SEAFLOOR SEDIMENT CHARACTERIZATION USING MULTIBEAM ECHOSOUNDERS WITHOUT GRAB SAMPLING: OPPORTUNITIES AND CHALLENGES

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Abstract: *In the last two decades, the use of multibeam echosounders has been growing for seafloor mapping and characterization. The former uses bathymetry data whereas the latter makes use of backscatter data. The use of backscatter data has been the subject of intensive research to gain insight into seafloor composition using either empirical or model-based methods. Model-based methods employ the available physical models for predicting the backscatter strength and determine the seafloor geoacoustic parameters in an inversion algorithm using optimization methods. These methods allow for direct coupling between the backscatter curve and sediment characteristics. But the methods usually suffer from a shortcoming associated to uncalibrated sonars, which is referred to as calibration curve. Grab samples at reference areas are required to estimate the calibration curve. A question may arise as to whether, or to what extent, the calibration curve can be estimated without grab sampling. Knowing that the calibration curve is an unknown function of incident angle, in principle, one can approximate it using the available estimation and optimization theories. This is elaborated in this paper and its opportunities and challenges will be addressed. The potential benefit is twofold. 1) The huge amount of MBES backscatter currently available in many hydrographic organizations can directly be used for seafloor characterization. 2) The available multiple-frequency MBESs can further improve the performance of the inversion process. There are also challenges to be addressed. 1) Estimation of the calibration curve is an unstable process because it is merely based on observed backscatter data without using grab samples. 2) The physical models, and component parts thereof, are not usually well-behaved functions, possibly due to their discontinuities or discontinuity of their derivatives. These issues will be elaborated in this paper.*

Keywords: Multibeam echosounder (MBES), Backscatter data, Angular calibration curve (ACC), Sediment mean grain size.

1. INTRODUCTION

Multibeam echosounders (MBESs) data have been intensively used in many marine research problems over the last decades. Two kinds of information are widely provided by an MBES: bathymetry and backscatter data. MBES-derived bathymetric data are used to map the topographic features of the seafloor for a wide range of applications such as maintaining safe navigation, off-shore construction and studying seafloor structure and morphology. Information on the seafloor composition can mainly be obtained from the backscatter data. The use of MBES backscatter data is prone to a few sources of fluctuations and uncertainties. They can be considered as deterministic effects, to be compensated for in a functional model. Unmodelled effects such as noise are to be taken into consideration in the stochastic model.

Although the stochastic nature of backscatter data can be an interesting research field by its own, the focus of this study is on all deterministic effects. We therefore reduce the backscatter fluctuations due to noise by an averaging procedure. The deterministic fluctuation of backscatter data, showing an angular dependence, is a function of seafloor sediment type, acoustic signal frequency, and calibration of the MBES. This is further investigated in the present study.

There are methods widely used to characterize seafloor using the backscatter data. The methods can be classified into two main categories as 'empirical methods' and 'model-based methods'. The model-based methods use available physical models and characterize the seafloor by maximizing the match between modelled and observed backscatter signal. These methods optimize an objective function for seafloor type or parameters indicative for seafloor type. These methods allow for direct coupling between the backscatter data and sediment characteristics if the MBES sensitivity is known. This is however not usually the case, indicating that the correction on the backscatter curve (backscatter as a function of angle) is to be estimated prior to the optimization process [1,2]. The empirical methods make use of a few statistical features extracted from the data, possibly after dividing the area/data into small regions/groups. The principal component analysis (PCA), linked with clustering algorithms—k-means for instance—can be used to classify backscatter data [3,4]. The clustering algorithms aim at partitioning observations into a few clusters in which each observation belongs to one cluster satisfying some pre-defined criteria. As a result, the outcome of clustering algorithms is a qualitative comparative description of the seafloor sediment distribution (e.g. finer, fine, coarse, and coarser). The advantage of the empirical methods is their ease of implementation and use. The complication is that ground truth is usually required to associate the classification results to sediment physical parameters such as mean grain size.

This contribution considers the model-based seafloor characterization methods. We aim at determining seafloor parameters based on the available physical model interrelating backscatter data with sediment geoacoustic parameters. Among such models, the model suggested by Jackson et al. [5] is frequently used in geoacoustic inversion algorithms. This model states that the total backscatter strength is a combination of the interface roughness scattering and volume scattering. Such a model-based method uses the backscatter data at the entire angular range, known as angular response curve (ARC). There is a complication that the observed backscatter curve, as a function of angle, is not always calibrated. Therefore the angular correction curve (ACC) is to be applied to the received backscatter. The ACC is usually determined by the calibration of the MBES in flat areas, having homogenous sediment types and known grain sizes values. This is achieved through the application of the angular range analysis (ARA) to the observed backscatter data [2]. This contribution attempts to avoid grab samples when estimating the ACC.

The above methods thus require grab samples to characterize sediment types. We elaborate on characterizing the seafloor without grab samples. Having the available physics-based models, one can predict the backscatter data for different sediment types, frequencies and incident angles. Given the frequency of the multibeam system, the angular response curve is affected by two main factors: 1) the sediment type, 2) the ACC as a function of incident angle. To estimate the calibration curve without grab sampling, we will employ the available advanced estimation and optimization methods. We propose a method to approximate the calibration curve of MBES by employing high-order polynomials as a function of incident angle. Having the ACC available, an inversion procedure can be implemented to estimate the geoacoustic parameters of the entire survey area.

The remainder of this paper is structured as follows. Section 2 proposes an algorithm to estimate the calibration curve of the sonar system. This section will then apply the method to a MBES data set collected in the Brown Bank area of the North Sea in 2017. Section 3 provides some opportunities and challenges of the proposed algorithm. The conclusions are presented in Section 4.

2. METHODOLOGY AND RESULTS

2.1 Methodology

This section presents our algorithm for estimating the sonar calibration curve. In many engineering problems, fitting a curve in one-dimensional (1D) space to a set of randomly scattered data points is a commonly encountered problem. The calibration curve is an unknown function of sonar beam angle, which is to be estimated using only the backscatter data, without grab sampling. Having an irregular data set, one can use an approximating function to obtain the function values at specific intermediate points. When the data are contaminated with random noise—backscatter data for instance—approximation provides more accurate results than interpolation. The approximation can be accomplished by using high-order polynomial functions. A more elegant alternative, to be considered for future research, is to use a spline function consisting of piecewise low-order polynomial segments connected together at known knots under some continuity conditions.

We hypothesize that the calibration curve of the sonar system is a function of signal frequency and grazing angle. The difference between the observed (BS^o) and modeled (BS^m) backscatter data is considered to be the calibration curve. One then has $C(f,\theta) = BS^o(f,\theta,AC) - BS^m(f,\theta,M_z,w_2,\sigma_2)$ where f is the signal frequency, θ is the incident angle, AC is the acoustic class number, see Ref. [6], and M_z, w_2 and σ_2 are the sediment mean grain size, spectral strength, and volume scattering parameter, respectively [7]. For a given frequency f, the above equation simplifies to

$$C(\theta) = BS^o(\theta,AC) - BS^m(\theta,M_z,w_2,\sigma_2) \tag{1}$$

This is the basis model considered to estimate the calibration curve. As a function of angular range, a high-order polynomial is employed

$$C(\theta) = a_0 + a_1\theta + a_2\theta^2 + \cdots + a_p\theta^p \tag{2}$$

Choosing an appropriate value for p is a challenging problem. Too small values can lead to under-parameterization and hence not capturing all variations along the angular range. Too large values can lead to the problem of instability and high oscillations of the approximating function, known as Runge's phenomenon [8]. The use of spline functions can resolve the above two problems.

The polynomial coefficients $a_0,\dots,a_p$ in Eq. (2) are unknown. To estimate them, one requires the backscatter data at the entire angular range, say $\theta_j = -65,\dots,65$ ($j = 1,\dots,\mathrm{m}$), with m the number of beam angles at which the backscatter data are observed. This will then make a linear model $y = Ax + e$, where y is an m-vector of observations, A is the $\mathrm{m} \times (\mathrm{n} = \mathrm{p} + 1)$ design matrix, and e is an m-vector of observation errors. At a specific incident angle, θ_j, the j^th^ entry of y is $y_j = BS^o(\theta_j,AC) - BS^m(\theta_j,M_z,w_2,\sigma_2)$, and its corresponding row of the design matrix is $A_j = [1,\theta_j,\theta_j^2,\dots,\theta_j^p]$. In principle, when the number of observations m is larger than the number of unknown parameters n (i.e., $\mathrm{m} > \mathrm{n}$, having redundancy in the linear model), one can use the least squares method to estimate the coefficients of the polynomial. There are however two complications regarding the implementation of the above problem. The details are as follows:

(1) The observed BS^o is directly available, while the modeled BS^m is a function of the unknowns M_z, w_2 and σ_2. One way out of this dilemma is to use the backscatter data at grab sample positions at which M_z (and thereby w_2 and σ_2) are known (see [9]). We however propose to estimate the three geoacoustic parameters along with the polynomial coefficients in an optimization method—differential evolution (DE) algorithm for example [10].

(2) So far we assumed, the observation vector y consists of one backscatter curve relating to one acoustic class: $BS^o(\theta,AC)$. This is however not sufficient because 1D data (even with arbitrary values for M_z, w_2 and σ_2) can be captured with a high-order polynomial. This indicates that the estimated calibration curve cannot be stable, when dealing with only one acoustic class. To ensure the stability of the results, backscatter curves for more than one acoustic class are required. The number of acoustic classes can thus ensure the redundancy and hence stability of the estimation of the calibration curve. Therefore the observation vector y should take into consideration the backscatter curve of all identified acoustic classes, i.e. $BS^o(\theta_j, AC_i), i = 1, \dots, I$, where I is the number of ACs [6]. This accordingly allows the geoacoustic parameters M_z^i, w_2^i and $\sigma_2^i, i = 1, \dots, I$ to vary among different acoustic classes.

After estimating the calibration curve, the method proposed by Ref. [9] is used to estimate the three geoacoustic parameters for the entire area.

2.2 Results

The Brown Bank, located in the North Sea, was surveyed using the Kongsberg EM 302 MBES system. The survey was conducted by the Royal Netherlands Institute for Sea Research (NIOZ) vessel, the Pelagia, from Oct. 27 to Nov. 03, 2017. The settings of the MBES were as follows: Central frequency of 30 kHz, Beam opening angles of 2° and 1° in the across and along track directions, respectively, Pulse length of 750 µs. The beam coverage of 432 beams was set to equidistant. A swath opening angle of 130° was used, with port and starboard coverage both being 65°.

The proposed algorithm was implemented to estimate the calibration curve. Prior to the optimization process, we implemented the Bayesian method, Ref. [6], to identify number of acoustic classes. Four acoustic classes were identified. Figure 1 shows the Bayesian acoustic classification results of the survey area, with some grab samples as ground truth. Lower acoustic class number (e.g. class no. 1) corresponds to lower backscatter value, whereas higher class (e.g. class no. 4) corresponds to higher backscatter value. The four classes make in general four backscatter curves, each having three unknown geoacoustic parameters (in total 12), but only one set of common coefficients for the calibration curve in Eq. (2) for which we set $p = 10$. This optimization process is implemented using the differential evolution (DE) method, see Ref. [10]. The search is performed to simultaneously estimate the 12 geoacoustic parameters along with the coefficients of the 10-degree polynomial in the optimization method.

The optimization process of estimating the calibration curve was repeated over 100 independent runs. Each run will then give the polynomial coefficients in Eq. (2). The results are presented in Fig. 2. There are some variations, among the 100 runs, when estimating the calibration curves. These variations could be associated to various sources of uncertainty among which sampling bias is the main contributor. Such a bias is averaged out through averaging over the 100 independent runs. The mean curve over all 100 runs is thus used as the backscatter curve correction of the sonar system for the subsequent inversion process using the DE optimization method.

After estimating the calibration curve, the observed backscatter curves of the entire area were used to perform the inversion. Three geoacoustic parameters M_z, w_2 and σ_2 were searched for using the DE optimization method. The parameters were constrained as $-1 \leq M_z \leq 9$, $0 \leq w_2 \leq 0.02$ and $0.00001 \leq \sigma_2 \leq 0.02$. Figure 3 shows the inverted values of w_2 and σ_2 versus those inverted for M_z. As a function of M_z, the range of variations of w_2 and σ_2 differs from the empirical model predictions proposed by APL-UW model [7]. The reported relations with M_z are known to be rather weak as there is a considerable range of variations in these two parameters and hence they are not much correlated with M_z [7]. This further confirms that the optimization is to be performed by at least the three parameters M_z, w_2 and σ_2. The parameters w_2 and σ_2 can provide further insight into seafloor structure and sediment composition, respectively. This is the subject of further research in the future.

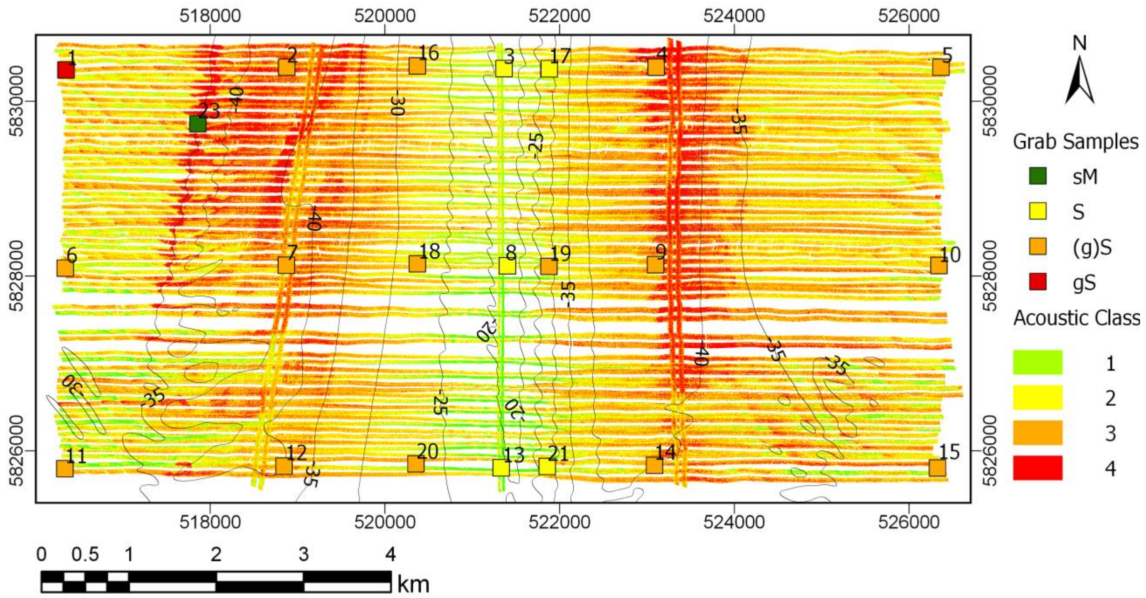

Fig. 1. *Bayesian classification map along with grab samples based on Folk scheme. Four acoustic classes ranging from lowest backscatters (green) to highest values (red), figure from Koop et al. (2019).*

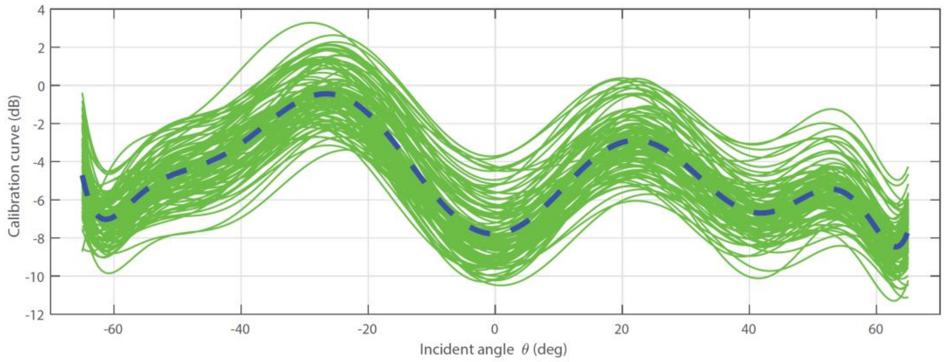

Fig. 2. *Calibration curve expressed as 10-degree polynomial in Eq. (2) obtained for 100 independent runs (green solid lines) along with their average curve (blue dashed line).*

3. OPPORTUNITIES AND CHALLENGES

The use of the proposed method can have a few potential benefits of which we point out two major issues. Seafloor characterization using MBES backscatter data usually requires grab samples to estimate the calibration curve. This can be avoided if the proposed algorithm is applied to MBES data for seafloor characterization. The huge amount of MBES backscatter currently available in many hydrographic organizations can directly be used for seafloor characterization. Further, the performance of the proposed algorithm can be improved if multiple-frequency MBES data are available. This can open new research areas in this field.

In Refs. [7] and [11], empirical representations of geoacoustical parameters in terms of the mean grain size M_z have been offered. They empirically relate M_z to the geoacoustical characteristics of the upper few centimetres of the sediments. There are specific empirical polynomial models that relate ratio of sediment mass density to water mass density (ρ), ratio of sediment sound speed to water sound speed (ν), sediment sound speed attenuation coefficient as a contributor to loss parameter δ (i.e. α_2/f). Although the expressions for these parameters are continuous over the entire mean grain size ranging from $M_z = -1$ to $M_z = 9$, their derivative are not continuous in the entire domain of definition.

A differentiable function is the one whose derivative exists at each point in its domain of definition $M_z \in [-1, 9]$. The graph of the empirical representation of the geoacoustical parameters shows sharp corners (see later Fig. 4), indicating that they are not differentiable in their entire domain. Having a smooth and differentiable function makes the subsequent optimization methods more stable and efficient when implementing geoacoustic inversion algorithms. Some of the optimization methods, based on iterative algorithms, require not only evaluation of the function values but also their higher-order derivatives. This study makes the bridge for implementing new optimization methods.

To further highlight the importance of a smooth function in the optimization process, we further investigate some of the inverted parameters w_2 and σ_2 versus estimated M_z (Fig. 3). It is observed that a kind of discontinuity exists in the estimated values for both parameters w_2 and σ_2 at $M_z = 1$. A similar observation has been also reported by Ref. [9] at $M_z = 5.3$ for MBES data at higher frequency, i.e. $\mathrm{f} = 300$ kHz. These kinds of discontinuities or bias in the estimates of the inverted parameters are due to the empirical relations expressing ρ and ν as a function of M_z. We observe that both ρ and ν have sharp corners, indicating a sudden change in their rates both at $M_z = 1$ and $M_z = 5.3$ (see Fig. 4). An approximating function using the cubic spline theory handles this problem.

We now present our proposal to make the above empirical formulas differentiable up to and including the second order. This is achieved based on an approximation of the above empirical representations using the cubic spline theory. Such splines consist of a series of piecewise third-order polynomial connected to each other at some intermediate points, known as knots. The consecutive pieces are joined together at the knots such that the first and second derivatives of the fitted curves are also continuous at these points. The method used is based on the least squares cubic spline approximation [12].

For each of the above parameters (i.e. $\rho, \nu, \alpha_2/f$ and w_2) a separate spline function is used. Each spline consists of a few cubic polynomials of the form $f_i(M_z) = a_{0i} + a_{1i}M_z + a_{2i}M_z^2 + a_{3i}M_z^3$, connected to each other. The coefficients $a_{ji}, j = 0,1,2,3$ of these third-order polynomials are presented in Table 1. The final spline function, consisting of all polynomials connected to each other, is presented in Fig. 4, for each of the above parameters. They closely follow their original representations, but now having continuous first and second order derivatives in their domain of definition $M_z \in [-1, 9]$.

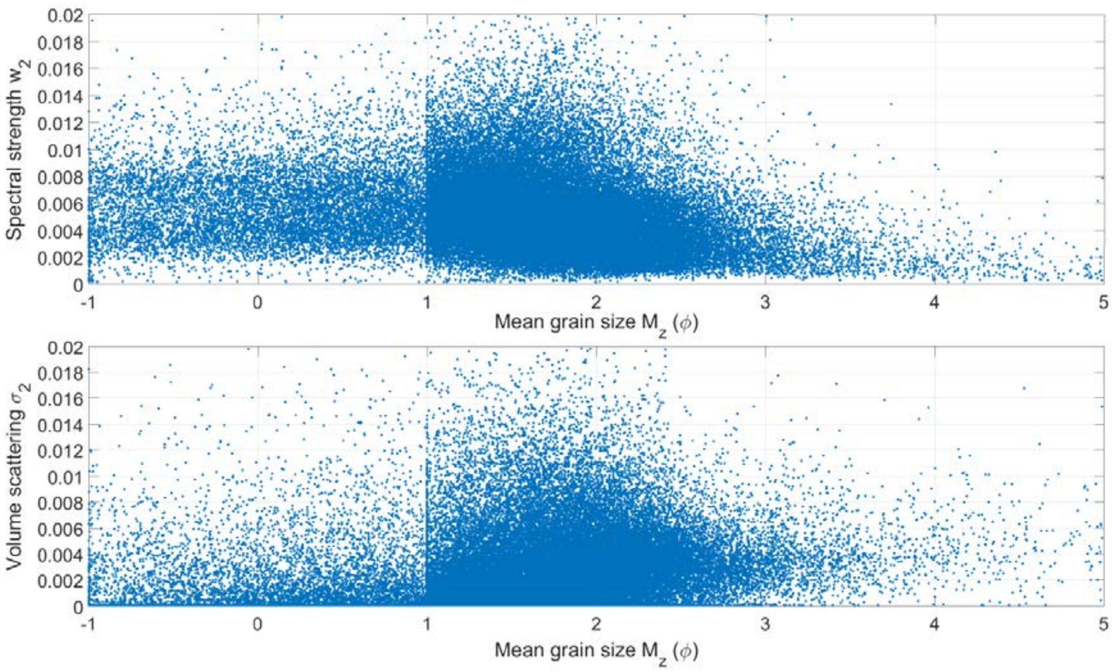

Fig. 3. *Inverted spectral strength w_2 (top) and volume scattering parameter σ_2 (bottom) versus estimated mean grain size M_z*

Table 1. *Polynomial coefficients of spline function for four geoacoustic parameters* $\rho, \nu, \alpha_2/f$ and w_2: $f_i(M_z) = a_{0i} + a_{1i}M_z + a_{2i}M_z^2 + a_{3i}M_z^3$, *connected to each other at some intermediate points*

Parameter	i	M_z range	a_{0i}	a_{1i}	a_{2i}	a_{3i}
ρ	1	[-1, 1]	2.363149906	-0.201790117	-0.056492156	0.016180867
	2	[1, 2.5]	1.794316816	1.110551799	-0.974676718	0.190856603
	3	[2.5, 5.3]	1.995533627	-0.224930836	-0.002874679	0.002935133
	4	[5.3, 9]	1.234233881	-0.020216334	0.001181053	-4.29060E-06
ν	1	[-1, 1]	1.285222133	-0.057546455	-0.005178733	0.000628855
	2	[1, 2.5]	1.244269004	0.038686795	-0.074785846	0.014955847
	3	[2.5, 5.3]	1.196631647	-0.001627891	-0.019668166	0.002407916
	4	[5.3, 9]	1.051173569	-0.013612915	0.000389345	2.71798E-05
α_2/f	1	[-1, 0]	0.455599999	2.07592E-09	1.43323E-08	1.26182E-08
	2	[0, 2.6]	0.455599999	2.07593E-09	0.012262365	-0.000966864
	3	[2.6, 4.3]	2.786522897	-2.265631606	0.720622671	-0.070880176
	4	[4.3, 6]	-27.66322511	17.3075376	-3.442709462	0.221737223
	5	[6, 9]	0.834517646	-0.174873566	0.00994903	-1.73210E-05
w_2	1	[-1, 2]	0.008933068	-0.003704703	0.000364354	6.46530E-05
	2	[2, 5]	0.006238244	-0.001091583	-0.000227648	4.42271E-05
	3	[5, 9]	0.001050034	-0.000123598	7.74266E-06	-6.48982E-08

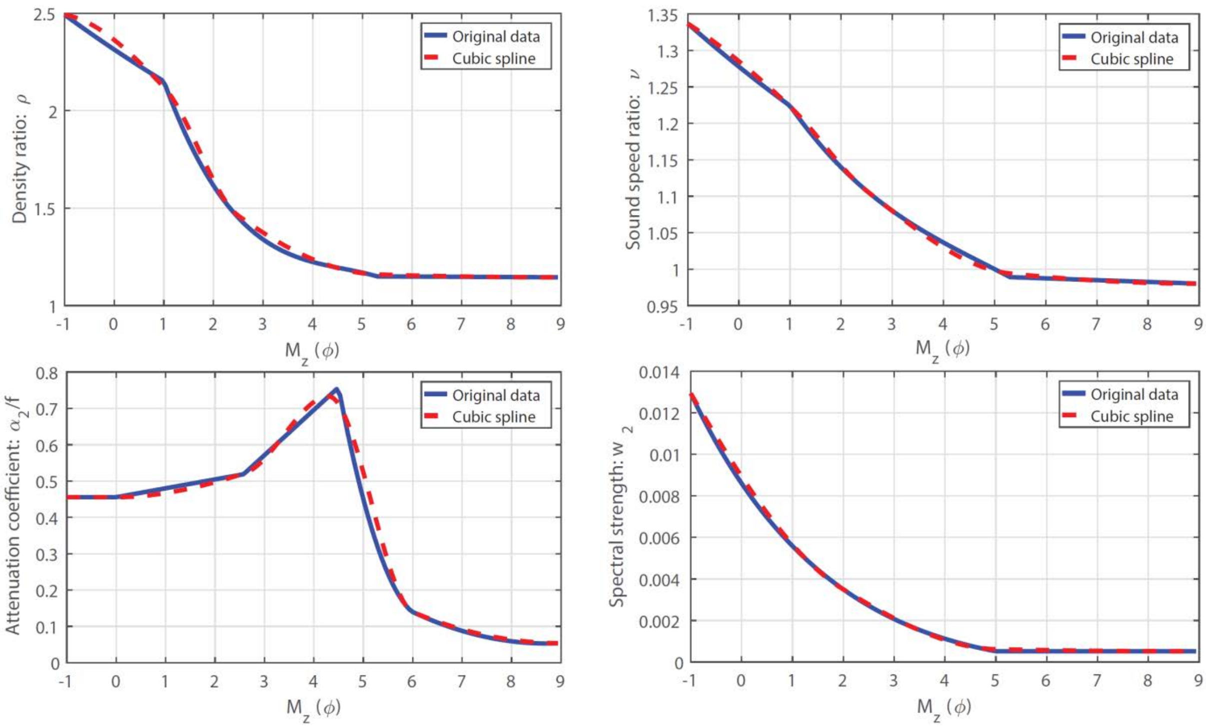

Fig. 4. *Empirical representations of four geoacoustical parameters, Ref. [6], along with their best approximation using spline functions; ratio* ρ *of sediment mass density to water mass density (top-left), ratio* ν *of sediment sound speed to water sound speed (top-right), sediment sound speed attenuation coefficient* α_2/f *(bottom-left), and spectral strength (bottom-right).*

CONCLUSIONS

Model-based methods were employed to estimate seafloor geoacoustic parameters in an inversion algorithm using an optimization method. The model-based methods usually suffer from a shortcoming associated to uncalibrated sonars. Grab samples at reference areas are usually required to estimate the calibration curve. This study presented an algorithm to estimate the calibration curve without grab sampling. Knowing that the calibration curve is an unknown function of incident angle, in principle, one can approximate it using the available estimation and optimization theories. The method was successfully applied to the MBES backscatter data collected at the North Sea. The potential benefit of the proposed method is twofold. A large amount of MBES backscatter currently available in many hydrographic organizations can directly be used for seafloor characterization. The available multiple-frequency MBESs can further improve the performance of the inversion process. We also highlighted a few challenges. The calibration curve estimation is an unstable process when there are no grab samples or reference areas. Also, the available empirical physical models are not usually well-behaved functions, possibly due to their discontinuities or discontinuity of their derivatives. We addressed this issue by approximating them using cubic spline functions.

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