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TOWARDS GAIN INVARIANT SEA BED CLASSIFICATION.

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1. INTRODUCTION

This paper outlines some progress made towards robust sonar-invariant and gain-invariant sea bed type classification. This work continues previous studies Pace and Gao [7], O'Brien and Agnew [2], Beck [1], Nicholls and Beck [5].

Pace and Gao [7] used a data library collected with a 48kHz side-scan sonar system. Using features of the power spectrum of the signals backscattered from the seabed they found a high probability (>0.97) of correctly classifying the sea bed type as either sand, mud, clay, gravel, stones, or rock. The values of the spectral features increase through this sequence of sea bed types. O'Brien and Agnew [2] showed the feasibility of using these features to classify the deep ocean seabed using 6.5kHz GLORIA side-scan data but the lack of suitably ground-truthed data prevented further progress. Beck [1], Nicholls and Beck [5] confirmed the conclusions of Pace and Gao [7] using data from several sonars and noted that the spectral features offered better prospects of classifying gravel, stones and rock than sand, mud and clay.

The previous analyses have been repeated in greater detail. Further 48kHz data was obtained from Dr. Pace and new sonar data for higher frequencies was also examined. Of particular interest is the question why the mud and clay types occurred out of the order expected when considering either the granularity or acoustic hardness. Figure 2 shows 64 grey level screen dumps of representative 128 line by 1024 pixel frames of 48kHz amplitude data from the 6 sea bed types mud, clay, sand, gravel, stones, rock, and shows the relative granularity.

2. SPECTRAL ANALYSIS

Consider the classification of the sea bed using the received signal amplitude, a(t), of a sea bed ensonifying sonar with a rectangular pulse. Let the signal amplitude within the ith fixed time duration rectangular window be denoted by $a_i(t)$. The mean value of this windowed signal amplitude is set equal to zero by subtraction of the mean within the window, μ_i. A window function, w(t), is applied, the resulting signal may be written as

$$g_i(t) = w(t)(a_i(t) - \mu_i) \qquad (1)$$

The window function used, in this analysis, is the cosine-tapered window, F. J. Harris, [4]. This window function represents an attempt to smoothly reduce the data to zero at the window boundaries while not significantly reducing the processing gain of the windowed transform. The window changes smoothly from the rectangular window to the Hann window as a parameter a varies from unity to zero. Following the analysis of Pace and Gao [7], $\alpha = 0.875$ is used. When a rectangular window, $\alpha = 1$, is used the high sidelobe level, -13dB, results in high frequency noise being added to the log power spectrum (equation 3). Figure 1 shows a comparison of two typical log power spectra obtained with $\alpha = 0.875$ and $\alpha = 1$. This noise increases the denominator terms in the spectral features (equations 5 - 7) significantly and catastrophically degrades the discrimination between the sea bed types. Insignificant differences are obtained by additional tapering of the window, using the current sonar data.

A Fourier transformation is performed on this windowed amplitude, $g_i(t)$. The averaged power spectrum is obtained by averaging n squared moduli of the resulting amplitudes at each frequency

$$\overline{P}(f) = \sum_{i=1}^{n} |F(g_i(t)|^2, \; i = 1, 2, \ldots, n \tag{2}$$

Given a suitable normalization factor, K, and a sonar-dependent scaling parameter, A (the "stretch" parameter), the log power spectrum may be defined as

$$P_L(f) = \log((A.\overline{P}(f) / K) + 1) / \log(A + 1) \tag{3}$$

If the log power spectrum is normalized so that its total sum value is set equal to unity, the area normalized log power spectrum is obtained

$$P_{NL}(f) = P_L(f) / \int_0^{f_{Ny}} P_L(f)\, df \tag{4}$$

where f_{Ny} is often chosen to be the digitizing Nyquist frequency. The Pace integral spectral features, which may be visualized as the ratios of low frequency to high frequency content of the normalized log power spectra, are

$$Df_1 = \int_0^{f_{Ba}} P_{NL}(f)\, df \Big/ \int_{f_{Ba}}^{f_{Ny}} P_{NL}(f)\, df \tag{5}$$

$$Df_2 = \int_0^{f_{Ba}/8} P_{NL}(f)\, df \Big/ \int_{f_{Ba}}^{f_{Ny}} P_{NL}(f)\, df \tag{6}$$

$$Df_3 = \int_0^{f_{Ba}/8} P_{NL}(f)\, df \Big/ \int_{3f_{Ba}/4}^{f_{Ny}} P_{NL}(f)\, df \tag{7}$$

where f_{Ba} ($< f_{Ny}$) is often chosen to be the bandwidth. In practice the integrals are often evaluated as simple summations.

It is possible to produce highly discriminating spectral features by selecting no normalization, i.e. K = 1, in equation (3), yielding a log "power" spectrum which owes a portion of its discrimination to the gain-dependent contribution resulting from the lack of normalization.

$$P_L(f) = \log(A\overline{P}(f) + 1) / \log(A + 1) \tag{3a}$$

In Pace and Gao [7], the normalization factor, $K = P_{max}$, the maximum value of P(f), is recommended, yielding the log power spectrum

$$P_L(f) = \log(A\overline{P}(f) \; / P_{max} + 1) / \log(A + 1) \tag{3b}$$

This normalization is not wholly independent of the gain. An alternative gain-invariant and partly sonar-invariant method is to use equation 3a, but to replace equation 1 by

$$g_i(t) = w(t)(a_i(t) - \mu_i) / \sigma_i \tag{1a}$$

normalizing the windowed amplitude by the standard deviation within the rectangular window, σ_i, after mean value removal. Figure 3 shows PDFs of the Df1 feature and the corresponding averaged normalized log power spectra for each of these three normalizations. These use the 48kHz sidescan sonar data for the six seabed types. 256-point Fourier transforms are made and the resultant spectra are averaged across 8 lines of data. With no normalization, equation 3a yields good discrimination between the seabed types and the ordering observed in previous studies, namely sand, mud, clay gravel, stones and rock. Normalization via equation 3b yields similar results but with poorer discrimination. The log power spectra obtained from the mud and clay data sets show some anomalous behaviour, possibly due to sonar self noise, at low frequencies. This behaviour might account for the unexpected ordering of the mud and clay data. Normalization via equations 1a, 3a yields discrimination in between the other two results but in this case the seabed types occur in the order mud, sand, clay,gravel, stones, rock. The choice of stretch parameter, f_{Ba} and f_{Ny} have not been optimized for the new normalization. It is likely that improved discrimination may be achieved by a suitable optimization. However initial attempts to produce more discriminating features directly from the averaged power or log power spectra, with the new normalization, were encouraging.

Examples of the performance of the spectral feature Df1 are shown in figures 5, 6, and 7. These figures show comparisons of 64 grey level screen dumps of frames of amplitude data with frames showing the feature value. Figure 5 shows results using data from a survey of a pipeline in a trench, with spoil banks on either side of the trench. The shadow region before the pipe is clearly detected as reported in Nicholls and Beck [5]. Figure 6 shows an example of discrimination of rocks on a sandy seabed. Figure 7 shows the excellent discrimination of a gravel bank on a mud/clay seabed. A wreck in the lower right portion of this frame yields rock-like values of Df1.

3. COMPARISON WITH OTHER FEATURES.

Several other features have been proposed in the literature for sea bed classification purposes. Analyses, of our data, have been performed using features derived from Co-Occurrence MAtrices(COMA), Sum and Difference Histograms(SDH), moment statistics, and Rank Order Statistics(ROS). The application of COMA to sonar data was initially explored in Pace and Dyer [6], the results were not encouraging. The definitions given in Gotlieb and Kreysig [3] are used in this work. Due to the need to evaluate many two dimensional matrices COMA are, computationally, inefficient. Unser [8] introduced SDH features, which approximate the COMA features. Results obtained from these two methods are practically identical. Several authors have investigated the use of gain-invariant moment based statistics, e.g. Pace and Gao [7]. Whilst the 3rd order normalized central moment, M3, yields some useful discrimination (figure 4) the performance has been shown to be significantly inferior to that of the spectral features. A related gain invariant feature, which does not figure prominently in the sea bed classification literature, is the Coefficient Of Variation

$$COV = s_i / m_i \tag{10}$$

ROS features such as the upper deciles have been used. Figure 4 shows PDFs of the most discrimating of these features using the 48kHz sidescan sonar data, for comparison with figure 3. COV and M3 show useful discrimination, but are much poorer discriminators than Df1. Some discrimination is shown by the Mean Grey Level and the COMA Contrast features. Not demonstrated here are the Coefficient of Concentration which shows very similar performance to the COV and the SDH Contrast feature which shows indistinguishable performance to the COMA Contast feature.

In spite of these PDF's good discrimination is often apparent for some of these features. Figure 5 which shows results using data from a survey of a pipeline in a trench presents screen dump frames for the Mean Grey Level and the COMA Contrast features. The Mean Grey Level shows excellent discrimination of the spoil banks beside the trench, the shadow behind the nearest spoil bank and parts of the pipeline and its shadow. The COMA Contrast also discriminates these details but less clearly. Apparently gain-dependent information is enhancing the discrimination of these features.

4. CONCLUSIONS.

A new gain-invariant normalization has been introduced for the Pace spectral features. The resultant Pace spectral features order the sea bed types mud, sand, clay, gravel, stones and rock. Previous studies placed mud between sand and clay in this sequence. Improved discrimination may be achievable by optimization of f_{Ba}, f_{Ny} and the stretch parameter or by using features directly from the averaged power or log power spectra, with the new normalization. It is confirmed that the spectral features offered better prospects of classifying gravel, stones and rock than sand, mud and clay. Care is required in the choice of window function. A novel gain-invariant feature, the Coefficient of Variation shows useful discrimination. Other features, e.g. Mean Grey Level, M3, COMA or SDH Contrast, show useful discrimination but are gain dependent. For sea bed classification when the sonar gain is available the features MGL, Df1, COV and either M3 or SDH Contrast are recommmended. Frequently data may be available but without any record of the sonar gain. In these circumstances the features Df1, Df2, COV and M3 are recommended.

5. REFERENCES.

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Figure 1. Effect of Window Function on Average Log Power Spectrum.

Data set:- SAND03, Sand Seabed, West English Channel, 48kHz Sidescan Sonar.

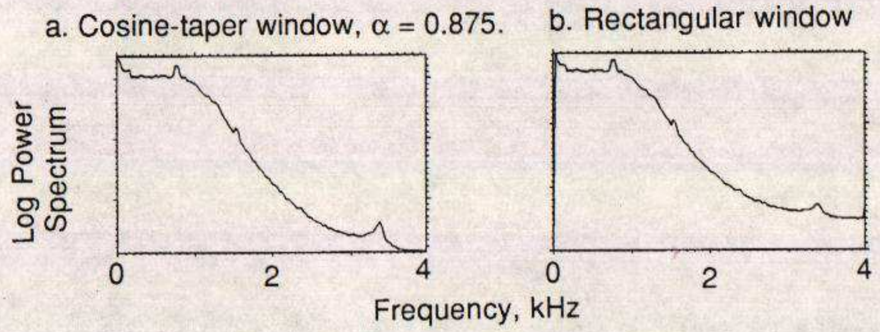


Figure 2. 64-Grey Level Display of 48kHz Sidescan Sonar 8-bit Data from 6 Seabed Types.

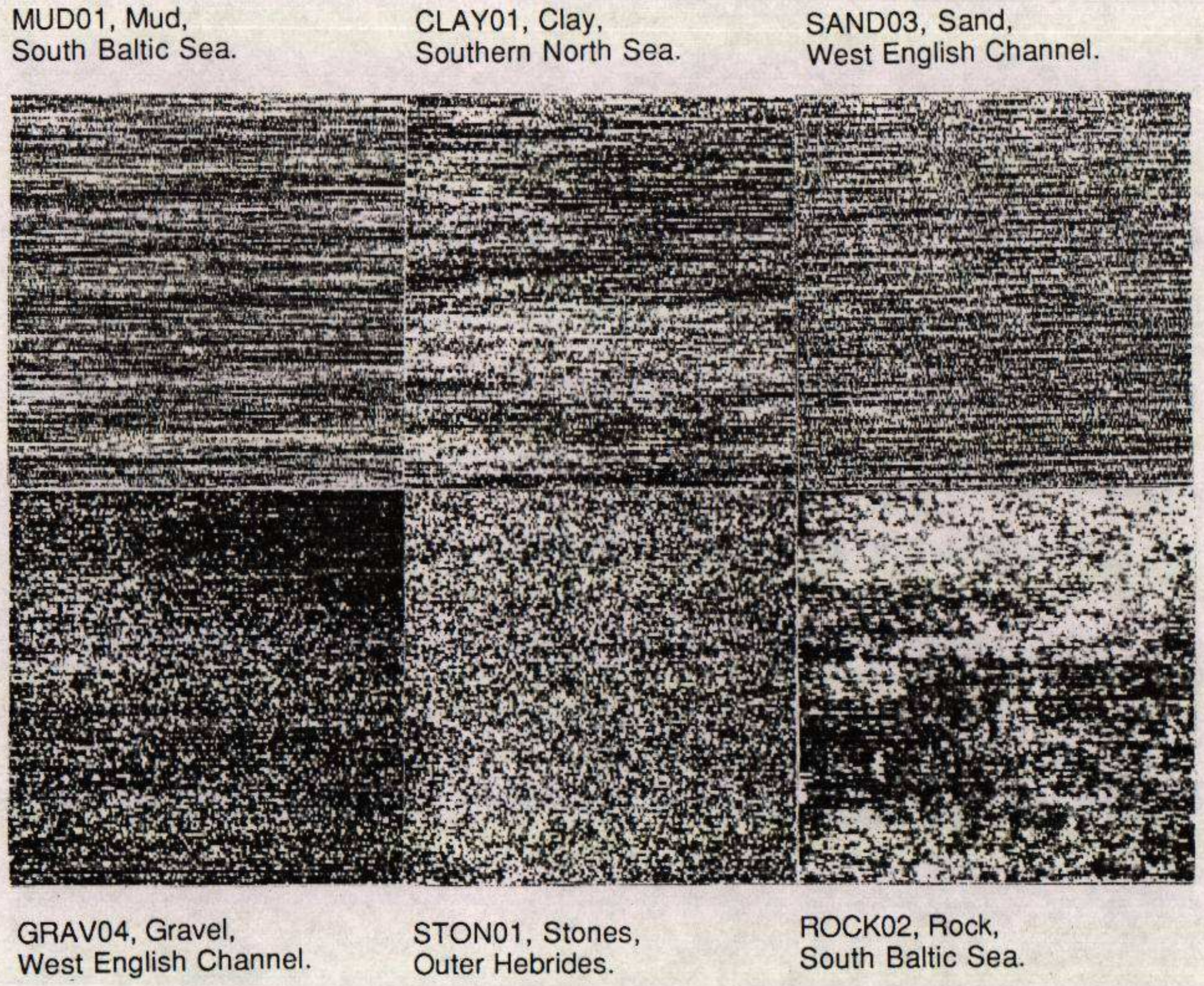
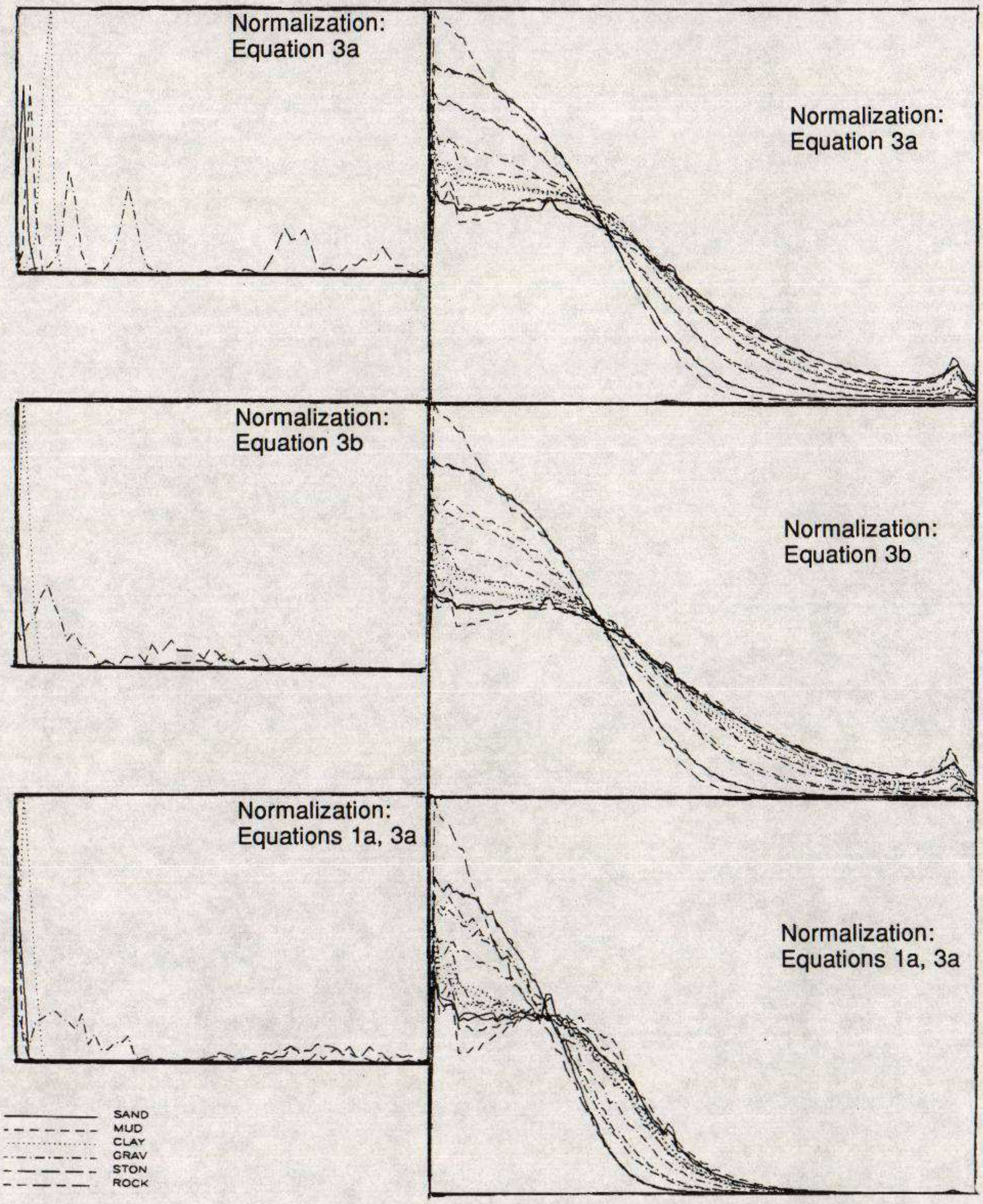


Figure 3. PDF's and Averaged Area Normalized Log Power Spectra for 3 Different Formulations of the Spectral feature, Df1, 6 Seabed Types, 48kHz Sidescan Sonar Data.



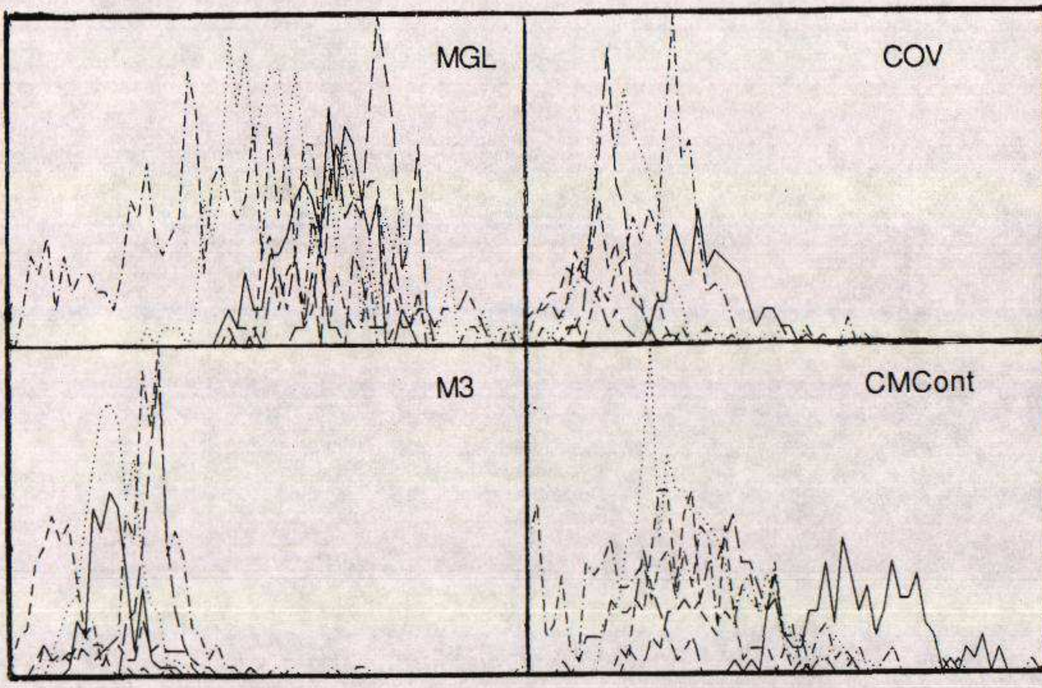


Figure 4. PDF's of best other features: a. Mean Grey Level, MGL, b. Coefficient of Variation, COV, c. M3, d. Correlation Matrix, Contrast, CMCont, for 6 Seabed Types, 48kHz Sidescan Sonar Data.

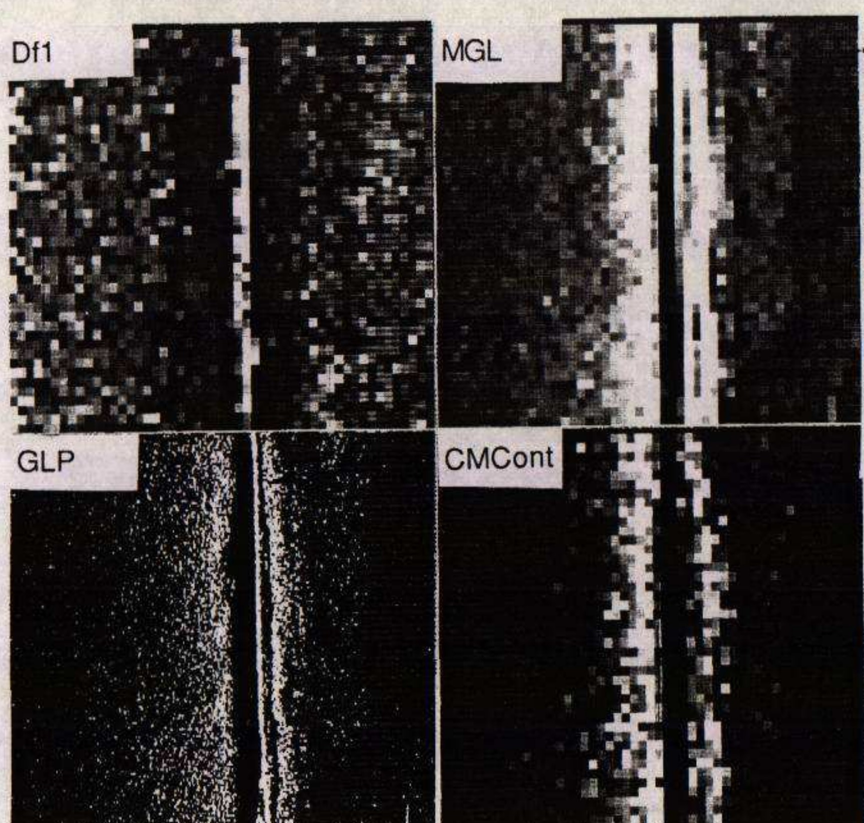


Figure 5. Comparison, with Grey Level Plot of Classification Performance of 3 Features:
a. Spectral Feature Df1,
b. Mean Grey Level, MGL,
c. Grey Level Plot, GLP,
d. Correlation Matrix, Contrast, CMCont.

Data Set: DATA1_1, North Sea, Sand Seabed, Pipeline in a Trench, 50kHz Sidescan Sonar.

(Cells: 4 lines x 32 pixels)

Figure 6. Example of Classification Performance of Spectral Feature, Df1.

Data Set: DATIM2, South West English Coast, Sand and Rock.

a. Grey Level Plot. b. Df1 (Cell Size: 4 lines x 132 pixels).

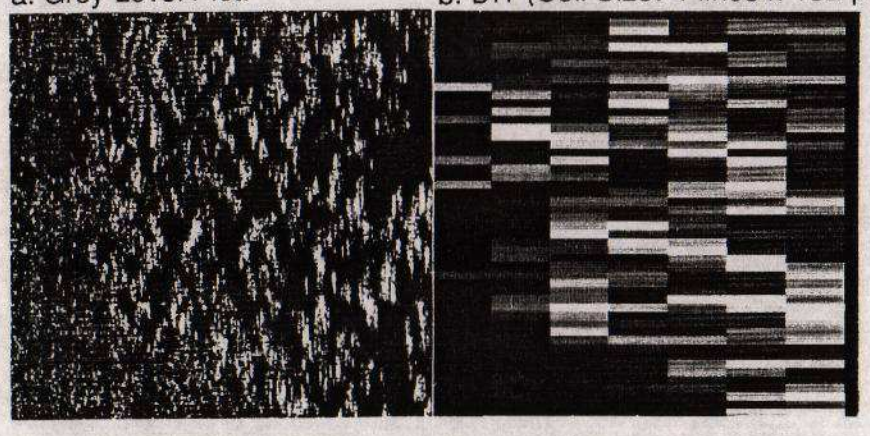
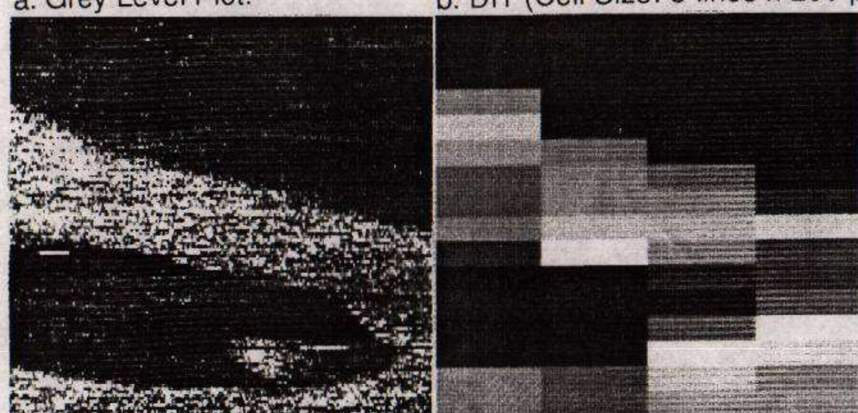


Figure 7. Example of Classification Performance of Spectral Feature, Df1.

Data Set: Grav01, Southern North Sea,
Gravel Bank on Mud/Clay with Wreck.

a. Grey Level Plot. b. Df1 (Cell Size: 8 lines x 256 pixels).



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