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Survey on Sediment Classification Methods Based on Multibeam Echosounder Backscatter Data

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Abstract—

Sediment classification using acoustic remote sensing techniques is an attractive approach because of its high coverage capabilities and limited costs. The multi-beam echo-sounder (MBES) system provides high-resolution bathymetry and backscatter information with 100% coverage. In this paper, we present a brief review of two analysis methods which are employed for sediment classification based on the MBES backscatter data. The first is a Bayesian estimation method that uses the average backscatter data per beam and, therefore, is independent of the quality of the MBES calibration. The second is a model-based method that matches the measured backscatter curves to theoretical curves, predicted by a physics-based model.

Keywords— Sediment classification, Multibeam echo-sounder, backscatter, Bayesian decision rule, model

I. INTRODUCTION

A conventional approach to obtain information about the sediment classes on riverbed or on seafloor is to take sediment grabs, cores or dredge samples. These techniques are expensive as they require dedicated ships and equipment, lengthy measurements, and a labour- intensive analysis afterwards. Another important drawback is that these techniques provide information on point positions only. Therefore, a very attractive alternative to the sampling methods consists of employing the data as acquired by acoustic systems. Riverbed sediment classification or measurements of seafloor bathymetry can be carried out through the use of the multi-beam echo-sounder system (MBES). The MBES is an acoustical mapping system which measures with a single transmission the water depths along a wide swathe perpendicular to the ship track. These systems can provide 100% coverage at moderate costs, and several approaches towards sediment classification through acoustic remote sensing have been described in the scientific literature ([1], [2]).

In general, sediment classification methods using MBES can be divided into phenomenological (or empirical) and model-based (or physical) methods. In the phenomenological methods, features that are indicative for sediment type (e.g., backscatter strength or features derived from the bathymetric measurements) are used for classification. These methods discriminate the sediments as belonging to different acoustic classes, each with its own acoustic features. These acoustic classes represent the different sediment types that are present in the survey area. However, independent information, e.g., from grab samples taken in the area, is usually needed to assign sediment type, such as mud, sand or gravel, or sediment parameters, such as mean grain size, to the acoustic classes ([3]–[6]). On the contrary, the model-based to the methods ([7]–[10]) determine the sediment type by maximizing the match between modelled and measured signals or signal features, where sediment type, or parameters indicative for sediment type, are input into the model. In principle, no independent information is required for model-based methods, since they provide the sediment type, or properties indicative for sediment type, instead of acoustic classes.This paper gives a short review about the two methods for sediment classification, Bayesian approach and a model based approach.

II. BAYESIAN APPROACH

The MBES is an acoustical mapping system which measures the water depths along a wide swathe with a single transmission. Due to the high-resolution bathymetric capabilities of MBES systems, the resulting detailed digital terrain models give insight into the morphology, which contains information on seafloor composition. In addition, the MBES can provide high-resolution backscatter maps.

The intensity of the backscattered beam varies with incidence angle. This angular dependence masks effects of variation in seafloor type and morphology in the backscatter images. Therefore, corrections are applied by MBES systems to the measured backscatter intensities to eliminate dependence on angle, e.g. by applying Lambert's law. The backscatter images obtained from the MBES after angle correction are comparable to those obtained with a side-scan sonar system (SSS). These maps can be used for classification purposes by resolving textures or spatial variability in the data.

A. Properties of the beam backscatter intensity

The echo amplitudes as measured by the MBES are determined by backscattering from the seafloor, a process dependent on the nature of the riverbed, i.e., its composition, orientation, roughness and geo-acoustic properties. Hence these backscattered signals can be employed for riverbed sediment classification purposes ([11], [12]). A shallow-water MBES system typically operates at a few hundreds of kHz, hence the acoustic signal is senses only the upper few cm of the sediment. The penetration depth of acoustic wave is determined by the attenuation coefficient. The echo amplitude can be mapped to a colour scale to form a backscatter image.

B. Implementation of the classification methodology

The averaged backscatter data at a single angle is employed by this classification approach. Due to statistical fluctuations, these data are subject to ping-toping variability, masking the influence that each sediment type has on the backscatter intensity. In practice, not only the probability density functions (PDFs) for the backscatter measurements, but also the number of sediment types present in the area is unknown. Therefore, in addition to the PDF per sediment type, also the number of sediment types needs to be estimated. The classification approach therefore comprises the following steps.

1) Non-linear curve fitting:

The algorithm fits a model to the histogram of selected measured backscatter strengths. The selected data consist of all averaged backscatter data as measured at a certain beam angle of the MBES system. It fits a number of Gaussian probability density functions (PDFs) to the histogram of the backscatter strength (BS) data at a given angle, i.e.

$$BS \approx f_{BS}(BS) = \sum_{i=1}^{r} c_i N(BS; \mu_{i,}, \sigma_i^2) \quad (1)$$

Where μ_i and σ_i^{2} are the mean and variance of the i^{th} Gaussian distribution N, respectively, and c_i is the contribution of the individual Gaussian functions to the total PDF. f_{BS} is the fitted histogram. The number of PDFs is increased until the chi-square distributed test-statistic of the residuals becomes less than a critical value.

This curve fitting procedure is carried out for various values of r and the number of sediment types present in the area is taken as that value of r for which a further increase in r does not result in a further improvement of the fit.

2) Acoustic classes identification:

Based on the resulting r Gaussian PDFs, the Bayes decision rule is applied to determine the r regions of backscatter values corresponding to the r acoustic classes. The Bayesian decision rule for multiple (r) hypotheses is simply an extension of that for the binary situation, i.e.

$$accept\ H_k\ if\ \underbrace{max}_{H_i}\{f(y_i|H_i)P(H_i)\} = f(y_k|H_k)P(H_k)\ with\ i = 1, \dots, r \quad (2)$$

This means that we choose the hypothesis that, given the observation y, maximizes the likelihood $f(y_j|H)$. Hence, we have to determine the intersections of the r Gaussian PDFs, resulting from the fitting procedure of Step 1, which results in r non overlapping acceptance regions, say A_k.

3) Assigning sediment type to acoustic classes:

After this, we need to assign a sediment type to each of the r acceptance regions A_k and corresponding mean values $\overline{y_k}$ as obtained in the previous step. It is known that there exists a relatively good association between acoustic backscattering strength and sediment mean grain size ([13],[14]). This implies that we can use the estimated $\overline{y_k}$ directly to determine the sediment types present in the survey area.

4) Quality assessment:

This step addresses the quality of the classification algorithm by calculating the so-called decision matrix of the multiple-hypothesis-testing problem. This matrix contains the probabilities of correct and incorrect decision. The decision matrix provides a measure of the quality of the classification algorithm and can be calculated prior to the actual mapping part of the algorithm.

5) Mapping:

This final step of the algorithm comprises the actual mapping, i.e., we allocate sediment type (i.e., a color) to all backscatter strength data points. As the MBES system provides a position to each backscatter strength measurement, we can map sediment type versus position. [15]

III. MODEL BASED APPROACH

Even though the Bayesian method makes use of the backscatter values per angle, one can use the complete backscatter curve, i.e., the backscatter as a function of angle. Models exist that predict these backscatter curves as a function of sediment properties and frequency. By searching for those sediment properties that result in an optimal agreement between modelled and measured backscatter curve, the sediments can be classified. In this case, the classification results consist of real sediment properties instead of acoustic classes. Reference [16] has presented one such model for predicting the backscatter curve, which is developed for frequencies between 10 and 100 kHz. In this model, the total backscatter strength is expressed as a combination of the interface roughness scattering and volume scattering

$$BS(\theta) = 10log_{10}\left(\sigma_r(\theta) + \sigma_v(\theta)\right) \quad (3)$$

with σ_r and σ_v the backscattering cross sections due to the interface roughness and volume scattering, respectively. σ_r is derived by an appropriate interpolation between three approximations as follows:

(1) the Kirchhoff approximation valid for fine to slightly coarse sediments and at grazing angles close to nadir;
(2) the composite roughness approximation appropriate for all other angles;
(3) for rough bottoms (e.g., gravel and rock) use is made of an empirical expression.

All three contributions are a function of the sediment roughness spectrum. An isotropic relief spectrum is assumed as $W_2(K) = (h_0K)^{-\gamma}w_2$, with K the bottom relief wave number, h_0 a reference length (1 cm), w_2 the spectral strength and γ the spectral exponent. Additionally, σ_r is determined by the sediment density, attenuation coefficient, and sound speed.

σ_v is modelled based on the following expression for the sediment volume backscattering cross section

$$\sigma_{pv} = \frac{5\delta\sigma_2|1-R^2(\theta)|sin^2\theta}{v ln10|P(\theta)|^2 Im(P(\theta))} \tag{4}$$

where ν is the ratio of sediment to water sound speed, δ the ratio of imaginary to real wavenumber in the sediment, R the amplitude reflection coefficient, θ the grazing angle, σ_2 the ratio of sediment volume scattering cross section to attenuation coefficient, and $P(\theta) = \sqrt{\kappa^2 - cos^2\theta}$, with $\kappa = (1 + i\delta)/\nu$. In addition to θ, R is also a function of the sediment parameters ν,δ and ρ. The latter is the ratio of sediment to water mass density. σ_v is determined from σ_{pv} accounting for shadowing and bottom slopes. [16].

There are empirical expressions present that relate σ_2, w_2, ρ, ν, and δ to mean grain size M_z. However, often values encountered for w_2 and σ_2 deviate significantly from the values obtained by the empirical expressions.

As a first step in assessing the agreement between model predictions and measured backscatter curves, backscatter curves measured close to locations of the grab samples are considered. The model is run for mean grain size values as determined from the grab samples, and values for all other model input parameters are derived from the empirical expressions relating them to the mean grain size. Differences between the resulting model predictions and measurements can be due to following reasons:

(1) changes in sediment types along the swathes;
(2) deviation in the values for the σ_2, w_2, ρ, ν, and δ from those obtained from the empirical expressions;
(3) imperfect calibration of the MBES backscatter measurements.

Following procedure is applied to solve these effects. An objective function is defined that quantifies the difference between the modelled and measured backscatter strength:

$$f(x) = \sum_\theta |b_i^{me}(\theta) - b_i^{mo}(\theta; x)| \tag{5}$$

where b_i^{me} and b_i^{mo} are the measured and modelled backscatter strength for the i^{th} grab, respectively. The use of Eq. (5), providing a measure for the absolute discrepancies between the measured and modelled backscatter curves based on the L1 norm, is motivated due to its robustness property compared to the ordinary least-squares (L2) norm. In general, σ_2 and w_2 are known to show the largest deviations from the empirical predictions and, therefore, these parameters are considered as unknowns, contained in vector x. An estimate for the mean grain size is available from the grab samples, but still this parameter is allowed to vary slightly. Consequently, x contains three unknowns, i.e., σ_2, M_z, and w_2. For minimizing Eq. (5), use is made of the differential evolution method as described in literature ([17], [18]).

The objective function will not become zero because of the imperfect calibration of the MBES and the noise in measurements. The average curve of the differences (between measured and modelled curves) for all grab samples can be considered as the calibration curve. However, as mentioned above, measurements can also be affected by variations in sediment types along the swath. Accounting for these measurements will result in differences between modelled and measured backscatter curves that differ significantly from the average, i.e., the calibration curve.

Therefore, an iterative procedure is followed to establish the final calibration curve. In this procedure, measurements in each iteration are corrected using the calibration curve of the previous iteration. The measurement with maximum discrepancy with the mean curve is masked as an outlier. Then, based on the remaining measurements, as the sum of the old curve and a correction to this curve, a new calibration curve is determined. After removing more and more outliers, at some iteration the discrepancies become negligible and no further corrections on the calibration curve are required.

The final calibration curve is then applied to all measured backscatter curves and the values of three parameters M_z, w_2, and σ_2 are determined over the entire area.

IV. SUMMARY AND CONCLUSION

In this paper two methods for classification of sediments are presented. These two methods base the classification on backscatter data from MBES. The first method uses the MBES backscatter data collected at a certain angle to obtain the number of acoustic classes and to discriminate between them by applying the Bayes decision rule for multiple hypotheses. The second method is model-based and matches the full measured backscatter versus angle curve of the MBES to the predicted backscatter curve using the model.

The Bayesian method provides acoustic classes, and is considered to be simple in principle and easy and fast to implement. The model-based method provided the sediment parameters mean grain size (M_z), spectral strength of sediment surface roughness (w_2) and volume scattering parameter (σ_2). Bayesian method has a slight limitation of converting acoustic classes to sediment parameters which can be overcome by using model based approach for sediment classification. But due to imperfect calibration of the measured backscatter values, caused by a limited number of grab samples available for the calibration, model based approach might result in the overestimation of the M_z values.

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