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Sources and magnitude of random errors in Acoustic Fish Abundance Estimates

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Abstract
The uncertainty of an acoustic fish abundance estimate originating from the integrator output is investigated. A series of 8 consecutive echo integrator surveys covering the same area in the Skagerrak are analysed, treating the integrator readings as a time series. The mean integrator output for one survey (160 observations) is estimated with a relative high precision as the standard deviation is found to be about 0.2% of the mean. The mean integrator output varied with survey indicating a real time trend.

Introduction
Hydroacoustic estimates of fish biomass are primarily based on two sets of data, integrated echolevel obtained using the echo integrator and information about the biological material obtained by trawling. Both data sets are subject to systematic (biases) and random errors. The biomass estimates can (for management purposes) be used as indices or as absolute figures. Used as indices it is very important to know the precision of the estimates, i.e. the level of random errors, while the biases, as long as they are constant, are unimportant. Used as absolute figures, both the random and the systematic errors play an important role.

Several authors have analysed the various sources of variance in the measured echolevel using theoretical models (Bodholt, 1977; Ehrenberg & Lytle, 1977; Lozow, 1977; Moose & Ehrenberg, 1971). Johanneson & Mitson (1983) discuss the possible sources of errors and how these may be combated. Aglen (1983) estimates the variation for repeated echo integration surveys and studies the effect of different degree of area coverage on the variance. Ona & Røttingen (1986) obtained comparable results from repeated surveys on small herring. However, none of these papers give a variance estimator suitable to survey data. This paper is an attempt to estimate the variances related to a specific acoustic survey.

On a typical acoustic survey the observations of echolevels show serial correlation which means that a simple random hypothesis as basis for the analysis of the data yields unrealiable confidence intervals. Nickerson & Dowd (1977) use a model given by Hagg & Craig (1968) to correct for serial correlation. Williamson (1982) presented results from a computer simulation study showing that using cluster sampling estimation techniques will give a more reliable confidence interval.

In this work the integrator output from a series of 8 consecutive acoustic surveys covering the same area are analysed.

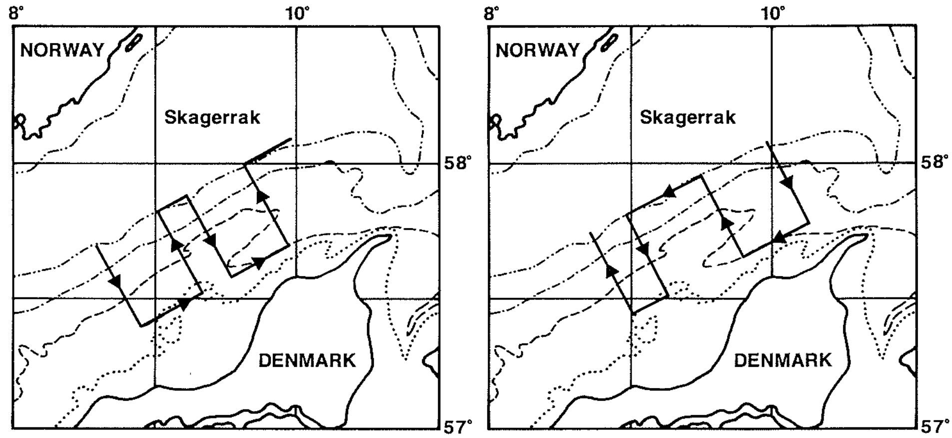

Fig.1. The survey area and the two grids.

Material

The hydroacoustic data presented were obtained by R/V *Dana* in the Skagerrak in the last week of July 1984. 8 consecutive coverages were made using two different grids alternately. The survey area and the two grids are shown in Fig. 1. The surveys are numbered in chronological order from 1 to 8. Surveys 1, 3, 5 and 7 were apart from minor deviations following grid A and 2, 4, 6 and 8 grid B. The duration of each survey was 24 hours, which means that there are samples from the same positions at the same time of the day with two days interval.

The acoustic data were collected using a Simrad EK400 sounder with a hull mounted transducer operating at 38 kHz. Integration of the signals was carried out by a Simrad QD integrator. The speed of the ship was 8 knots and the integrator readings were recorded every one nautical mile. The total length of all 8 surveys was 1280 miles, but only 760 readings were recorded.

Data analyses

In the analysis the integrator readings are treated as a time series, the 'time' unit being 1 nautical mile. To each observation was attributed a mile figure between 1 and 160. The actual length of a survey was approximately 160 miles and the attributed figure was chosen such that observations with the same mileage had (nearly) the same geographical position.

The data were analysed using two different models: two-way classification and Fourier series. The two-way model is a simple and rather inaccurate model, but it gives an idea about the results that can be obtained from more relevant models. The main problem is a presence of a trend. If a trend is present the residual variance will contain contributions from the trend and thus be an overestimate of the true variance. The use of a Fourier series model is an attempt to overcome this problem. The two-way classification has, however, an advantage as compared to the Fourier series approach: The Fourier series model demands a full set of observations (i.e. 160 observations for each survey), whereas the two-way classification can be carried through on existent observation. As some observations are missing the data set was repaired for the Fourier series analysis as explained later on.

Two-way classification

The model is:

$$\mathrm{OBS(SURVEY,MILEAGE)} = \{\mathrm{INTERCEPT} + \mathrm{A}(8) + \mathrm{B}(160)\} + \{\mathrm{A(SURVEY)} - \mathrm{A}(8)\} + \{\mathrm{B(MILEAGE)} - \mathrm{B}(160)\} + \varepsilon\mathrm{(SURVEY, MILEAGE)}$$

where A(SURVEY) only depends on survey no., B (MILEAGE) only on mileage,and ε are independent stochastic components. The A's are a stepwise approximation to the trend and the B's describe the geographical variation. The observations used in the analysis were water depth, mean volume backscattering strength (S_v), mean area backscattering strength (S_a), antilog (S_v)·1E8 (s_v, proportional to biomass per volume unit), and antilog (S_a)·1E8 (s_a, proportional to biomass per area unit).

Fourier series

A different way to examine the data is to fit a Fourier series to the observations. When doing this a regression model of the form:

$$\mathrm{OBS(`TIME')} = \mathrm{mean} + \frac{1}{\sqrt{N}} \sum_{\substack{n=-N1 \\ n \neq 0}}^{N1} A_n \cdot e^{\frac{i \cdot 2 \cdot \pi \cdot n \cdot \mathrm{`TIME'}}{N}} +$$

$$\frac{1}{\sqrt{N}} \sum_{n=-N/2}^{-N1-1} A_n \cdot e^{\frac{i \cdot 2 \cdot \pi \cdot n \cdot \mathrm{`TIME'}}{N}} + \frac{1}{\sqrt{N}} \sum_{n=-N1}^{N/2} A_n \cdot e^{\frac{i \cdot 2 \cdot \pi \cdot n \cdot \mathrm{`TIME'}}{N}}$$

$$= \mathrm{mean} + \frac{1}{\sqrt{N}} \sum_{\substack{n=-N1 \\ n \neq 0}}^{N1} A_n \cdot e^{\frac{i \cdot 2 \cdot \pi \cdot n \cdot \mathrm{`TIME'}}{N}} + \varepsilon(\mathrm{`TIME'})$$

is used, where 'TIME' stands for (survey − 1)·160 + mileage (surveys 1,3,5,7) or survey·160 − mileage (surveys 2,4,6,8), N the number of observations used, and $N1$ the (assumed) number of oscillations. The dataset is conceived as one period of a periodic series with period N disturbed by noise (ϵ'TIME' supposed to be independent random variables). The validity of the model was examined by means of the periodograms, i.e. the amplitudes $\sqrt{(A_n \cdot A_{-n})}$ as a function of the frequency n.

The periodogram for each of the mentioned data types has been found by means of a Fast Fourier Transform program (NAG). As FFT demands complete series (i.e. no missing observations) the data set has been repaired by interpolation in the case of the depth and by using the mean S_v from the two way classification (corrected for depth and/or transformed) for all other missing values. As an example Fig. 2 shows the periodogram for S_a and $N = 1280$. The point is now that the squared amplitude for each frequency is an independent estimate of the variance of the stochas-

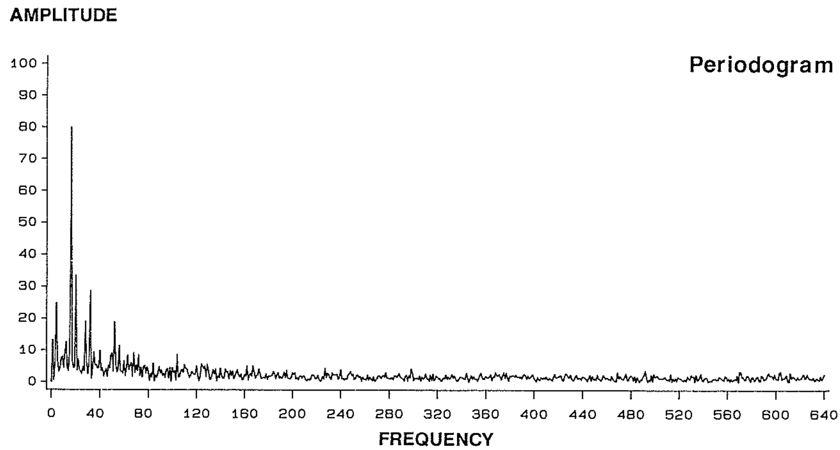

Fig. 2. Periodogram (Amplitude = $\sqrt{(A_n \cdot A_{-n})}$ as function of frequency n) for S_a (the whole dataset, $N = 1280$).

tic component (the noise) with two degrees of freedom (except the highest frequency with only one degree of freedom), if only noise is present ($N1 = 0$).

This is still true for the shortwaved part of the periodogram if real longwaved oscillations are present ($N1 > 0$). For all five data types it looked like the variance could be determined with a comfortable number of degrees of freedom. Fig. 2 indicated e.g. that amplitudes for frequencies >200 could be used for estimating the noise in the full data set ($N=1280$).

Results

Two-way classification

In Table 1 the results of the two-way classification for water depth, S_a and s_a are summarized. The analysis for water depth gives an indication of whether the surveys were following the same grid concerning depth. The results of the analysis show that the depth profile is rather stable and that the random component is large. An examination of the data shows that the major contribution to the variance are from observations taken at the deepest part of the grids, where the depth was changing very fast during the surveys.

The analyses for S_a and s_a give rather matching results. The survey levels are different from each other, but the survey shapes are rather similar as the fitting of the B's reduces the sum of squares considerably.

Fourier analysis

The results of the Fourier analysis of S_a and s_a for all surveys combined (N=1280, $N1 = 499$), degrees of freedom for the variance = $1280 - 2 \cdot 499 - 1 = 281$) and for

Table 1.Two-way classification. Analyses of variance and parameter estimates.

DEPENDENT VARIABLE: Water depth (m)

Source	Degrees of freedom	Sum of squares	Mean square	F
Fitting B	158	8182045		
Fitting A	7	46011	6573	1.81
Fitting model	165	8228056		
Remainder	594	2158631	3634	
Total	759	10386687		
Fitting A	7	83272		
Fitting B	158	8144784	51549	14.2
Fitting model	165	8228056		
Remainder	594	2158631	3634	
Total	759	10386687		

Parameter	Estimate	Standard deviation
Intercept+A(8)+B(160)	289.2	25.4
A(1)-A(8)	–28.5	11.6
A(2)-A(8)	–12.6	9.5
A(3)-A(8)	1.4	8.6
A(4)-A(8)	–3.5	8.9
A(5)-A(8)	4.4	9.2
A(6)-A(8)	–9.7	10.2
A(7)-A(8)	–4.4	8.7

DEPENDENT VARIABLE: S_a dB (mean area back scattering strength)

Source	Degrees of freedom	Sum of squares	Mean square	F
Fitting B	158	9147		
Fitting A	7	587	83.9	8.39
Fitting model	165	9734		
Remainder	594	5937	9.99	
Total	759	15671		
Fitting A	7	469		
Fitting B	158	9265	58.6	5.87
Fitting model	165	9734		
Remainder	594	5937	9.99	
Total	759	15671		

Parameter	Estimate	Standard deviation
Intercept+A(8)+B(160)	–50.32	1.33
A(1)-A(8)	0.41	0.61
A(2)-A(8)	–0.51	0.50
A(3)-A(8)	–0.15	0.45
A(4)-A(8)	–2.20	0.47
A(5)-A(8)	–1.87	0.48
A(6)-A(8)	–1.61	0.54
A(7)-A(8)	–1.77	0.46

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Table 1 continued

DEPENDENT VARIABLE: s_a ($\propto$ biomass).

Source	Degrees of freedom	Sum of squares	Mean square	F
Fitting B	158	2.214E8		
Fitting A	7	1.818E7	2.597E6	5.76
Fitting model	165	2.396E8		
Remainder	594	2.680E8	4.512E5	
Total	759	5.076E8		
Fitting A	7	1.790E7		
Fitting B	158	2.217E8	1.403E6	
Fitting model	165	2.396E8		
Remainder	594	2.680E8	4.512E5	3.11
Total	759	5.076E8		

Parameter	Estimate	Standard deviation
Intercept+A(8)+B(160)	847.6	282.7
A(1)-A(8)	338.0	129.0
A(2)-A(8)	–75.1	105.7
A(3)-A(8)	–56.7	96.1
A(4)-A(8)	–226.0	99.5
A(5)-A(8)	–297.3	102.2
A(6)-A(8)	–213.1	113.8
A(7)-A(8)	–217.1	97.1

single surveys ($N = 160$, $N1 = 64$, degrees of freedom $= 160 - 2 \cdot 64 - 1 = 31$) are shown in Table 2 and 3.

It is difficult to compare the two models, as the two way classification operates with a constant trend (the A's) for each survey, while the FFT analysis includes a sliding trend within each survey. The main difference, however, seems to be in the variances: two way classification $5937/594 = 9.99$ against Fourier analysis 1.5 for S_a. This is partly due to the trend type.

The reproducibility is investigated by a modified Fourier model. The idea is to see how similar the four double surveys 1 + 2, 3 + 4, 5 + 6 and 7 + 8 are.

Table 2.The results of Fourier analysis for S_a and s_a for all surveys combined.

	S_a	s_a
Mean	–55.65 dB	487.94
Variance	2.25 dB^2	224999
Standard deviation	1.50 dB	474.34
Standard deviation of the mean	0.042 dB	13.26
Degrees of freedom	281	281
Number of observations	1280	1280
95% confidence limits	–55.73, –55.56	461.84, 514.04

Table 3. The results of Fourier analysis for S_a and s_a for single surveys.

S_a dB

Survey	Mean	Variance	Stand. dev.	Stand. dev. of mean	95% confidence limits
1	–54.84	1.18	1.09	0.086	–55.02,–54.67
2	–55.50	3.03	1.74	0.138	–55.77,–55.22
3	–54.57	2.34	1.53	0.121	–54.82,–54.32
4	–56.33	2.53	1.59	0.125	–56.58,–56.07
5	–55.63	1.95	1.40	0.111	–55.86,–55.41
6	–56.44	1.57	1.25	0.099	–56.64,–56.24
7	–56.05	2.36	1.53	0.156	–56.30,–55.80
8	–55.81	3.41	1.85	0.146	–56.10,–55.51

s_a

Survey	Mean	Variance	Stand. dev.	Stand. dev. of mean	95% confidence limits
1	614	1277625	1130	89.4	432,797
2	478	36878	192	15.2	447,509
3	584	141007	376	29.7	523,644
4	413	38602	196	15.5	381,445
5	452	22754	151	11.9	428,477
6	391	14673	121	9.6	371,411
7	461	98276	313	24.8	410,512
8	511	128242	358	28.3	453,568

(number of observations = 160 (= period); degrees of freedom = 31)

The model is:

$$\mathrm{OBS}(\text{'TIME'}) = \text{mean} + \frac{1}{\sqrt{1280}} \sum_{\substack{n=\pm1,\pm2,\pm3,\\ \pm4,\pm2\cdot4,\ldots,\pm4\cdot26}} A_n \cdot e^{\frac{i\cdot2\cdot\pi\cdot n\cdot\text{'TIME'}}{1280}} +$$

$$\frac{1}{\sqrt{1280}} \sum_{\substack{n=-640\\ n\neq0,\pm1,\pm2,\pm3,\\ \pm4,\pm2\cdot4,\ldots,\pm4\cdot26}}^{640} A_n \cdot e^{\frac{i\cdot2\cdot\pi\cdot n\cdot\text{'TIME'}}{1280}}$$

$$= \text{mean} + \frac{1}{\sqrt{1280}} \sum_{\substack{n=\pm1,\pm2,\pm3,\\ \pm4,\pm2\cdot4,\ldots,\pm4\cdot26}} A_n \cdot e^{\frac{i\cdot2\cdot\pi\cdot n\cdot\text{'TIME'}}{1280}} + \varepsilon(\text{'TIME'})$$

using the whole dataset. The model is a modification of the original, consisting of three parts: a 'trend' (mean and frequencies 1, 2, and 3) a periodical part with period 320 (frequencies $n\cdot4$, N = 1, 2, ..., 26), and a stochastic component. The result

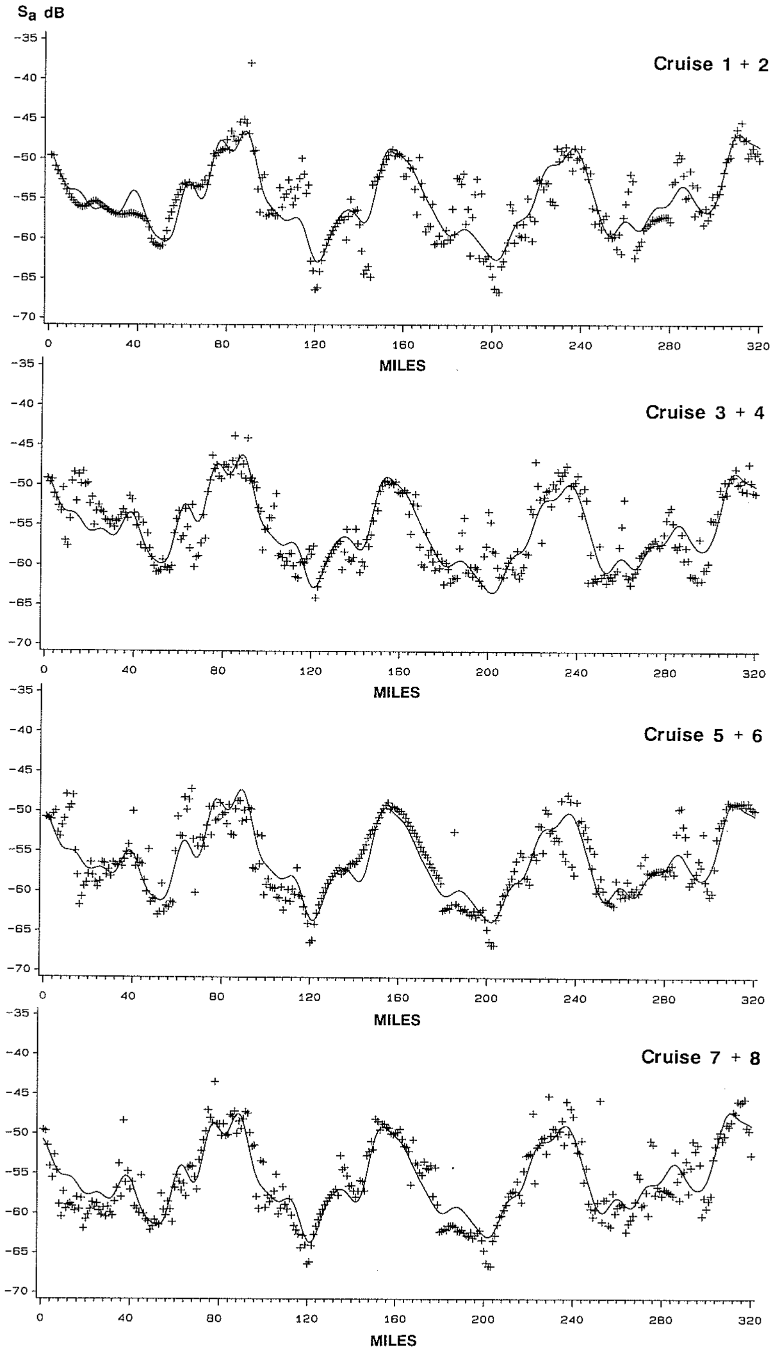

Fig. 3. S_a as function of mileage. + = observations ———— = sum of mean and oscillations with frequencies 1, 2, 3, 4, 8, 12, 16, 20, 24, 28, 32, 36, 40, 44, 48, 52, 56, 60, 64, 68, 72, 76, 80, 84, 88, 92, 96, 100, 104.

Table 4. The results of the Fourier analysis of S_a and S_a for double surveys.

S_a dB

Survey	Mean	Variance	Stand. dev.	Stand. dev. of mean	95% confidence limits
1:2	–55.17	2.06	1.43	0.080	–55.33,–55.01
3:4	–55.45	2.29	1.51	0.085	–55.62,–55.28
5:6	–56.04	1.73	1.32	0.074	–56.18,–55.89
7:8	–55.93	3.06	1.75	0.098	–56.12,–55.73

s_a

Survey	Mean	Variance	Stand. dev.	Stand. dev. of mean	95% confidence limits
1:2	546	672432	820	45.8	455,637
3:4	498	79120	281	15.7	467,530
5:6	422	21408	146	8.2	405,438
7:8	486	130669	361	20.2	446,526

(number of observations = 320 (= period); degrees of freedom = 71).

is shown in Fig. 3. We think that the similarity is rather convincing. The similarity is also clearly indicated on Fig. 2 as most peaks correspond to frequencies which are multiples of 4.

The four double surveys have also been studied by the first model and the results are given in Table 4 ($N = 320$, $N1 = 124$, degrees of freedom $= 320 - 2 \cdot 124 - 1 = 71$). The main result is that it was possible to a certain degree to reproduce the first double survey, but the mean level varied from double survey to double survey, and this indicates that a real trend was present. The cause of this trend is so far unknown. Fig. 4 is a simplified edition of Fig. 3 showing the 'trend' and the periodic component.

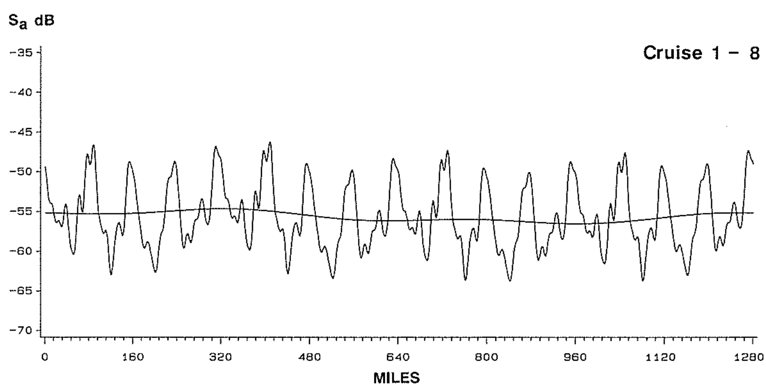

Fig. 4. S_a as composed of a trend and a periodic component. Trend = (mean +) oscillations with frequencies 1, 2 and 3. Periodic component = sum of oscillations with frequencies $4 \cdot N$, $N = 1\ldots, 26$. Period = 320 miles.

The results should, however, be taken with some caution. The data set was not perfect as 520 of the 1280 observations were missing. The way the data set was replenished will probably give underestimates of the variance. As survey 1 and survey 6 have most missing values Table 3 and 4 is in accordance with this. The true variances are probably some 50%-100% higher than those given in the tables.

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