Region-Growing Techniques Based on Texture for Provincing the Ocean Floor

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Abstract - Categorization of areas of the ocean floor is referred to as provincing. Identification of these provinces is needed for military tasks, geological studies, environmental studies etc. Side scan sonar provides a mechanism to obtain gray scale images of the ocean floor. Automated processing of these images to find interesting textural features may be accomplished by computing co-occurrence matrices of groups of adjacent pixels and computing textural features from these matrices. The grouping of pixels may be done using fixed size rectangular texels or by building irregular shaped regions from small groups of pixels. A comparison of the two methods applied to sonar images has shown that the region growing approach is successful at identifying sand waves in irregular shaped regions.

1. Introduction
Provincing the ocean floor is an ongoing process. Side-scan sonar can be used to collect gray scale images of the ocean floor. These images are then processed manually by trained geologists, and color-maps are constructed by the geologists that identify regions of the ocean floor of similar visual texture.

Knowledge discovery in databases (KDD) is the process of extracting non-trivial patterns from large amounts of data through the use of software that is closely monitored by human experts. The work described in this paper is part of a project in which knowledge discovery techniques are being applied to the task of provincing the ocean floor. This paper describes techniques based on textural analysis that may be used to aid the geologist in provincing the ocean floor. Specifically, the initial task of this system is to identify provinces characterized by sand-waves. Two basic approaches are investigated to accomplish this goal. Both approaches use a Gray Level Co-occurrence Matrix (GLCM) [4] and are discussed in Hodges et al. [3]. The first technique establishes fixed rectangular regions of pixels called texels, and uses these texels as the basic building block to develop co-occurrence matrices. The second technique grows irregular regions from similar groups of pixels (called cells). These cells are much smaller than the texels used in the first technique but the regions may be significantly larger. The region is then used as the basis for the computation of the Gray Level Co-occurrence Matrix. In both cases, each GLCM has five different transformations [4] applied, generating five different features from each of four different angles for a total of 20 features. The regions are then classified using AutoClass [1]; an unsupervised learning system based on Bayesian probabilities.

2. Data
The images used in the experiments are part of a research project in collaboration with the Naval Oceanographic Office at the Stennis Space Center. The specific images used for this paper were obtained through a contract with non-military consultants. The images are stored in a format that is specific for the software (UNISIPS) developed at the Stennis Space Center. The images are 4000 pixel rows by 1799 pixel columns where each of the pixel’s dimensions is 0.1 meter.

3. Grouping Techniques
The topological grouping of the pixels distinguishes the two techniques addressed by this paper. The first technique builds GLCMs from rectangular groups of pixels called texels. The size of the rectangles that were chosen for experiments associated with this paper are 35 by 35.

The second technique grows irregularly shaped regions, which in turn are used to compute the GLCMs. These regions are grown from small rectangular groups of cells (2 by 16 for this experiment). Although the cells are much smaller than texels, the regions defined by these cells may be significantly larger than texels. In the region growing process every cell is classified as either a boundary cell or a region cell. Region cells are those that are relatively homogeneous in texture. The homogeneity of a cell is determined by comparing the ratio of the standard deviation to the mean with a threshold value chosen by a user. A homogeneous cell (classifying the cell as a region cell) will have a low ratio. The cells that do not qualify as region cells are called boundary cells. Boundary cells do not participate in the region growing process or any future
classification procedures. The cells that qualify for region status may be annexed to an adjacent region or may begin a new region. The potential regions available for joining are identified by cells that are located (see Figure 1) to the (1) left (west), (2) above and left (northwest), (3) above (north), and (4) above and right (northeast). All of the cells listed (which could all be one region) have already been processed by the time the current cell is inspected. If the mean of the current cell differs from the means of the regions of the cells being considered, it becomes the first cell in of a new region. Otherwise, it is annexed to the adjacent region of the most similar mean. A sample result of the region growing process is pictured in Figure 2. In this figure, all cells of the same pattern are considered part of one region. The blank cells are boundary cells that do not fit into any region.

4. Computation of GLCMs
There are four GLCMs computed for each texel (or region) by changing the angle used to identify adjacent pixels (0, 45, 90, and 135 degrees). The GLCMs are square matrices that contain counts of occurrences of specific adjacent values. The dimension of the matrix is determined by the maximum value of the pixels in the texels or regions. Large GLCMs would contain very little information. To compensate for this, the pixel values are normalized to either 16 or 32, resulting in dimensions of 16*16 or 32*32 for the GLCMs. An example of computing a GLCM is shown in Figure 3. This example uses 0 degrees rotation, so only pixels to the left and right participate in the computation. In Figure 3, all pixel values have been normalized to 4 (0..3), so the GLCM is a 4 by 4 square. The

5. Computation of Features
The computation of attributes to represent textual features include five the computations outlined in Reed and Hussong [1] for each of the GLCMs, along with the standard deviation and mean for each region or texel. There are four GLCMs computed for each region or texel giving a total of 20 features computed from GLCMs and two more features computed from the pixels (standard deviation and mean). In the following equations: S is the GLCM, R is a normalization factor described later, Ng is the dimension of the square GLCM matrix. The five attribute computations are:

Angular Second Moment $ASM = \sum_{i=1}^{N_x} \sum_{j=1}^{N_y} \left( \frac{S(i, j)}{R} \right)^2$

Contrast $CON = \sum_{n=0}^{N_x-1} n^2 \left( \sum_{i=1}^{N_x} \sum_{j=1}^{N_y} \frac{S(i, j)}{R} \right)$

$|i - j| = n$

Entropy $ENT = -\sum_{i=1}^{N_x} \sum_{j=1}^{N_y} \frac{S(i, j)}{R} \log \left( \frac{S(i, j)}{R} \right)$
Angular Inverse Difference Moment

$$AIDM = \sum_{i=1}^{N_x} \sum_{j=1}^{N_y} \frac{S(i,j)}{((1 + (i - j)^2) \times R)}$$

Correlation

$$COR = \frac{\sum_{i=1}^{N_x} \sum_{j=1}^{N_y} (i \times j) \times S(i,j)}{R - \mu_x \mu_y}$$

where $\mu_x$ and $\mu_y$ represent the means of the rows and columns, respectively; $\sigma_x$ and $\sigma_y$ are the standard deviations of the rows and columns, respectively; and R is a normalization factor. The normalization factor is the count of adjacent pixels used in the creation of the GLCM. For texels, this count is defined for each of the rotations as follows:

Normalization Factor for Texels

- $R_0 = 2N_y(N_x - 1)$
- $R_{90} = 2N_x(N_y - 1)$
- $R_{45} = R_{135} = 2(N_y - 1)(N_x - 1)$

The normalization factor is twice the number of pixels less the border elements that can not be matched with another pixel going in the direction to get to the border. For the region growing, you count the number of pixels in the region, then subtract the number of cells on the border of the direction of the counting. To compute the normalization for diagonals, start with the total number of cells then subtract the number of cells on borders, but add back two for each upper left (or upper right) corner and two for each upper left corner (or upper right if 135 degree rotation) that is connected on this corner but not on the left or above.

6. Clustering

The objective is to put regions or texels that have similar textures into the same class. A vector of features as discussed above represents each region (or texel). These feature vectors are input to AutoClass, an unsupervised Bayesian classification system [1]. The results of AutoClass include the instance number along with the class associated with, if the pixel falls within a region, or b) the color assigned to the cluster the region is associated with, if the pixel falls within a region. In step 1, the colors are assigned to the cluster by calculating the average pixel value for each cluster; sorting these clusters by this average, and assigning gray levels in ascending values equally distributed over the range 0..255.

Conversion of the UNISIPS images to *.pgm images were accomplished with specialized conversion programs. After converting the images to “*.pgm” files, “xv” was used to view and print the images.

8. Results And Conclusions

The first step of the process described in this paper builds GLCMs from an image consisting of gray scale pixels. Next, features are computed from these GLCMs for each for each region or texel and placed in a feature vector and this vector is referred to as an instance. These instances are then categorized using an unsupervised learning system called AutoClass. The results from AutoClass are mapped into an image that is a modified duplicate of the original but with the pixel color chosen from: a) the original, if the pixel is not within a region, or b) the color assigned to the cluster the region is associated with, if the pixel falls within a region. In step 1, the colors are assigned to the cluster by calculating the average pixel value for each cluster; sorting these clusters by this average, and assigning gray levels in ascending values equally distributed over the range 0..255.

The visualization of the results are accomplished by mapping each of the original regions (or texels) to a cluster (produced in the classification step) and giving each pixel in this region (or texel) a color associated with this cluster. This resulting image is in the same format as the original image, so the same software (UNISIPS) can view it as the original image. This mapping process consists of two steps. The first step is to reorganize the data produced by the classification step while accumulating statistics to determine the color appropriate for each cluster. Then an image is built that is a duplicate of the original but with the pixel color chosen from: a) the original, if the pixel is not within a region, or b) the color assigned to the cluster the region is associated with, if the pixel falls within a region. In step 1, the colors are assigned to the cluster by calculating the average pixel value for each cluster; sorting these clusters by this average, and assigning gray levels in ascending values equally distributed over the range 0..255.

Finally, these images are viewed simultaneously for visual inspection of the results.

This stage of the project is concentrating on the identification of provinces characterized by sand-waves. The visual inspection shows the provinces identified by both techniques correlate very well to the identification of sand waves in the original image. The images shown in Figure 4 give an example original image, the image clustered using texels, and the image clustered using regions. The lightest colored regions in the classified images correspond to provinces consisting of sand waves.

The texel approach is relatively easy to implement and visualize. Although this approach can identify provinces containing sand waves, the results are not smooth, in addition you have a large number of instances that must be processed by the clustering system. The region growing approach is significantly more complicated to implement...
and has much more overhead managing the cells and there relationship to regions. This approach has the benefit of giving a smaller number instances, thereby reducing the time required for clustering. The region growing technique has the added benefit of following the original contours more closely since regions of sand-waves on the ocean floor generally have an irregular shape. The number and shape of these regions correspond closely to those identified by the oceanographers.

This success is the first step in the overall project of building a tool that should save the geologist time in the provincial of the ocean floor. There are several directions in which to advance from the current status of the project. The first is a refinement in the identification of the sand-waves. This would include information about direction, height, and frequency of the sand-waves. The second direction involves looking at the areas that are not sand-waves and identifying an additional useful texture. A third direction involves the use of an object oriented data base management system. This would allow the collection, storage, and retrieval of data from multiple sources (including the results of AutoClass) thus allowing data mining techniques to be applied to a wider range of existing informational attributes.

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References


Figure 4. a) Side-scan sonar image, b) texture classification based on texels, c) texture classification based on region-growing