Echoview.

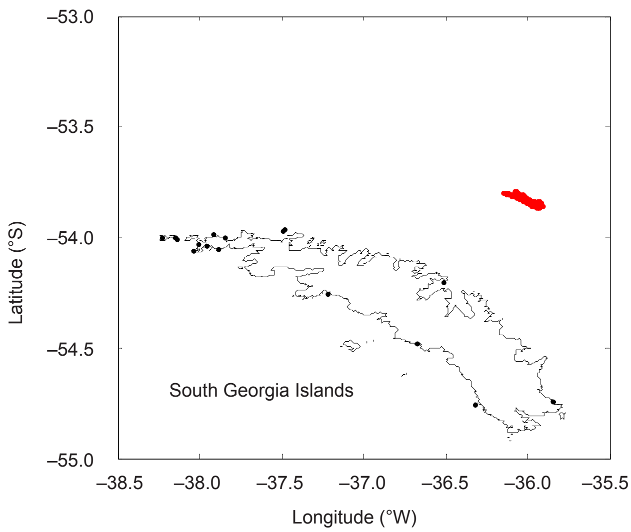

Figure 3: Locations (red) of acoustic data and krill sample collection during normal fishing activities around South Georgia on 24 August 2013.

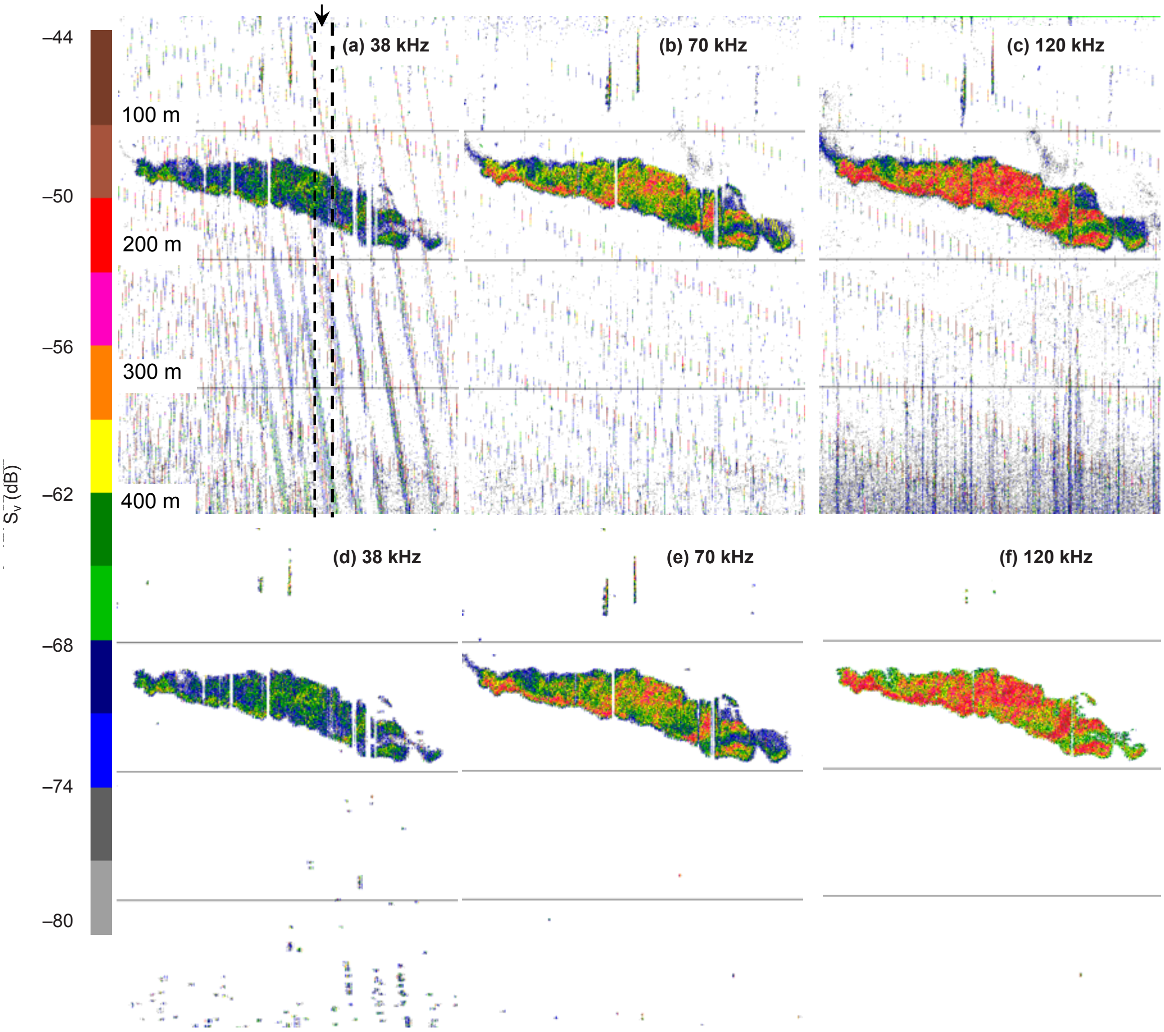

Figure 4: An example of applying the interference noise removal to ca. 500 ping echograms (38, 70 and 120 kHz). A krill swarm is evident between depths of 100 and 200 m. (a) to (c) are the 38, 70 and 120 kHz raw echograms; (d) to (f) are the 38, 70 and 120 kHz virtual echograms with interference noise reduced (see Figure 5 for details of the region between the dashed lines in (a).

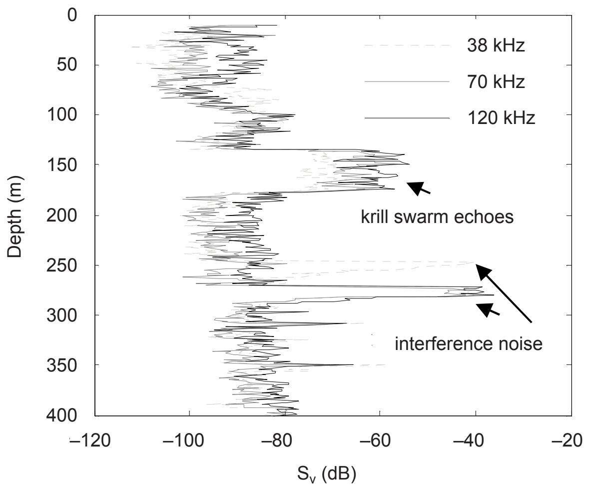

Figure 5: Vertical distribution of mean S_v in a ping randomly selected from the region between the dashed lines in Figure 4(a). The S_v values were vertically averaged over 1 m bins.

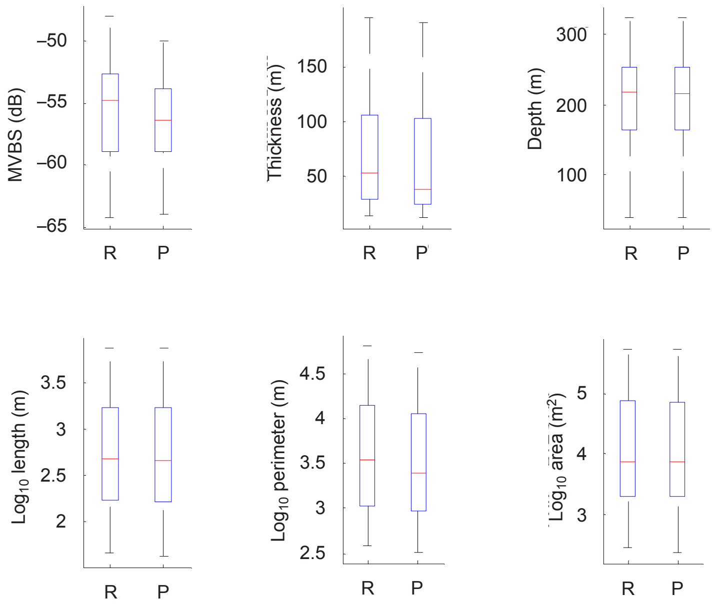

Figure 6: Swarm properties for the 51 krill swarms obtained from the raw (R) and processed (P) data at 120 kHz.

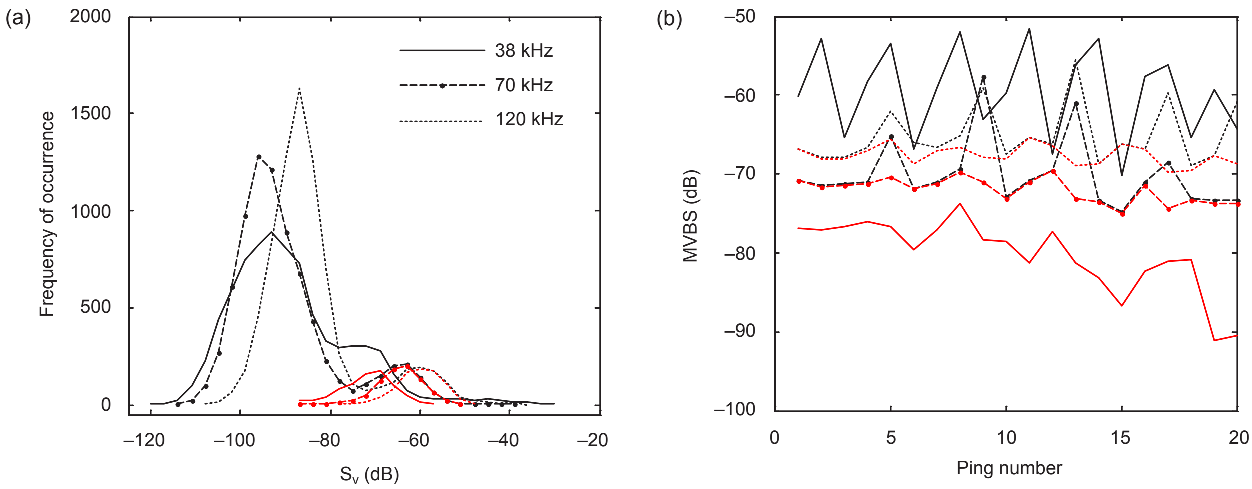

Figure 7: Frequency distribution of mean S_v (a) and variation of MVBS (b) for 20 consecutive pings (without vacant samples) from the region between the dashed lines in Figure 4(a). The black lines and the red lines represent results obtained from the raw data and the processed data respectively. The frequency occurrence of mean S_v is the number of mean S_v grouped in 3 dB intervals, while the mean S_v values were averaged over 1 m depth bins. The MVBS were the arithmetic mean of the S_v samples over each ping performed in the linear domain.

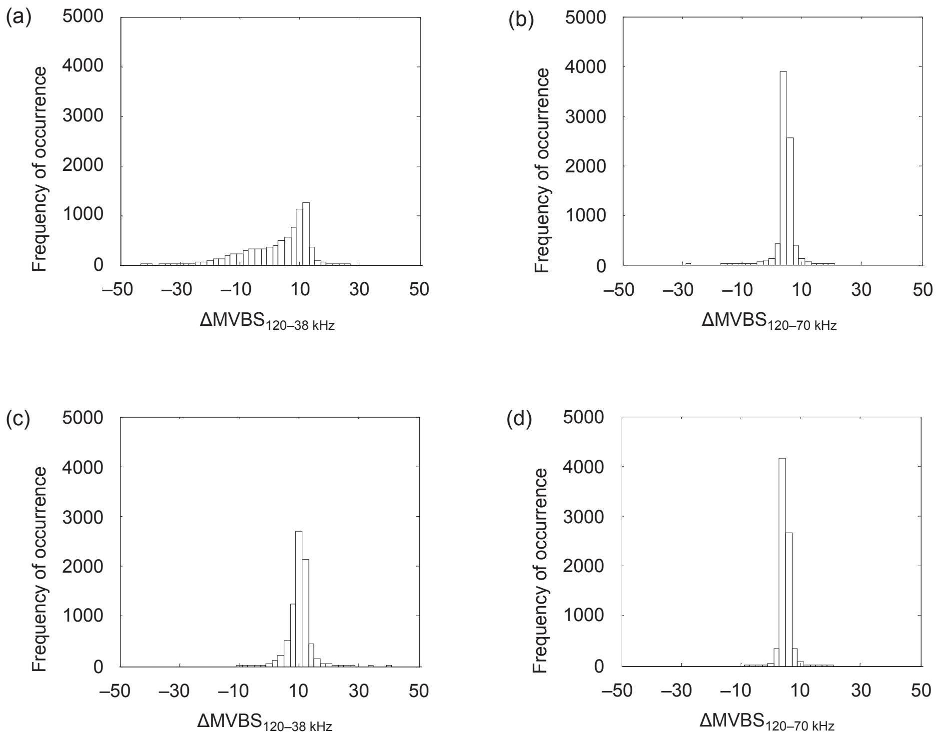

Figure 8: Frequency distribution of the dB-difference for krill swarm echoes. (a) and (b) represent results obtained from the raw data; (c) and (d) represent results obtained from the interference noise removed data.