Acoustical Boundary Location through Texture Analysis of Multibeam Bathymetric Sonar Data

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ABSTRACT

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SEAFLOOR IMAGERY FROM MULTIBEAM SONAR DATA

The impetus for generating seafloor acoustic imagery from multibeam sonar data is that more detailed information is available from the returning pulse than is discernible through simple computation of a set of bottom depths (de Moustier, 1986). This is due to the additional information contained in the signal intensity and to the typically high hydrophone sampling rates which provide finer across-track resolution than is possible through beamforming. The resulting imagery displays the response of the seafloor to the acoustic pulse, which is a combination of the local topography as well as the bottom composition. Past efforts have attempted to provide methods for segmenting acoustic imagery into geoaoustic provinces via various image texture processing methods to allow automated classification of the seafloor (Reed IV and Hussong, 1989; Bourgeois and Walker, 1991). However, the process of generating imagery from the raw beamformed data filters at a low-pass rate and distorts the image, and full resolution acoustic imagery is too noisy for successful fine-scale segmentation. In this work analysis is performed on the returning energy, as a function of time, that has been angularly discriminated by beamforming. This approach allows analysis on data that have not suffered the additional generation of noise and introduction of smoothing that occurs when forming an image.

The data used are from the Navy's Sonar Array Survey System (SASS), and complete navigational information is not available; we do not have information as to the actual orientation of the sonar array from ping to ping. Since the data are not fully georeferenced, each ping's swath is processed individually. The results of the texture feature extraction for each ping is then appended, line by line, to form a multiband texture feature set. Parameters used for georeferencing can be used later to find accurate correspondences between seafloor location and bottom characteristics as computed from the texture analysis.

MULTIBEAM DATA PROCESSING

System Hardware

Multibeam bathymetric sonar systems such as SASS, the SeaBeam series, and the EM100 are capable of collecting data which, after proper processing, may be used to accurately map the bottom of the ocean. It is possible to obtain both bathymetry and sidescan-like images from the original raw data. Information about texture of the ocean's bottom may also be generated directly from this data.

For the SASS, the sonar energy from the projector array located on the hull of the survey ship impinges on the bottom of the ocean as a narrow beam perpendicular to the ship's heading. The echo from this swath is received by an array of hydrophones mounted athwartships (perpendicular to the projector) under the survey vessel. The beam width depends on the angle of arrival to the bottom and increases with increasing angle. The unsteered beam width is 0.7° at 45° it is 0.9°.

Data Processing

Processing starts by reading the raw data recorded by SASS during a survey mission. A detailed description of the original data is given by Bourgeois (1991) and one of the complete processing is given by Kaminsky et al. (1992). The beamforming process is done next by performing delay, filtering, and summing operations through the use of Fourier transforms. This yields an array of return intensities—an intensity for each beamformer bin and each sample time—allowing the returning energy to be resolved into angular bins. Each of the K beamformer bins k correspond to a particular steering angle $\phi_k$.

The beamformed data then give us a time history of the energy received from the K look directions. This data must be further processed to determine the time corresponding to the center of the beam, $t_c$. The peak of the envelope corresponds to the intersection of the maximum response axis (MRA) of the steered beam.
Spatial Gray Level Dependence Method is the most powerful method because of its ability to discriminate among a set of textures (Conners and Harlow, 1980). Mastin et al. used co-occurrence methods for SAR (synthetic aperture radar) imagery of water (Mastin et al., 1985). Consequently, we decided to use an analysis based on co-occurrence statistics because of the performance of the method and also the nature of the data acquisition (proper georeferencing information was not available). The data available to the authors do not allow georeferencing or even referencing between pings. Therefore, we only analyze the texture along the one-dimensional path of each ping.

**Co-Occurrence Statistics**

A histogram is an estimate of the first order statistics of an image (or a region). The normalized histogram is computed as

\[ P(i) = \frac{N(i)}{N}, \quad i = 0, 1, \ldots, 2^b - 1 \]  

where \( N(i) \) is the number of pixels in the image (region) with intensity value \( i \), \( N \) is the total number of pixels in the image (region), and \( b \) is the number of bits per pixel in the image.

The analog to the histogram for second order statistics is the co-occurrence matrix. The co-occurrence matrix is also computed in a "census" fashion by counting pairs of occurrences of pixels values given a certain spatial relationship for the pair. The normalized co-occurrence statistics are computed as

\[ P(i_1, i_2, d, \theta) = \frac{N(x_1, x_2)}{N}; |x_1 - x_2| = D(d, \theta) \]  

for pairs of pixels at locations \( x_1 \) and \( x_2 \) having values \( i_1 \) and \( i_2 \), respectively. The distance measure \( D(d, \theta) \) states that the spatial relationship of the pair of pixels is that they are located at a distance magnitude \( d \) apart and at an angle \( \theta \) (or \( \theta + \pi \)) from each other.

A complete set of co-occurrence statistics would cover all values of \( d \) and \( \theta \) over a meaningful range. The values for \( \theta \) would vary between 0 and \( \pi \) using some number of discrete steps. The values for \( d \) would range from 1 up to some distance where the correlation between pixels is still significant.

In practice, several co-occurrence matrices are computed for several pairs of \((d, \theta)\). Figure 1 shows several computed co-occurrence matrices for a simple example 2 bit/pixel image.

One of the disadvantages of the method of co-occurrence matrices is the potentially large amount of data computed for different pairs of \( d \) and \( \theta \). Only four of the many possible co-occurrence matrices are computed in Figure 1. However, co-occurrence statistics are powerful...
FIGURE 1. Sample co-occurrence calculations (Haralick and Shapiro, 1992).

<table>
<thead>
<tr>
<th>Gray Level</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
</tr>
<tr>
<td>1</td>
</tr>
<tr>
<td>2</td>
</tr>
<tr>
<td>3</td>
</tr>
</tbody>
</table>

\[
P_{\theta=0^\circ, d=1} = \frac{1}{16} \begin{pmatrix}
4 & 2 & 1 & 0 \\
2 & 4 & 0 & 0 \\
1 & 0 & 6 & 1 \\
0 & 1 & 1 & 2 \\
2 & 1 & 3 & 0 \\
1 & 2 & 1 & 0 \\
3 & 1 & 0 & 2 \\
0 & 0 & 2 & 0
\end{pmatrix}
\]

\[
P_{\theta=90^\circ, d=1} = \frac{1}{16} \begin{pmatrix}
6 & 0 & 2 & 0 \\
0 & 4 & 2 & 0 \\
2 & 2 & 2 & 2 \\
0 & 0 & 2 & 0 \\
4 & 1 & 0 & 0 \\
1 & 2 & 2 & 0 \\
0 & 2 & 4 & 1 \\
0 & 0 & 1 & 0
\end{pmatrix}
\]

\[
P_{\theta=135^\circ, d=1} = \frac{1}{16} \begin{pmatrix}
4 & 2 & 1 & 0 \\
2 & 4 & 0 & 0 \\
1 & 0 & 6 & 1 \\
0 & 1 & 1 & 2 \\
2 & 1 & 3 & 0 \\
1 & 2 & 1 & 0 \\
3 & 1 & 0 & 2 \\
0 & 0 & 2 & 0
\end{pmatrix}
\]

\[
P_{\theta=45^\circ, d=1} = \frac{1}{16} \begin{pmatrix}
6 & 0 & 2 & 0 \\
0 & 4 & 2 & 0 \\
2 & 2 & 2 & 2 \\
0 & 0 & 2 & 0 \\
4 & 1 & 0 & 0 \\
1 & 2 & 2 & 0 \\
0 & 2 & 4 & 1 \\
0 & 0 & 1 & 0
\end{pmatrix}
\]

In that they are invariant to monotonic intensity transformations (Haralick and Shapiro, 1992).

**Texture Features**

Texture features can then be computed from the co-occurrence matrices. Ballard and Brown (1982) suggest a set of five features, but a more comprehensive set of 14 features is given by Haralick et al. (1973). It is often not clear how these features relate to observable phenomena. However, they have been demonstrated to be useful in classifying images. Using the co-occurrence statistics, these 14 features are computed for each beamformer bin. In this application, only a co-occurrence matrix for \( d=1 \) and \( \theta=0 \) is computed. We keep \( \theta=0 \) since the pings are not georeferenced. The distance \( d \) is kept small since we expect the primitives to be relatively small. However, we can still compute more sets of these features for various values of \( d \), but \( d=1 \) for initial results.

We will follow the notation used in Haralick et al. (1973):

- \( p(i,j) \) is the \((i,j)^{th}\) entry in the normalized co-occurrence matrix, \( p(i) \) is the \( i^{th} \) entry in the marginal-probability matrix obtained by summing the rows of co-occurrence matrix,

- \( N_g \) is the number of gray levels in the image,

- \( p_y(k) = \sum_{i=1}^{N_g} \sum_{j=1}^{N_g} p(i,j), k = i+j = 2, 3, \ldots, 2N_g \),

- \( p_{x,y}(k) = \sum_{i=1}^{N_g} \sum_{j=1}^{N_g} p(i,j), k = |i-j| = 0, 1, \ldots, N_g - 1 \),

- \( \epsilon \) is a small constant to prevent taking the log of zero.

The features computed are as follows:

1. **Angular second moment**: a measure of homogeneity of the image,

\[
f_1 = \sum_{i=1}^{N_g} \sum_{j=1}^{N_g} [p(i,j)]^2.
\]

2. **Contrast**: a measure of the contrast or the amount of local variations present,

\[
f_2 = \sum_{i=1}^{N_g} \sum_{n=0}^{N_g-1} \sum_{m=0}^{N_g-1} p(i,j) \epsilon^{-|i-j|}.
\]

3. **Correlation**: a measure of intensity linear dependencies in the image,

\[
f_3 = \sum_{i=1}^{N_g} \sum_{j=1}^{N_g} \frac{\sum_{x=-N_x}^{N_x} \sum_{y=-N_y}^{N_y} (i-x)(j-y) p(i,j)}{\sigma_x \sigma_y}
\]

where \( \mu_x, \mu_y, \sigma_x, \sigma_y \) are the means and standard deviations of \( p_x \) and \( p_y \).
4. sum of squares variance: a measure of the variation in the image,
\[ f_1 = \sum_{i=1}^{N} \sum_{j=1}^{N} (i - \mu)^2 p(i,j). \] (6)
5. inverse difference moment:
\[ f_5 = \sum_{i=1}^{N} \sum_{j=1}^{N} \frac{1}{1 + (i-j)^2} p(i,j). \] (7)
6. sum average:
\[ f_6 = \sum_{i=1}^{2N} sp_{xy}(i). \] (8)
7. sum variance:
\[ f_7 = \sum_{i=1}^{2N} (i-f)^2 p_{xy}(i). \] (9)
8. sum entropy:
\[ f_8 = -\sum_{i=2}^{2N} p_{xy}(i) \log \{ p_{xy}(i) + \epsilon \}. \] (10)
9. entropy:
\[ f_9 = -\sum_{i=1}^{N} \sum_{j=1}^{N} p(i,j) \log \{ p(i,j) + \epsilon \}. \] (11)
10. difference variance:
\[ f_{10} = \text{variance of } p_{xy}. \] (12)
11. difference entropy:
\[ f_{11} = -\sum_{i=0}^{N-1} p_{xy}(i) \log \{ p_{xy}(i) + \epsilon \}. \] (13)
12. information measure of correlation 1: for this and the next feature, \( HX \) and \( HY \) are the entropies of \( p_x \) and \( p_y \), respectively and
\[ HXY = -\sum_{i=1}^{N} \sum_{j=1}^{N} p(i,j) \log \{ p(i,j) + \epsilon \}, \]
\[ HXY1 = -\sum_{i=1}^{N} \sum_{j=1}^{N} p(i,j) \log \{ p_x(i)p_y(j) + \epsilon \}, \]
\[ HXY2 = -\sum_{i=1}^{N} \sum_{j=1}^{N} p_x(i)p_y(j) \log \{ p_x(i)p_y(j) + \epsilon \}. \]
\[ f_{12} = \frac{HYX - HXY1}{\max[HX, HY]}. \] (14)
13. information measure of correlation 2:
\[ f_{13} = (1 - \exp[-2.0(HXY2 - HXY)])^{12}. \] (15)
14. maximum correlation coefficient:
\[ f_{14} = (\text{Second largest eigenvalue of } Q)^{12}, \] (16)
where,
\[ Q(i,j) = \sum_{k} p(i,j)p_x(j) \sum_{k} p_x(i)p_y(k). \]

These features are computed for each ping along all 256 bins. Actual processing leaves off approximately 30 bins on each end since these represent "near horizontal" directions that produce no useful return information and are mostly noise. Also bins with "dropout" features have been discarded. We know that some pings are missing and that the ones we have are not necessarily parallel to each other. Due to lack of positioning data, we display pings (rows in the image) as if they were parallel to one another. Thus, the features computed for each ping are appended to one another forming 14 "texture feature images" that form the multidimensional feature set.

**DATA REDUCTION**

It is difficult to interpret large data sets. Therefore, if we can reduce the amount of output to the essentially "useful part" of the data, the reduction will make it easier to manipulate the data and interpret it.

Data reduction is also performed on the multidimensional texture data itself (Kaminsky et al., 1992). However, in this case we are concerned with the reduction of the output from the texture analysis.

We have a fourteen-dimensional feature set that was produced from the texture analysis. We cannot just indiscriminately throw away some of the texture features since we do not know which ones will be useful in the characterization of the seafloor bottom. In order to pull out only the most useful features, we need to find the principal components of the feature space. This will give us a feature space where each of the new "features" are decorrelated. Also, the importance of each new feature basically corresponds to the relative size of its associated eigenvalue. So, we now also have a way of distinguishing those components with the greatest information content.

**Principal Components**

The feature space is currently fourteen-dimensional. We can reduce the dimensionality of the feature space significantly by first transforming the data into a new feature space (still of the same dimensionality). This new feature space should be one in which the data between the features is uncorrelated and also one in which most of the "useful information" is contained in just a few of those features. The Hotelling transform (the discrete formulation of the Karhunen-Loève transform) is used in this case to achieve the principal components of the feature space. Unlike many other transformations, the Hotelling transform is data dependent.

The Hotelling transform is computed as follows (Gonzalez and Woods, 1992). Consider a
multispectral image consisting of n bands of size \( N \times N \). We form the column vector

\[ x = [x_1, x_2, \ldots, x_n]' \]  

(17)

for each pixel in the image. Therefore, each location in the image is a vector \( x \) consisting of the \( n \) pixel values from each of the \( n \) bands at that particular location. There are \( N^2 \) such vectors in the multispectral image. The mean vector and covariance matrix of \( x \) are defined as

\[ m_x = E[x] \]  

(18)

and

\[ C_x = E[(x - m_x)(x - m_x)'] \]  

(19)

We can estimate both of these statistics using

\[ \hat{m}_x = \frac{1}{N^2} \sum_k x_k \]  

(20)

and

\[ \hat{C}_x = \frac{1}{N^2} \sum_{k=1}^{N^2} x_k x_k' - m_x m_x'. \]  

(21)

Once we have calculated these statistics from the multispectral data, we compute the Hotelling transform using the equation

\[ y = A(x - m_x) \]  

(22)

where \( A \) is the matrix formed from a sorted set of eigenvectors of the covariance matrix \( C_x \).

From this we see two important properties:

1. the transformed data \( y \) has zero mean. That is,

\[ m_y = E[y] = 0 \]  

(23)

2. and that the data are decorrelated

\[ C_y = E[(y - m_y)(y - m_y)'] = A C_x A' \]  

(24)

which is a diagonal matrix. The matrix \( A \) is composed of the eigenvectors of \( C_x \) and it will thus diagonalize it. Therefore, the diagonal elements of the covariance matrix of the transformed data are nothing more than the set of eigenvalues:

\[ C_y = \begin{bmatrix} \lambda_1 & & \\ & \lambda_2 & \\ & & \lambda_3 \\ & & & \ddots \\ & & & & \lambda_n \end{bmatrix} \]  

(25)

Assuming that the eigenvalues are sorted from highest to lowest (and the matrix of eigenvectors is correspondingly sorted), then the set of principal components as given in (22) will be sorted so that the first component is the component with the highest variance, the second component is the component with the second highest variance, and so on. We can reconstruct the original set of vectors \( x \) using

\[ x = A^{-1}y + m_x = A'y + m_x \]  

(26)

We note that \( A^{-1} = A' \) since the matrix is orthonormal. In any case, suppose we decide that the principal components associated with the lowest eigenvalues were of little use. This is often true since the magnitude of the smaller eigenvalues are negligible when compared with the others. Therefore, the images associated with these lowest eigenvalues have relatively small variance, that is, there is relatively little useful information contained in these components. We can reduce the dimensionality of the feature space by discarding these components. Suppose we want to keep \( K \) of the \( n \) components, thus reducing our feature space to only \( K \)-dimensional instead of \( n \)-dimensional. We can do this by forming a matrix \( A_K \) composed of the \( K \) eigenvectors corresponding to the \( K \) largest eigenvalues. We can alter (26) to form approximations of the original data as

\[ \hat{x} = A_K'y + m_x. \]  

(27)

The mean square error between \( x \) and \( \hat{x} \) is

\[ e_{ma} = \sum_{j=1}^{n} \lambda_j \sum_{j'=1}^{K} \lambda_{j'} \]  

(28)

The Hotelling transform is optimal for minimizing the quantity \( e_{ma} \) (Gonzalez and Woods, 1992).

For the purposes of feature extraction, we can loosely interpret this method as a means to

1. find a new set of features (the principal components), such that these features are decorrelated and have a "measure of relative importance" associated with them, and
2. reduce the dimensionality of the feature space providing data compression.

RESULTS

Figures 2 through 5 show the first four principal components. The contrast has been improved so that the characteristics of the features are more visible. The horizontal band across the center of each feature corresponds to the nadir and near-nadir (almost vertical) beam steering angles. This band represents a uniform texture which is expected for this region since, at high incident angles, the acoustic return is largely due to specular reflection instead of backscatter. The returning pulse will typically be relatively smooth for high angles, and a texture measure of this sort will not reveal interesting
features until the acoustic return is predominately non-specular.

It is evident from these features that there are regions with similar texture characteristics. The texture is computed from the backscatter returns and represents spatial relationships of the way in which the backscatter varies along the pings. Thus, regions with similar features represent regions of similar acoustical backscattering properties. The acoustical
boundaries are the locations of significant transition between acoustical properties.

Figure 6 (see the outside back cover of this issue) shows the first principal component (the one with the most variance) mapped to a terrain obtained from the bathymetric data. The center band running through the middle represents the nadir and near-nadir positions as explained earlier.

CONCLUSION

The texture analysis provides a description of the directional backscatter returns using second order statistical properties and is a useful measure. This is especially useful even for non-calibrated systems. Regions of homogeneous acoustical properties are brought out through this texture analysis. Variations in backscatter are due to changes in bottom types, surface orientation, and roughness. Due to the method used in this analysis the effect of orientation is reduced and, assuming a small enough acoustic footprint, the bottom type may be considered homogeneous. Thus these texture measures provide an indication of micro-roughness (i.e., the small-scale surface roughness that exists below the resolution of the resolvable bathymetry).

Clearly, proper georeferencing information would improve the results so that a more accurate classification of the acoustical properties and the corresponding bottom location would result. Thus, the texture analysis contributes and plays an important role in seafloor bottom classification and mapping. In addition, work is currently being performed at Tulane University and the Naval Research Laboratory to classify the acoustical properties using neural models trained by the texture features.

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