Abstract: Seafloor characterization is important in many fields including hydrography, marine geology, coastal engineering and habitat mapping. The advantage of non-invasive acoustic methods for sediment characterization over conventional bottom grabbing is the nearly continuous versus sparse sensing and the enormous reduction in survey time and costs. Among the various acoustic systems for seafloor characterization, the single-beam echo sounder is of particular interest due to its simplicity and versatility. Seafloor characterization algorithms can be roughly divided into two categories: model-based and empirical, where the latter simply relies on the observation that certain echo features, such as amplitude, duration and skewness of the echo, are correlated with sediment type. Here we apply the model-based approach where we compare the measured echo signal with theoretically modeled echo envelopes in the time domain. For modeling the received echo sounder signals use is made of a physical backscatter model that fully accounts for water-sediment interface roughness and sediment volume scattering. We use differential evolution, a fast variant of a genetic algorithm, as the global optimization method to invert the model input parameters mean grain size, spectral strength of the interface roughness and volume scattering cross section. In the model grain size determines geo-acoustic parameters like sediment sound speed, density and attenuation. The analysis is applied to simulated data.

Keywords: Single-beam echosounder, seafloor classification, optimization
1. INTRODUCTION

Up-to-date information regarding sea- or river floor composition is of high importance for a large number of applications. These include e.g. cable and pipeline route planning, geology and off-shore construction projects. Currently the most common method for obtaining the required information is to take sediment samples. These samples are then analysed in a laboratory, a time-consuming and costly process. An appealing approach therefore consists of using acoustic remote sensing techniques for classification of the sediments, employing measurement equipment such as single-beam and multibeam echosounders, which are already widely used.

Different approaches towards acoustic remote sensing for classification can be found in the literature. In general, these approaches can be divided into two groups, viz., a phenomenological and a physical approach. In the phenomenological approaches, features such as energy or time spread are determined for the received echo signals. These features are known to be indicative for the sediment type. However, independent measurements, such as cores, are needed to link the sediment classes obtained from the features to real sediment properties or sediment type. In contrast, the physical approaches make use of model calculations and determine the seafloor type by maximizing the match between modeled and measured signals, where seafloor type, or parameters indicative for seafloor type, are input into the model. The advantage of this approach is that in principle, no independent measurements such as sediment samples are needed.

In section 2 the model which is used in the remainder of this article for predicting the signals as received by a single beam echo sounder (SBES) system is described. Section 3 presents a short description of the global optimization method employed for maximizing the match between measured echo signals and model outputs. Section 4 presents a comparison between modeled and measured echo shapes. Hereto, use is made of simulated data. Conclusions and way ahead are presented in section 5.

2. MODELLING THE SINGLE-BEAM ECHOSOUNDER SIGNALS

For the shape of the echo intensity as received by the SBES we can write

\[ y(t) = \int_{A(\theta)} \sigma_b(\theta) B(\theta) \frac{e^{-\alpha r}}{r^4} \, dA \]  

(1)

with \( \theta \) the angle of incidence, \( \sigma_b(\theta) \) the backscattering cross section, \( A(\theta) \) the instantaneous ensonified area that contributes to the sound received at time \( t \) and \( B(\theta) \) the transmit/receive directivity pattern of the transducer. \( \alpha \) is the water attenuation coefficient and \( r \) is the slant range, i.e., \( r = \sqrt{x^2 + H^2} \) with \( x \) the horizontal distance towards the receiver and \( H \) the water depth.
This can be further worked out as

\[ y(t) = \int_{x_1(t)}^{x_2(t)} \sigma_0 \left( \tan^{-1} \left( \frac{x}{H} \right) \right) B \left( \tan^{-1} \left( \frac{x}{H} \right) \right) \frac{e^{-4ar}}{r^4} - 2\pi x \, dx \]  

(2)

Here, \( x_1(t) \) and \( x_2(t) \) denote the two \( x \)-values that bound \( A(\theta) \). For \( x_2(t) \) we have

\[ x_2(t) = \sqrt{\frac{c^2 t^2}{4} - H^2}, \]  

with \( c \) the speed of sound in the water, which is assumed to be constant. \( x_1(t) \) is dependent on \( t \) according to

- For \( t \leq t_0 + T \): \( x_1(t) = 0 \)
- For \( t > t_0 + T \): \( x_1(t) = \sqrt{\left( \frac{ct - cT}{2} \right)^2 - H^2} \)

with \( t_0 = \frac{2H}{c} \) and \( T \) the pulse duration.

\( B(\theta) \) is known given the transducer configuration. In literature several expressions for the backscattering cross section \( \sigma_b(\theta) \) are described. For the work described here, we have considered the backscattering cross section as presented in [1]:

\[ \sigma_b(\theta) = \sigma_r(\theta) + \sigma_v(\theta) \]  

(3)

Thereby, both the backscatter cross section due to interface roughness scattering \( \sigma_r \) and the one due to volume scattering \( \sigma_v \) are accounted for. Both are calculated per unit area and per unit solid angle.

\( \sigma_r \) is obtained by appropriate interpolation between the three following approximations.

- The Kirchhoff approximation, valid for smooth to moderately rough sediments and grazing incidence angles near 90°;
- The composite roughness approximation, valid for smooth to moderately rough sediments and grazing incidence angles away from 90°;
- The large-roughness scattering with a scattering cross section determined from an empirical expression which is derived for rough sediments like gravel and rock.

Parameters that are input into the model are listed in Table 1. While the interface roughness scattering mainly varies with the spectral strength \( w_2 \), the volume parameter \( \sigma_2 \) is the crucial parameter for the volume scattering.
<table>
<thead>
<tr>
<th>Seafloor parameter</th>
<th>Symbol</th>
<th>Lower bound</th>
<th>Upper bound</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean grain size</td>
<td>$M_z$</td>
<td>1</td>
<td>9</td>
</tr>
<tr>
<td>Sediment – water ratio of mass density</td>
<td>$\rho$</td>
<td>1.145</td>
<td>2.5</td>
</tr>
<tr>
<td>Sediment – water ratio of sound speed</td>
<td>$\nu$</td>
<td>0.98</td>
<td>2.5</td>
</tr>
<tr>
<td>Imaginary to real wave number ratio</td>
<td>$\delta$</td>
<td>0.00148</td>
<td>0.01374</td>
</tr>
<tr>
<td>Sediment volume scattering cross section to attenuation coefficient ratio</td>
<td>$\sigma^2$</td>
<td>0.0002</td>
<td>0.005</td>
</tr>
<tr>
<td>Exponent of the bottom relief spectrum</td>
<td>$\gamma$</td>
<td>n.a.</td>
<td>n.a</td>
</tr>
<tr>
<td>Strength of the bottom relief spectrum $[^{cm^4}]$</td>
<td>$w_2$</td>
<td>5e-5</td>
<td>3e-2</td>
</tr>
</tbody>
</table>

Table 1: Seafloor parameters, their symbols and lower and upper bounds from [1]

For $\rho$, $\nu$, and $\delta$ empirical expressions exist that couple these parameters to a single parameter, i.e. the mean grain size $M_z[\phi]=-\log_2 d[mm]$. In general, measurements of these parameters show a small spread around the empirical expressions. In contrast, the spectral strength $w_2$, and the volume parameter $\sigma^2$ are known to deviate more significantly from default values obtained from expressions relating them to $M_z$. A value of 3.25 for $\gamma$ is known to work well for many types of sediment.

Simulated signals are shown in Fig. 1 for three different sediment types. As model inputs use is made of default values for the seafloor parameters [1].

![Simulated signals](image)

Fig. 1: Simulated signals for $M_z = -1\phi$ (solid blue line), $M_z = 3\phi$ (dashed green line), and $M_z = 9\phi$ (dash-dotted, red line).

3. MAXIMISING THE MODEL-DATA AGREEMENT
In the model based approach, parameters of the seafloor are derived by maximising the match between the measured signal and the modelled signal. Those parameters corresponding to the maximum match should reflect the seafloor composition. As a measure for the agreement between model echo signal and measured echo signal, the following energy function has been selected:

$$E = \frac{1}{\sum_k [y_{meas}(t_k) + y_{mod}(t_k)]} \sum_k [y_{meas}(t_k) - y_{mod}(t_k)]^2$$

Here $y_{meas}$ and $y_{mod}$ denote the measured and modeled echo shape, respectively.

Table 1 lists all input parameters. For the current approach, however, these will not all be inverted for. We limit ourselves to three parameters, i.e., $w_2$, $\sigma_2$, and $M_z$, employing the empirical expressions for deriving the values for $\rho$, $\nu$, and $\delta$ from $M_z$ [1]. This results in three unknown parameters to be inverted for.

For the optimization (minimization of $E$) use is made of the global optimization method differential evolution (DE). DE, just like the generic algorithm (GA), starts with an initial population of randomly chosen parameter value combinations [2]. These $m_{k,i}$ are improved during $N_G$ successive generations of constant size $q$, i.e., $k = 1, ..., N_G$ and $i = 1, ..., q$.

A partner population is constructed from the initial population ($k = 1$) according to

$$p_{k,i} = m_{k,i} + F (m_{k,j_2} - m_{k,j_3})$$

Here, $p_{k,i}$ is the partner for $m_{k,i}$, and $m_{k,j_1}, m_{k,j_2}, m_{k,j_3}$ are three different parameter value combinations chosen at random from the population. $F$ is a scalar multiplication factor between 0 and 1. Higher values for $F$ result in an increasing difference between the original parameter values and those contained in the partner population. Small values for $F$ result in parameters in succeeding generations that differ only a little from those in previous generations. This setting actually corresponds to that of a local search, i.e., the exploration of the search space is limited.

Descendants $d_{k,i}$ result from applying crossover to $m_{k,i}$ and $p_{k,i}$ with crossover probability $p_c$. With DE, crossover leads to parameter values of $m_{k,i}$ being replaced by parameter values of $p_{k,i}$. The number of parameter values of $p_{k,i}$ copied into the new parameter value combination is dependent on the value of $p_c$. For higher value of $p_c$ more (on the average) values contained in $p_{k,i}$ are copied into $d_{k,i}$. For low $p_c$-values generations will differ only slightly from the previous generations. This is the case even if a high value for $F$ is selected.

Values for the energy function are determined for all descendants. Descendant $d_{k,i}$ replaces $m_{k,i}$, becoming its successor, only if its energy is lower. This process is repeated for $N_G$ generations.

Optimal settings of the DE parameters were derived in [3] and are:

- Population size $q$: 16
• Multiplication factor $F$: 0.6
• Crossover probability $p_c$: 0.55

Based on preliminary inversion results the number of generations $N_G$ was set to 200.

4. RESULTS

For the current contribution we have limited ourselves to the use of simulated data to assess the performance of the approach. The simulated data have been created for a series of sediment types. These are listed in Table 2.

The SBES considered has the following characteristics

• Transducer diameter: 0.24 m;
• Pulse length: 0.25 ms;
• Frequency: 38 kHz.

For each setting 10 independent optimization runs have been carried out. Figure 2 presents the results of the optimization for setting 3 and 2 as given in Table 2. The plots indicate the typical convergence behaviour of the three parameters. It can be seen that all optimizations converge to the true parameter value, i.e., true values are found precisely. The volume scattering parameter $\sigma_2$ requires a somewhat larger number of generations for convergence than the other two.

For all other settings similar conclusions regarding parameter sensitivity can be drawn. However, the exact parameter sensitivities differ as can be seen in the differences in convergence behaviour of $\sigma_2$ for settings 2 and 3 (lower plots of Fig. 2). The lower $M_z$ of setting 2 limits the contribution of the volume scattering to the total backscatter strength. Consequently, the echo signal is less affected by the volume scattering parameter, resulting in a lower sensitivity of the energy function to this parameter.

<table>
<thead>
<tr>
<th>Setting</th>
<th>$M_z$ [$\phi$]</th>
<th>Grain size [mm]</th>
<th>$w_2$ [cm$^4$]</th>
<th>$\sigma_2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>8</td>
<td>0.0039</td>
<td>0.0005</td>
<td>0.0005</td>
</tr>
<tr>
<td>2</td>
<td>2</td>
<td>0.2500</td>
<td>0.0035</td>
<td>0.0020</td>
</tr>
<tr>
<td>3</td>
<td>5</td>
<td>0.0313</td>
<td>0.0005</td>
<td>0.0020</td>
</tr>
<tr>
<td>4</td>
<td>5</td>
<td>0.0313</td>
<td>0.0050</td>
<td>0.0020</td>
</tr>
</tbody>
</table>

Table 2: True and inverted seafloor sediment parameters for the 4 sets of inversions.
Fig. 2: Inversion results. The plots indicate the parameters corresponding to the lowest energy as a function of generation for two settings as given in Table 2 (left: setting 3, right: setting 2).
5. CONCLUSIONS AND OUTLOOK

It can be concluded, based on the simulations presented in this paper, that seafloor classification using a model-based approach on single-beam echosounder data is feasible. All unknown parameters can be retrieved correctly. As a next step the method will be applied to real SBES data. These data have been acquired in the Cleaver bank area (North Sea). This area is an attractive area for testing sediment classification methods as it contains a large range of sediment types with mean grain sizes ranging from $5\phi$ to $-1\phi$ [4].

REFERENCES