Seafloor Sediment Classification Based on Multibeam Sonar Data

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ABSTRACT The multibeam sonars can provide hydrographic quality depth data as well as hold the potential to provide calibrated measurements of the seafloor acoustic backscattering strength. There has been much interest in utilizing backscatters and images from multibeam sonar for seabed type identification and most results are obtained. This paper has presented a focused review of several main methods and recent developments of seafloor classification utilizing multibeam sonar data or/and images. These are including the power spectral analysis methods, the texture analysis, traditional Bayesian classification theory and the most active neural network approaches.

KEYWORDS seafloor classification; multibeam sonar; backscattering strength; sonar images

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Introduction

The problem of sea bottom identification and classification is important in many fields including marine geology, hydrography, marine engineering, environmental sciences, and fishery. In the past years, acoustic methods for bottom classification are well recognized as a useful tool in the fast preliminary geological analysis. These methods provide a capability for detection of local geological formation and fast bottom sediment mapping. In addition, acoustic methods are non-invasive and more cost effective than conventional geological sampling methods.

A new high resolution source of data has recently become available using amplitude from multibeam sonars. The multibeam sonars can provide hydrographic quality depth data (in the absence of roll, heave, refraction or positioning errors) as well as hold the potential to provide calibrated measurements of the seafloor acoustic backscattering strength. There has been much interest in utilizing backscatters and images from multibeam sonar for seabed type identification and most results were obtained in the last decades. As a result an across-track map of the seafloor backscattering strength from multibeam sonar is presented to the user somewhat equivalent to conventional sidescan sonar.

The backscattering of sound by the ocean seafloor is a complex process, owing to the diversity of ocean floor types, lateral inhomogeneity and potential contribution of sub-bottom layers. Consequently, the theoretical treatment of bottom reverberation poses a formidable analytical problem. Two complementary approaches have evolved. One is the so-called “physical” method, whereby a solution of the wave equation is sought with appropriate boundary conditions describing the surface. Typically, the Helmholtz formula with the Kirchoff approximation is used. This method may be used to relate certain statistics of the random surface to the scattered

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acoustic field\[^3\]. However, its usefulness is somewhat limited by restrictive assumptions it is based on. An alternative approach is to describe reverberation as a random process, constructed superposition of the individual echoes emanating from a large number of point reflectors distributed independently in a homogeneous medium. This is known as the “point-scattering” or “quasi-enomenological” of reverberation\[^2\]. This model is quite general and allows the estimation of a large number of statistical measures of reverberation. However, these statistics are only weakly connected with the physical characteristics of the scattering region.

The disadvantage of acoustic methods is associated with complicated inverse theory of acoustical wave scattering on rough and layered seabed. The existing theoretical models do not give satisfactory results in such inversion procedures. This is why these methods are still the subject of extensive research. There are various methods for characterizing and classifying the sea bed types utilizing backscatter data and images from multibeam sonars. These methods can involve several approaches, such as power spectra analysis of echo amplitudes, texture analysis, statistical methods, neural networks, etc.

1 Spectra analysis

Methods for extracting features from the power spectra and cepstra of side-scan sonar data for sea-bed classification has been devised by Reut et al. (1985)\[^4\] and by Pace and Gao (1988)\[^5\]. Features are defined as the ratios of integrals over windows on specially defined “power” spectra. References [6] and [7] both use the approach of the power spectral analysis method, and the difference that is Reference [6] analyzed the power spectrum of the signals returned from six sea-bed types, while Reference [7] derived directly the feature from the power spectrum and provided superior discrimination between different seabed types. Tamsett (1992) developed the spectral modeling approach based on the method by Pace and Gao, which is to fit an appropriate low-pass filter response curve to observed spectra by parameter optimization and to use one or more of the optimized parameters for defining features. The parametric modeling approach yields features that give a meaningful description of the power spectra from which they are derived, provide excellent sea-bed discriminants, and have a degree of immunity to changes in signal noise\[^3\].

The methods described above have been developed for extracting features from traditional side-scan sonar data. In Reference [9], the method proposed by Pace & Gao were used for extracting features from a multibeam sonar data. The power spectrum is obtained by applying a window function to the input data, performing a Fourier transform to the windowed data and then taking the sum square of the resulting amplitudes. The windowing is done by adjusting the data to have a zero mean value, applying the window function and then re-adjusting the data.

\[ P_i = \left| \mathcal{F}[g_i(t)] \right|^2, \quad 1 \leq i \leq n \]

where \( i \) is the ping (i.e., transmission cycle) number, and \( g_i(t) \) is the windowed input data (amplitude).

The power spectrum is then averaged over \( n \) pings, giving

\[ P_i(f) = \frac{1}{n} \sum_{i=1}^{n} P_i(f) \]  

(2)

In Reference [7], the “log power spectrum” is defined as

\[ P_L(f) = \log \left( \frac{\overline{P}(f)}{P_m} + 1 \right) / \log (A + 1) \]  

(3)

where \( P_m \) is the maximum value of \( P(f) \), and \( A \) is a constant multiplier. Finally, applying normalization, we obtain:

\[ P_{NL}(f) = P_L(f) / \int_{0}^{f_N} P_L(f) \, df \]  

(4)

From the normalization log-power spectrum, Pace & Gao defined three features, \( D_{i_1}, D_{i_2} \) and \( D_{i_3} \).\[^9\]

\[ D_{i_1} = \int_{0}^{f_{BA}} P_{NL}(f) \, df / \int_{f_{BA}}^{f_N} P_{NL}(f) \, df \]

\[ D_{i_2} = \int_{0}^{f_{3/4BA}} P_{NL}(f) \, df / \int_{f_{3/4BA}}^{f_N} P_{NL}(f) \, df \]  

(5)

\[ D_{i_3} = \int_{0}^{f_{1/2BA}} P_{NL}(f) \, df / \int_{f_{1/2BA}}^{f_N} P_{NL}(f) \, df \]

In multibeam sonar data from several pings are
merged together into a long array, and then
Fourier transform will be applied to this array.
The mean of all Fourier transforms are calcul-
eted and the \( D_f \) features are computed, the zero
frequency is not used in the computation and
these features are called the "pace features"\(^\text{[\(d\)]}\).

2 Texture analysis

An important approach to image analysis is to
quantify the texture content\(^{[9]}\). Even though a
precise definition of texture does not exist, im-
age texture can be qualitatively described as hav-
ing one or more properties of fineness, coarseness,
smoothness, roughness, irregularness, or hummocky.
Most surfaces of natural things are not smooth. The feature of material corresponds
to the surface of the material and may, there-
fore, be used to identify structures. In sonar im-
ages the variation in reflectivity may correspond
to structures on the seabed. For seabed classifi-
cation from multibeam sonar, texture analysis
is usable to both sonar image and reflectivity data
as well as depth data. Several well-known tech-
niques exist in this field, e.g. co-occurrence ma-
trices, Markov random fields, fractal compo-
nents.

2.1 Co-occurrence matrices

Texture features can be calculated from the
gray level spatial co-occurrence matrix. For the
multibeam sonar, if a ping is treated as a se-
quence of reflectivity data, the co-occurrence
\( p(i,j) \) of reflectivity \( i \) and \( j \) is defined as the
number of pairs of samples having reflectivity \( i \)
and \( j \), respectively, which are in a fixed spatial
relationship \( d \). The co-occurrence matrix can be
normalized by dividing each entry by the sum of
all entries in the matrix giving \( p(i,j) \). A lot of
papers describe the statistics of the co-occurrence
matrix\(^{[9,13-14]}\). Some of the most important
features are:

- Energy type features:
  \[ f_1 = \sum_i \sum_j p(i,j) \]  
  (6)
- Contrast type features:
  \[ f_2 = \sum_i \sum_j p(i,j)(i-j)^2 \]  
  (7)
- Local homogeneity type features:
  \[ f_3 = \sum_i \sum_j \frac{p(i,j)}{1+|i-j|} \]  
  (8)
- Entropy type features:
  \[ f_4 = \sum_i \sum_j p(i,j) \log p(i,j) \]  
  (9)
- Correlation type features:
  \[ f_5 = \sum_i \sum_j p(i,j)(i-\mu_i)(j-\mu_j) \]  
  (10)
- Shade type features:
  \[ f_6 = \sum_i \sum_j p(i,j)(i-j-\mu_i-\mu_j)^2 \]  
  (11)

Reference \([9]\) introduces a new feature:
\[ \log \text{contrast} = \sum p(i,j)(|i-j|) \log (|i-j|+1) \]  
(12)

This feature has almost the same properties as
contrast type features, but it is less affected by
noise.

2.2 Markov random fields (MRFs)

Markov random fields (MRFs) are probabilis-
tic models, which are appropriate for describing the distribution of grey levels and the inter-pixel
dependence in stochastic texture images. The
general form of the model \( \omega^{[13]} \),

\[ p(d) = \frac{e^{-U(d)}}{Z} \]  
(13)

where \( D = d \in \Omega \) is a texture image realization
from the image space \( \Omega \), while \( U(d) \) is the ener-
gy function and \( Z \) is the normalizing partition
function. Various definitions of \( U(d) \) lead to
Gaussian, Gibbsian and other forms of the MRF
model. References \([16], [17] \) and \([18]\) em-
ployed the MRFs with a Gibbs distribution
(MRFs/GD) to segmenting sidescan sonar image
and multibeam sonar image, respectively. In
general, a real world seafloor sonar image is
clearly textured and noisy. Particularly at large
scales, i.e. where the length of detected seafloor
features is much larger than the acoustic wave-
length, seafloor sonar image is roughly domina-
ted by seafloor appearance featured by various
textures. Noting the generality of Gibbs distri-
bution to statistical mechanics processes, we
might naturally expect to approximately model
seafloor appearance on the plane of seafloor so-
nar image using MRFs/GD, or at least to correlate MRFs/GD with major geomorphological features of seafloor sonar image.

3 Traditional statistical classification

Bayesian decision theory is the basis of statistical classification methods\(^{(12)}\). It provides the fundamental probability model for well-known classification procedures such as the statistical discriminant analysis. References \(^{[20]}\) and \(^{[21]}\) investigated the Bayesian statistical method for seabed classification from backscatter data collected by Simrad EM1000 Multibeam Echo Sounder. The results show that it is possible to differentiate between seafloors of various sediment types.

Consider a pixel corresponds to a backscattering values which belongs to one of \(K\) classes with prior probabilities, \(\pi_k\), \(\cdots\), \(\pi_k\). Pixels or feature vectors from class \(k\) are distributed according to the density \(f_k\). The Bayes decision rule\(^{(19)}\) assigns a feature vector to class \(k\) where \(k\) maximizes

\[
P(C = k | X) = \frac{\pi_k f_k (X)}{\sum_j \pi_j f_j (X)}
\]

is the posterior probability of class \(k\) given the feature vector \(X\).

Now assume that the class densities are multivariate normal, thus

\[
f_k (x) = (2\pi)^{-d/2} \left| \det(\Sigma_k) \right|^{-1/2} e^{-\frac{1}{2} (x - \mu_k)^T \Sigma_k^{-1} (x - \mu_k)}
\]

where \(d\) is the dimension of the feature vector space, \(\mu_k\) is the mean vector, \(\Sigma_k\) is the covariance matrix. The parameters \(\mu_k\) and \(\Sigma_k\) are unknown and will be replaced by estimates in computation of \(P(C = k | X)\).

The training of the classifier consists of estimating \(\mu_k\) and \(\Sigma_k\) for \(k = 1, \cdots, K\). Let \(X^{(i)}_1, \cdots, X^{(i)}_{N_k}\) be feature vectors which are known to be of class \(k\). The parameters are estimated by \(\hat{\mu}_k\) and \(\hat{\Sigma}_k\), and

\[
\hat{\Sigma}_k = \frac{1}{N_k - 1} \sum_{i=1}^{N_k} (X^{(i)} - \hat{\mu}_k) (X^{(i)} - \hat{\mu}_k)^T
\]

The classification of unknown feature vector is now a simple task. It can be shown\(^{(19)}\) that the classification rule becomes (assigning to a pixel class \(k\) where \(k\) minimizes)

\[
\ln(\det(\Sigma_k)) + (X - \hat{\mu}_k)^T \Sigma_k^{-1} (X - \hat{\mu}_k)
\]

An inherent drawback of statistical approaches, however, is that most assume the probability distribution function of each class is explicitly known or computable. This means their performances are highly dependent on how well the used statistical model can describe the real data and on how much prior information can be found. Unfortunately, there is still no practical 2-D statistical model of sidescan imagery for seafloor characterization. Moreover, it is particularly difficult to use statistical methods for classifying seafloor data sets of varying sources, types, reliabilities, and scales. This lack of portability between different data sets is a critical limitation of statistical classifiers for general seafloor classification problem.

4 Neural network

Classification is one of the most active research and application areas of neural networks. The literature is vast and growing\(^{[21]}\). Over the past decade, neural networks have emerged as important tools for processing and classifying complex signals. Neural networks are data driven, nonlinear and nonparametric models. There are two kinds of neural networks applied to seafloor classification, i.e., supervised classification with ground truth data and unsupervised classification that do not require supervised learning. Several experimental results have achieved with neural network approaches for seafloor sediment classification using sidescan imagery\(^{[22]-[24]}\), multibeam sonar images\(^{[25]}\) and backscattering data\(^{[26]-[27]}\).

4.1 Multilayer perceptron network (MLP)

The most common supervised neural network
model applied to sonar signal classification problems is the multilayer perceptron network with nonlinear processing unit. References [25] and [27] employed a feed-forward neural network with back propagation of error for classification of backscatter data from Simrad EM12 and Sea Beam multibeam sonars, respectively. Structurally, the network consists of three or more layers: an input layer where information enters the network, an output layer where the processed information is retrieved, and one or more hidden layers between the input and output. Node connections commonly exist between neighboring layers, but not within the same layer (Fig. 1). During the classification, information passes through the network in one direction: from input layer, through hidden layer(s), to output layer. Each node actually performs two functions, collecting the activation from nodes of previous layer and setting an output activation. An exception is the input layer where the nodes are directly activated by the input data. The output activation of the current node is determined by:

\[ a_i = f\left(\sum_j w_{ij} a_j\right) \]  

where \(w_{ij}\) is a connection weight between the current node \(i\) to the \(j\)th node in the previous layer, \(a_j\) is the activation of the \(j\)th node, and \(f\) is a sigmoid function such as:

\[ f(x) = \frac{1}{1 + e^{-x}} \]

The key task is the determination of connection weights. The process of adjusting connection strengths among neighboring-layer nodes according to the training output pattern and the training input patterns is called “learning”, through which the knowledge of patterns to be recognized is stored in the network connections. Then, when the unknown input is presented, the network can decide to which class it belongs. In back propagation learning, the network performs a nonlinear optimization to minimize the global error \(E\), the sum of squared differences between the output-layer nodes and the desired outputs. During this procedure, the connection weights are adjusted repeatedly according to the delta rule:

\[ \omega_{n+1} = \omega_n + \Delta \omega_n = -\eta \nabla E \cdot \Delta E = \frac{\partial E}{\partial \omega_n} \]  

where \(\eta\) is a small positive parameter called learning rate, \(\omega\) is the weight vector, and \(n\) is the iteration index. When this iteration converges according to some criterion of acceptable error, learning end and network “knows” how to separate the class.

The most important parameters of a back-propagation network are the number of hidden layers and the number of nodes in each hidden layer. There are no universally accepted criteria for the “optimum” network configuration. References [25] and [27] selected a network with the structure of two hidden layers. The use of two hidden layers is necessary for nonlinear problems, i.e., overlapping groups of data in feature space.

Knowledge of the number of different seafloor classes and of a set of ground truth data from each class is necessary for carrying out the training phase of the multilayer perceptron; the ground truth information could be bottom photographs and core samples. Acquiring this information is not always straightforward. As a potential solution to the problem, there exist self-organizing algorithms capable of unsupervised learning.

### 4.2 Self-organizing map

The Kohonen self-organizing maps (SOM) operate as clustering system and do not require supervised learning, in contrast to multilayer perceptrons. They consist of only two layers, i.e., input layer and output layer. Their nodes
are connected through weights, which will adapt to values by following a minimization distance criterion (correlation maximization is occasionally applied) (Fig. 2). In this way, the output layer will consist of nodes divided in “neighborhoods”, if the weights calculations are performed correctly. The network will assign each “neighborhood” to a special class of input patterns.

![Fig. 2 Two-dimensional array of output nodes in the self-organizing feature map network](image)

The principle of SOM is the estimation of the probability density function (PDF) of the input vectors; for this reason we can view its output as contours of multidimensional distributions. However, a way to optimal PDF estimation using such a network is not currently known. The SOM algorithm operates as a clustering process, assigning a given set of data patterns to clusters or neighborhoods. Because the SOM does not require supervised learning, it is a valuable classification tool in the absence of ground truth information about the prevailing seafloor classes. This result will hopefully facilitate the exploration of unknown seafloor regions and can serve as a useful preprocessor to supervised learning with multilayer perceptrons. Reference [22] presents a hybrid neural classifier applied to seafloor classification of the sidescan sonar images. This classifier consists of a supervised multilayer perceptron network driven by an unsupervised SOM.

### 5 Conclusions

Classification of seafloor sediment types with the backscatter data is the mostly researched topic of underwater acoustic signal processing. This paper has presented a focused review of several main methods and recent developments of seafloor classification utilizing multibeam sonar data or/and images. These include the power cepstral, power spectral analysis methods and the spectral modeling approach, the texture analysis based on co-occurrence matrices and Markov random fields, traditional Bayesian classification theory and the most active neural network classifiers.

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