USING MULTI-BEAM ECHO SOUNDER BACKSCATTER DATA FOR SEDIMENT CLASSIFICATION IN VERY SHALLOW WATER ENVIRONMENTS

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Abstract: *In a recent work described in Ref. [1], an angle-independent methodology was developed to use the multi-beam echo sounder backscatter (MBES) data for the seabed sediment classification. The method employs the backscatter data at a certain angle to obtain the number of sediment classes and to discriminate between them by applying the Bayes decision rule to multiple hypotheses. This method is adopted and applied to very shallow-water applications. There are two issues when dealing with riverbed classification in shallow water. Shallow water depth results in a small beam-footprints and hence a small number of scatter pixels, which makes the classification results to be less discriminative. The significant bottom slopes will also affect the backscatter data and hence the classification results. We aim to handle these issues using the high resolution bathymetry and backscatter data. A methodology is developed to estimate the precise bottom slopes using the high resolution bathymetry data. Corrections are then applied to convert the arrival angle of the signal into the true incident angle and to compensate for the effect of the ensonified area. The high resolution backscatter data allows one to reduce the statistical fluctuations using an averaging procedure. The methodology will then be tested on a MBES data set from the river Waal, the Netherlands. The acoustic classification results are correlated with the mean grain sizes of the sediment obtained from core analysis of the grab samples. The dependence of acoustic backscatter classification on sediment physical properties is verified by observing a significant positive correlation coefficient of 0.70 between the classification results and sediment mean grain sizes of the grab samples.*

Keywords: *Multi-beam echo-sounders (MBES), Backscatter data, Slope correction, Bayes decision rule, Gaussian distribution.*

1. INTRODUCTION

Multi-beam echo sounder (MBES) systems produce high-resolution bathymetry and backscatter data throughout the survey area. The bathymetry data is used to locate topographical features on the seafloor and to make topographical maps (e.g. harbour charts), which are the task of many hydrographic surveying institutes. The MBES backscatter data can be used to obtain information about the sediment composition and physical properties of the riverbed and seafloor. Proper analysis and subsequent interpretation of the backscatter data is currently the task of many research institutes of acoustic remote sensing. The ultimate goal of acoustic classification methods is to remotely measure the physical properties of the surficial sediments such as porosity and mean grain size.

We use a classification method, which was developed by [1] for the seabed sediment classification. The method, based on the Bayesian decision rule, was applied to MBES backscatter data for the classification in a test area in the North Sea with well-known lithology. In order to adopt the method for shallow water applications, two issues need to be addressed. 1) The lower water depths result in smaller beam footprints and hence higher variances for the backscatter data. The discriminating power between sediments will accordingly decrease. 2) There exist significant bottom slopes which affect the backscatter data and hence the classification results. We elaborate these issues in detail and improve the results of the classification method for a shallow-water environment.

This contribution is organized as follows. In section 2, we briefly describe MBES classification method proposed by [1] and discuss our methodology to compute the bottom slopes using the precise bathymetry data and then to apply corrections to the backscatter data. We explain how to combine the classification results at different angles. In section 3, the acoustic classification results are presented for a recent data set carried out at Waal river. The classification results are then correlated with the mean grain size of grab samples. Section 4 concludes this paper.

2. MBES BACKSCATTER DATA

2.1 Classification method

In Ref. [1] a method was developed for seafloor sediment classification in deep water applications. The method fits a few Gaussian PDFs (normal distributions $\mathbf{N}$) to the histogram of the backscatter data (BS) at a given grazing angle (each Gaussian PDF then represents one acoustic class):

$$BS \sim f_{BS}(BS) = \sum_{i=1}^{r} c_i \mathbf{N}(BS; \mu_i, \sigma_i^2) \tag{1}$$

This is achieved by consecutively increasing the number of PDFs until a chi-square distributed test-statistic (on the residuals) becomes less than a certain critical value. In the preceding equation, μ_i and σ_i^2 are the mean and variance of the i^{th} PDF, respectively, and c_i is the contribution of the individual Gaussian functions to the total PDF. For further description of the method and the steps involved we refer to Ref. [1].

The main issue regarding the classification method is the normality assumption. This is valid for deep-water environments like seas and oceans where the beam footprint is large—it is proportional to depth—and hence many scatter pixels fall within the beam footprint. The central limit theorem states that the distribution of the averaged (over scatter pixels) backscatter data in the beam footprint tends to a normal distribution if the number of scatter pixels N is large enough. This holds obviously in deep water, while, in shallow water, N is not large enough to use the central limit theorem. Therefore, we may use the averaged backscatter strength over the small surface patches. In addition, bottom slopes can be significant in the river environment considered in this paper. Therefore, two intermediate steps are added to the approach in Ref. [1]. These steps are as follows:

Step I (*correcting and averaging procedure*)**:** In shallow water environments such as rivers, the number N of the scatter pixels inside the beam footprint is not large because N is proportional to the water depth. In order to restore the normality of the backscatter strength by means of the central limit theorem, one can use the average backscatter values over the small surface patches. Each patch consists of a few beams in the across-track direction and a few pings in the along-track direction. It also allows one to apply the slope corrections to the backscatter data, namely, correction due to the changes of the area of the signal footprint, and correction due to the true beam grazing angle. Therefore, for angle θ the 'averaged corrected' (over patches) backscatter data will be used. Further explanation is given in Section 2.2.

Step II (*combination of different angles*)**:** The method in Ref. [1] takes observations from one single angle only. In practice, to use the full high-resolution mapping potential of the method, we consider multiple beams and individually perform the classification. This consequently allows one to obtain a continuous map over the whole area. The classification method at angles close to nadir (e.g. $\theta = 20^\circ$), however, becomes less efficient as the backscatter values of different sediment types have values close to each other. One remedy, followed in this contribution, is to first use the backscatter data at a few low grazing angles (e.g. reference angles of $\theta = 64,\ 62,\ 60^\circ$) and apply the classification method. This analysis gives the number r of the sediment types, the means μ_i , the variances σ_i^2 and the coefficients c_i. The nonlinear curve fitting in Eq. (1) is based on the bounds on the variables. Based on this information the curve fitting procedure is then executed and extended to all other angles ranging from $\theta = 60^\circ$, $\theta = 58^\circ$, $\ldots, \theta = 20^\circ$, but now i) for a fixed number r of the Gaussian PDFs, where r has been determined from the application of the classification method to the backscatter data of the low grazing reference angles (say $\theta = 64,\ 62,\ 60^\circ$), ii) by obtaining a good initial guess for the mean parameters, i.e. μ_i^0 ($i = 1,\ldots,r$), of the backscatter data at the angle under study. This is achieved by using the mean values μ_i ($i = 1,\ldots,r$) of the reference angles, and equally shifted by the difference between the mean backscatter values at the angle under study (of entire histogram) and the mean backscatter values at the reference angles, and iii) by using more strict bounds on the mean parameters μ_i ($i = 1,\ldots,r$) for the classification of backscatter data at the angle under study (e.g. $\mu_i^l = \mu_i^0 - 0.5$ and $\mu_i^u = \mu_i^0 + 0.5$ dB). The bounds considered are still wide enough to compensate for the angular dependence of the statistical distributions for the backscatter data.

2.2 Local slope correction

The significant local slopes of the riverbed will affect the classification results. To compensate for these effects one has to estimate the along- and across-track slopes. Multi-beam echo-sounders (MBES) provide detailed and precise bathymetry information from which the local slopes (along- and across-track slopes) can be estimated using the least-squares method. This allows one to improve the seabed classification results by applying the corrections to the backscatter data. The literature has paid little attention to the question of how such corrections should be taken into account. Two effects are discussed: 1) correction due to the changes in the signal footprint (ensonified area) to which the backscatter data refers, and 2) correction due to the true beam grazing angle. Both corrections can be applied when the along- and across-track slopes of the seafloor (riverbed) are available.

Estimation of slopes:

A discrete surface patch $z_i = f(x_i, y_i),\ i = 1,...,m$ includes a few angles around the central beam angle (e.g. with deviation of one degree), where the angular dependence of the statistical distribution of the backscatter data is negligible. Also, because the ping rate is high (40 Hz), we may in addition include a set of neighboring pings to make a surface patch and hence to be able to estimate the along- and across-track slopes. This results in a window (e.g. 0.5×0.5 m) that contains, say, m=8×7=56 beams. The average backscatter data and the average depth in this small patch will be used. Using this strategy, to divide the area under survey into small surface patches and to use the average values, one can i) compute the along- and across-track slopes and correct for the true grazing angle and the backscatter data, ii) assure that the normality assumption is achieved by means of the central limit theorem. This is a prerequisite for using the classification method, and iii) decrease the variance and hence increase the discriminating power between sediments. This makes the classification method more discriminative.

A bi-quadratic function consisting of six unknown coefficients is used to model (estimate) the surface patch: $z = f(x, y) = a_0 + a_1x + a_2y + a_3x^2 + a_4y^2 + a_5xy$. The depth measurements z_i at the discrete points of the surface patch allow one to compute the unknown coefficients $[a_0, a_1, a_2, a_3, a_4, a_5]$ using the least-squares method. And a procedure called datasnooping can be used to test for the presence of outliers in the bathymetry data ([2, 3]). This subsequently allows one to obtain the along-track (x) and across-track (y) bottom slopes a_x and a_y (take partial derivatives with respect to x and y). The slope angles α_x and α_y that the tangent plane makes with the positive directions of x and y axes can accordingly be obtained. For more information we refer to Ref. [4].

Grazing angle and backscatter corrections:

Suppose that the local surface is estimated as $\hat{z} = \hat{f}(x, y)$. The angle between the normal vector to this surface patch and the nominal receiving-beam direction (based on the flat surface) is the true incident angle θ_t, which is a function of both α_x and α_y. A general formulation can be given for θ_t as a function of φ (the nominal grazing angle), α_x and α_y. In a special case when $\alpha_x = 0$ it follows that $\theta_t = 90 - (\varphi + \alpha_y)$.

Another correction due to the local slopes a_x and a_y is the fact that the signal footprint (ensonified area) will change if the surface is not flat. For a sloping surface the signal footprint is obtained as

$$A_f = \frac{cTR\Omega_x}{2\sin(\theta - \alpha_y)\cos\alpha_x} \tag{2}$$

where $R\Omega_x$ is the along-track resolution, c is the sound speed in water, and T is the transmitted pulse length. The correction for the backscatter strength (in dB) can accordingly be obtained (see Ref. [4] for further information).

3. CLASSIFICATION RESULTS AND DISCUSSIONS

The Waal river is a major river that serves as the main waterway connecting the Rotterdam harbor and Germany. For keeping the Waal river suitable for commercial activities bottom stabilizing measures are planned to counteract the subsidence and to keep the bottom more stable. To monitor the suppletion effectiveness at the river Waal, multi-beam echo sounder (MBES) bathymetry and backscatter measurements accompanied with extensive sediment grabbing were carried out in May 2008. The MBES used for the measurements is an EM3002, typically working at a frequency of 300 kHz for shallow water; the pulse length is 150 μs; the maximum number of beams per ping is 254; and the maximum ping rate is 40 Hz. The bathymetry of this study area is shown in Fig. 1. Except for the flat area (sediment suppletion to prevent deformation in the outer part of the bend) in the middle of the area, the river exhibits significant bottom slopes. This section presents the results of the acoustic sediment classification based on the methodology developed by [1], which was modified in section 2 for shallow water applications. To assess the MBES classification results a comparison is made with the analysis of the grab samples.

We apply the classification method of section 2 to the averaged backscatter strength (over the small surface patches). The surface patches include a few angles around the central beam angle (with deviation of 1° as $\theta-1^\circ<\theta<\theta+1^\circ$). For such close angles, the angular dependence of the backscatter distribution can be ignored. Also a few consecutive pings (e.g. 7 pings) have been included, because the ping rate (40 Hz) is high in shallow water. This results in a small surface patch that contains, say, 56 beams. The precise bathymetry data over the patches allows correcting the backscatter data for the bottom slope effects. The 'averaged corrected' (over patches) backscatter data will then be used.

The number of seafloor types is unknown and needs to be determined. This is achieved by increasing the number of Gaussian functions to well describe the histogram of the averaged backscatter strength. A plot (not presented here) of a chi-square distributed test statistic versus the number r of the Gaussian PDFs shows that this value is $r=3$ (the 'real' number of riverbed types). Figure 2 shows the histogram and its best Gaussian fit for the averaged backscatter values at $\theta=60^\circ$. Three Gaussian PDFs, indicating three acoustic classes, are identified. The contribution of the PDFs is roughly 5%, 30%, and 65%. It is worthwhile mentioning that the classification method is independent of the absolute values of the backscatter data. In this respect, one may for instance think of the angular dependence of the backscatter data, or the intrinsic difference between the backscatter data of the left and right

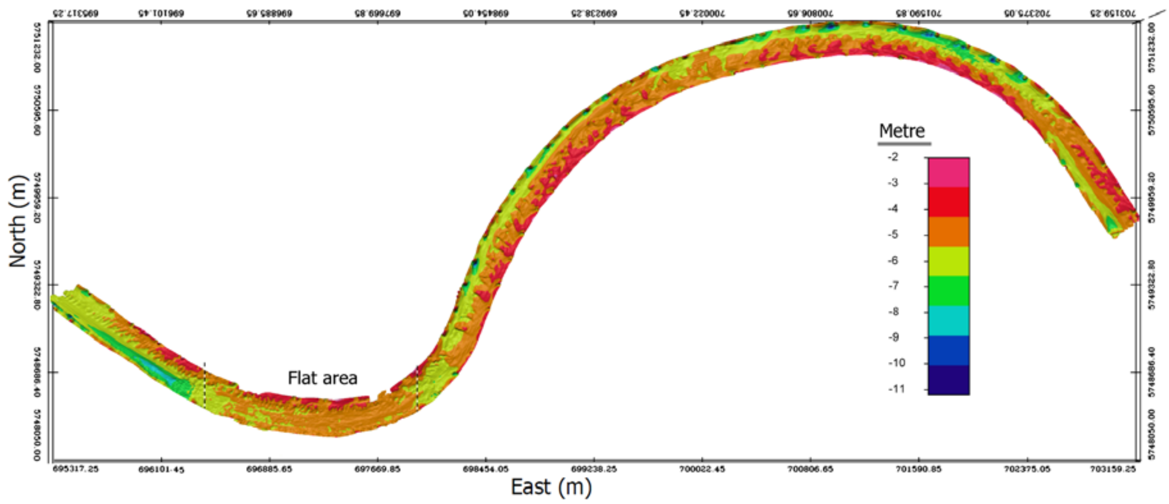

Fig. 1 *Bathymetry map of river Waal, the Netherlands; Km 876–886 (close to Nijmegen).*

transducers due to their calibration effects.

In order to explore the full high-resolution mapping potential of the method, one may consider using multiple beams instead of only one (section 2, step II). The ultimate goal of the acoustic classification method is to obtain a continuous map over the whole region, as for the bathymetry map. The classification map obtained from the averaged backscatter data using beam angles at $\theta = 64,\ 62, ...,\ 20^{\circ}$ is shown in Fig. 3, where the three sediment classes are presented by the colours red, yellow, and green. The green represents low values, the yellow represents intermediate values, and the red represents high values of the backscatter data. At a typical angle $\theta = 60^{\circ}$, the acceptance regions are as follows: [$-\infty$ to -18.5] dB (class I), [-18.5 to -15] dB (class II), and [-15 to $+\infty$] dB (class III).

The ultimate goal of MBES data analysis is to transform the backscatter classification results into estimates of seafloor sediment properties such as mean grain size. The goal of the sediment grab sampling and grain-size analysis is to evaluate the potential correlation between the mean grain size and the results from acoustic classification. 28 grab samples taken at the central axis of the river and at both sides (70 m apart from the central path) were collected and analyzed for grain size distribution. The grab samples were washed, dried, and sieved through a series of mesh sizes ranging from 30 mm to 0.1 mm. The sieve sizes were converted into ϕ (phi) units using the equation ϕ=-log$_2$ d, where d is diameter of grain in mm. Note that fine sediments have large ϕ values. Based on the comparison with the acoustic classification results it can be concluded that the areas of high backscatter values correspond to gravel (class III) and lower backscatter values correspond to sand (class I).

We now make a comparison between the classification results and the mean grain size of the samples. Our strategy is to use the results of core analysis for comparison and to perform a correlation analysis afterward. The mean grain sizes were sorted from fine to coarse sediment. Considering the grab samples as an unbiased representative for the whole area, the percentages of 5%, 30%, and 65% were then applied to the 28 samples. This corresponds to 1, 8, and 19 samples, respectively for sand, sandy gravel, and gravel areas. The classification results show good overall agreement with the ground truth information obtained from the

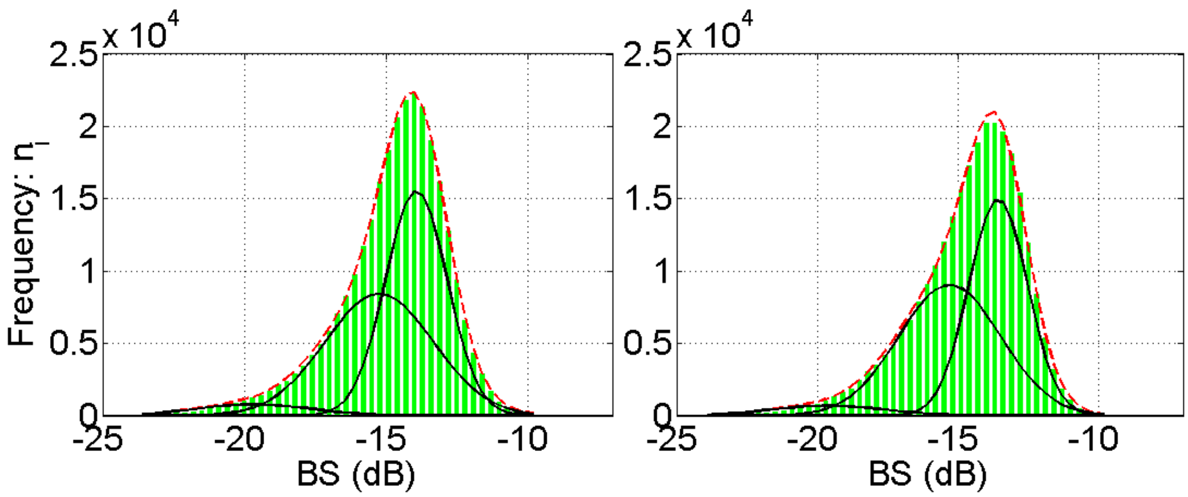

Fig 2. *Histogram (light bar) of averaged (over small surface patches) backscatter data corrected for local slopes, its three Gaussians (solid line), and its best fit (dashed line) at angle* $\theta = 60^{\circ}$ *over the whole area; left transducer (left); right transducer (right); number of Gaussian PDFs* $r = 3$.

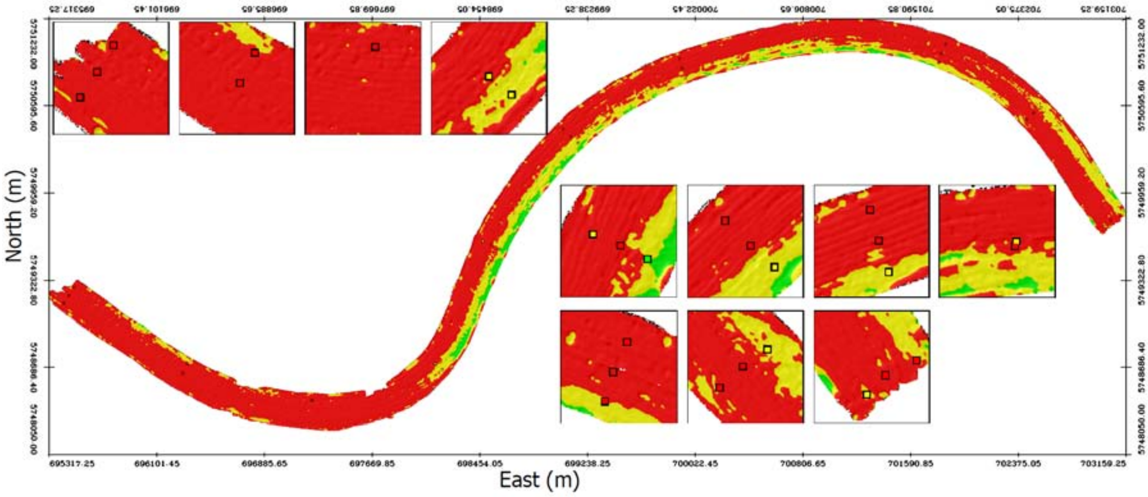

***Fig 3**. Acoustic classification map of Waal river (Km 876–886) obtained from backscatter data at θ = 64, 62, ..., 20°. For each angle separate classification has been applied and results put in a single map. The frames indicate a zoom-in of classification results for areas where grab samples have been taken.*

core analysis (Fig 3 zoom-in part).

Most of the differences belong to the areas where the grab samples are in the boundary region of two classes. The dependence of acoustic backscatter techniques on sediment physical properties is examined using the Pearson correlation between mean grain size of the samples and the classification results. Larger grain sizes are expected to produce stronger backscatter for sandy and gravelly sediment. The Pearson correlation coefficient between the mean grain size and the results of the classification is 0.70. It indicates a high positive correlation (it is negatively correlated with ϕ values).

Due to the river currents interaction with bottom sediments, the rivers are dynamic environments and hence sediment distribution is highly heterogeneous. Ground truthing our classification results from core analysis of the sediments is prone to a few sources of uncertainty. We can at least mention: i) positioning error of the grab samples which is considered to be about 4-5 m, ii) the complexity inherent in ascertaining whether a single sample is representative of a larger region. This originates from the heterogeneity of the river sediment distribution, iii) a finite number of grab samples when assigning sediment types to acoustic classes. For example, the percentage of the class I (green) is 5% which leads to just one sample (if any) from 28 samples, iv) large standard deviation of backscatter data due to the shallowness of water, which leads to a small beam-footprint. This has been accounted for, to a large extent, due to the averaging procedure, and v) considering other physical properties of sediments rather than just the mean grain size.

4. SUMMARY AND CONCLUSIONS

Riverbed sediment classification using multi-beam echo-sounders (MBES) backscatter data is a promising approach. This contribution presented the methodology, developed in Ref. [1], to use the MBES backscatter data for the sediment classification in shallow water applications. The method employs the backscatter data to obtain the number of acoustic classes and to discriminate between them by applying the Bayes decision rule for multiple hypotheses. This is achieved by fitting a series of Gaussian PDFs to the backscatter strength histogram. Since the classification is done per beam, the method is considered to be independent of the possible incorrect calibration effects and the angular behaviour of the backscatter data.

Shallow water depth results in a small beam-footprints and hence a small number of scatter pixels per beam. That makes the backscatter data highly variable and consequently the classification method becomes less efficient. In order to increase the discriminating power of the classification results we used an averaging procedure over small surface patches (0.5×0.5 m). The high resolution bathymetry data provides precise bottom slope corrections to convert the arrival angle of the signal into the true incident angle, and the high resolution backscatter data allows one to reduce the statistical fluctuation in backscatter strength. Both make the classification method more efficient.

The performance of the method was tested by using the backscatter data acquired in the river Waal, the Netherlands (Fig. 3). For keeping the Dutch rivers suitable for commercial activities bottom stabilizing measures are planned to counteract the subsidence. To monitor the suppletion effectiveness, MBES measurements were used to apply the classification method. Extensive sediment grab samples analyzed for the grain-size distribution were used to evaluate the performance of the classification results.

We performed a correlation analysis. The dependence of acoustic backscatter classification on sediment physical properties was verified by obtaining a Pearson correlation coefficient of 0.70 between the classification results and sediment mean grain-size. Because ground truthing the classification results from core analysis of the sediments is prone to a few sources of uncertainty, further analysis of the correlation coefficient is required. We can in particular think of a disattenuated correlation coefficient.

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