SEGMENTATION OF SONAR IMAGES


detection from the background whereas multilevel thresholding is exercised to detect multi regions.

II. LITERATURE REVIEW

Acoustic waves are the basis of SONAR (Sound Navigation and Ranging). High frequency SONARs provide images of underwater areas. These images are not always easy to interpret, because of their nature and the complex process involved during the reflection of the acoustic wave on the seafloor. These images are important for much practical applications like marine geology, oil exploration, commercial fishing, mine detection etc[6].

Acoustic remote sensing is the only means to map and study the surface morphology of the seafloor at all depths. Side scan sonar (SSS) is effective tool for high resolution mapping of the seabed. Most of the energy arriving on the seafloor is scattered forward in specular direction. A small portion is lost in the ground, and a small portion is scattered back to the sonar, amplified and recorded.

The time-shift between the transmission and reception is directly proportional to distance between the sensor and its target. The frequency shift indicates the speed of the target relative to sensor.

III. PROPOSED WORK

The images obtained from Side scan Sonar are complex in nature. They can identify three types of regions: acoustical highlight, shadow and seafloor reverberation. The highlight area originates from acoustical wave reflection, whereas the shadow zone is due to lack of wave reverberation from the object. The remaining areas consist of seafloor reverberation. The seafloor reverberation contains large amount of speckle noise. Hence the images are to be preprocessed before segmentation process.

A. Preprocessing

The raw sonar image is preprocessed before any further techniques are applied. The two major processing techniques are filtering and enhancement. The sonar images are subjected to noise due to seafloor reverberation. The speckle noise produced from reverberation can be removed using the median filter. The median filter has excellent noise reduction capabilities with less blurring. Median filters are order-statistic (non-linear) filter, these are spatial filters, whose response is based on ordering the pixels contained in the image area encompassed by the filter and replacing the center pixel value determined by ranking result.

To improve the filtering process to obtain better image one can apply wiener filter and then apply median filter. In the wiener filter, the image and noise are considered as random variables. Here the degradation and statistical characteristics of the noise is considered. The main objective is to find the estimate of the uncorrupted image f, such that the mean square error (MSE) is minimized.

\[ e^2 = E[(f - \hat{f})^2] \]

\[ F(u, v) = \left[ \frac{1}{|H(u, v)|} \frac{|H(u, v)|^2}{|H(u, v)|^2 + \frac{\partial^2 |H(u, v)|}{\partial u \partial v}} \right] g(u, v) \]
H(u,v): Degradation function
\[ H(u,v) = \text{complex conjugate of } H(u,v) \]
\[ |H(u,v)|^2 = |H(u,v)^*|^2 \]
\[ S_j(u,v) = \left| N(u,v) \right|^2 \]
\[ S_j(u,v) = \left| F(u,v) \right|^2 \]

A GLCM is a matrix where the number of rows and columns is equal to the number of gray levels, G, in the image. The matrix element \( P(i,j | d, \omega) \) represents the relative frequency with two pixels separated by a pixel distance \((\Delta x, \Delta y)\), occur within a given neighborhood, one with intensity ‘i’ and the other with intensity ‘j’. The matrix element \( P(i,j | d, \omega) \) contains the second order statistical probability values for changes between gray levels ‘i’ and ‘j’ at a particular displacement distance \( d \) and at a particular angle \((\omega)\). Using a large number of intensity levels \( G \) implies storing a lot of temporary data, i.e. a \( G \times G \) matrix for each combination of \((\Delta x, \Delta y)\) or \((d, \omega)\). Due to their large dimensionality, the GLCM’s are very sensitive to the size of the texture samples on which they are estimated. Thus, the number of gray levels is often reduced.

Gray Level Co-occurrence Matrix (GLCM) has proved to be a popular statistical method of extracting textural feature from images. According to co-occurrence matrix, Haralick defines fourteen textural features measured from the probability matrix to extract the characteristics of texture statistics of remote sensing images. In this paper four important features, contrast, correlation, energy and homogeneity are implemented[4].

The formulas for computing four statics are as follows

<table>
<thead>
<tr>
<th>Static</th>
<th>Formula</th>
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<tbody>
<tr>
<td>Contrast</td>
<td>[ \sum_{i=1}^{L} \sum_{j=1}^{L} \sum_{n=1}^{n^2} P(i,j) ]</td>
</tr>
<tr>
<td>Correlation</td>
<td>[ \sum_{i=1}^{L} \sum_{j=1}^{L} \frac{ijP(i,j) - \mu_1\mu_2}{\sigma_1^2\sigma_2^2} ]</td>
</tr>
<tr>
<td>Energy</td>
<td>[ \sum_{i=1}^{L} \sum_{j=1}^{L} P(i,j)^2 ]</td>
</tr>
<tr>
<td>Homogeneity</td>
<td>[ \sum_{i=1}^{L} \sum_{j=1}^{L}</td>
</tr>
</tbody>
</table>

Where \( \mu_1, \mu_2 \) are mean values and \( \sigma_1^2, \sigma_2^2 \) are variances.

Contrast: The intensity between a pixel and its neighbour is determined over an entire image. It is known that the similar values of pixels in observation results in low contrast causing a poor dissemination of boundaries between features. It represents the clarity of the textures.

Correlation: It brings out how correlated a reference pixel is to its neighbor over an image. It is uncorrelated to energy, contrast and homogeneity. The correlation measurement considers the mean and standard deviation for row and column in the matrix. It measures the linear dependence of the gray level of the neighbourhood.

Energy: This infers that maximum constant values or periodic uniformity in gray level distribution will form maximum energy of texture. Clear domain of group of textures is deciphered on account of higher value in energy measure. It represents the uniformity of distribution of gray levels in the image.
Homogeneity: The closeness of gray levels in the spatial distribution over image is inferred by homogeneity. Homogeneous textured image is comprised of limited range of gray levels and hence, the GLCM image exhibits a few values with relatively high probability.

Roundness: Measure of how closely the shape of an object approaches that of a circle.

Roundness is dominated by the shape's gross features rather than the definition of its edges and corners, or the surface roughness of a manufactured object. Roundness of an object can be determined using the formula:

\[ \text{Roundness} = \frac{4 \cdot \text{Area} \cdot \pi}{(\text{Perimeter})^2} \]

C. Classification

The classification process used here is the nearest neighbor classification method. Nearest neighbor algorithm is a method for classifying objects based on closest training examples in the feature space. This algorithm is among the simplest of all machine learning algorithms. Training process for this algorithm only consists of storing feature vectors and labels of the training images. In the classification process, the unlabelled query point is simply assigned to the label of its k nearest neighbors [8]. Typically the object is classified based on the labels of its k nearest neighbors by majority vote. If k=1, the object is simply classified as the class of the object nearest to it [9]. After the image is converted to a vector of fixed-length with real numbers, the most common distance function for KNN which is Euclidean distance is used:

\[ d(X, Y) = \sum_{i=1}^{m} ((w_i(x_i - w_i y_i)^2))^{1/2} \]

where X represents the feature vectors of the trained images and Y represents the feature vector of the test image and w represents the weights.

IV. RESULTS
Fig (a) and 9c) represent the original training and testing image and (b) and (d) represent the respective output images

CONCLUSION

In this paper, a segmentation based on nearest neighbors is implemented. The experiment results show that the proposed method can get satisfactory segmentation results

REFERENCES


