

## VARIOUS SONAR IMAGE ANALYSIS TECHNIQUES FOR UNDERWATER OBJECT DETECTION

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**Abstract:** The development in seafloor imaging towards using several sonar sensors with improved resolution has resulted in better-quality degree data sets. As a significance, users need enhanced, more capable tools for data processing and interpretation. This manuscript describes two data processing tools useful for underwater object detection using sonar images. All have been validated on real data and all are TEI application products. The applications support automatic object detection, automatic sea-floor classification, and sonar patch tests using backscatter information.

**Keywords:** TEI, , automatic sea-floor classification, sonar patch tests, backscatter information.

### I. INTRODUCTION

As the resolution of sonar sensors increases, the volume of acquired data increases. Immediate with increased data volumes is the requirement for efficient, automatic processing of such data sets to aid our interpretation and understanding of survey areas. Image processing tools provide some useful solutions. A basic example is the image mosaic where the geo coded view leads to a better sonar image interpretation. This manuscript illustrates the use of dealing out techniques originating in the image processing pasture for two different sonar applications. As a commercial product, the goal was not to develop new processing methods but rather to optimize several classical image tools into an efficient, adaptive, and minimally complex software product.

### II. OBJECT DETECTION

#### A.PURPOSE

When an object is lying on the seafloor, two major pieces of information can be observed on the sonar image: the echo of the object and its outline. Echoes are high-level signals reflected to the sonar when the sonar's incident beam hits the object. Shadows exist in the area at the back the object where no image occurs (i.e., the area from which no power returns to the sonar). The length of the shadow is a function of the object height above the seabed and the beam-grazing angle.

The purpose of additional processing is to automatically detect echo and shadow regions that are properties of objects. Here, there is no recognition process; we only take into account sonar basic principles to locate targets. Thus targets can be rocks, wrecks, or man-made objects.

probable applications of such a tool comprise object searching (e.g., wrecks, containers, mines), pipeline inspection, obstacle evasion from forward-looking sonar's, and AUV navigation aiding through comparison of information extracted from a side scan sonar with the

location of known features in a database .

#### B.PROCESSING CHAIN

Object detection requires several image processing stages, each of which must be optimized to achieve real-time processing capabilities (Fig. 1). One key component of our optimization efforts was to implement a ping-by-ping treatment of the data. In other words, the processing algorithms do not take an image as input but rather handle each ping alone. A second key optimization point is the detection efficiency in various configurations. We compared more than a few methods to assess the best trade-off between product complexity and adaptively.

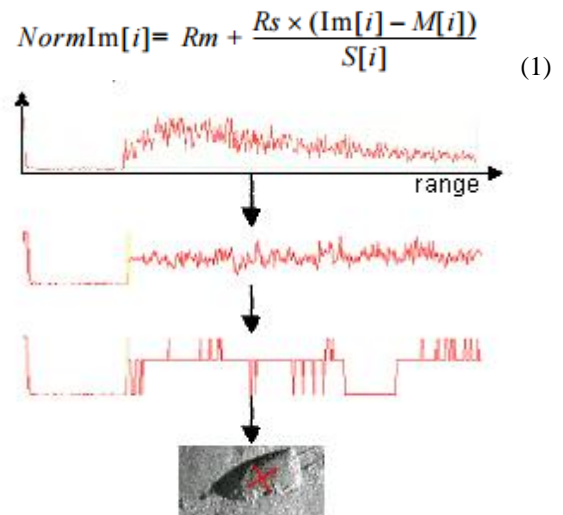


Fig 1. Object detection processing chain

**Despeckling:** The despeckle step reduces the noise level. Despeckling is a low-pass filter realistic either in the spatial or frequency domain.

**Range Normalization:** Range normalization is a signal amplitude correction designed to conserve the across-track signal dynamic. Because of attenuation in the water column, signal amplitudes decrease with time or distance from the sonar. Consequently, a processing step such as segmentation that is tuned on signal level at the beginning of the swath becomes more ineffective for farther ranges. Range normalization improves the efficiency of the process across the entire signal range. The planned normalization uses the second order statistics of the signal (mean, deviation). Let  $M[i]$  and  $S[i]$  be the local mean and local deviation of the signal at the range number  $i$ . Assume two constant values  $R_s$  and  $R_m$ . Then the normalized pixel at range  $i$  is given by (1). As a result, the normalized signal tends to follow the

reference mean,  $R_m$ , and the reference deviation,  $R_s$ , throughout the ping range.

**Segmentation:** Many segmentation techniques exist. Two analyzed for this project included histogram thresholding [2,3] and fuzzy segmentation [4]. Histogram thresholding is good for defining the gray level borders between regions, whereas fuzzy segmentation has proven to be capable for sonar images.

Segmentation consists of assigning a class type to each pixel. Class types for this application were echo, shadow, or reverberation. Segmentation is one of the most important steps of the processing chain because it results in an important loss of image information. Our tests showed that the main problem was obtaining an efficient segmentation for both large and small shadow regions; this problem was best addressed by the histogram thresholding method.

**Object Detection:** The last step for object detection is image description in terms of regions. At the segmentation step, only individual pixel in sequence is available (each pixel has been assigned to a class). This local information must be grouped in some fashion to lead to a more regional description. The grouping is done by a connected component analysis. The purpose of the connected component analysis is to merge the segmentation classification from two successive pings to gradually create and update regions of the image.

Object detection is based on a region association which aims at identifying possible objects as an echo-shadow pair. The organization adheres to some basic sonar image rules: i.e., shadow and echo regions are not too small, they are close to each other, shadow is behind echo, and shadow and echo are aligned. Those criteria validate some segmented regions as possible objects.

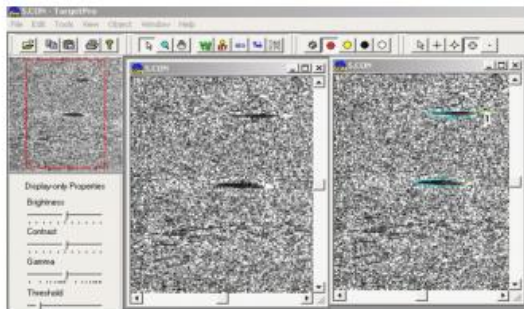


Fig. 2. Automatic object detection with TargetPr

### III. SEAFLOOR CLASSIFICATION

Seafloor classification (SFC) is another automated process based on classical image processing tools. SFC aims at separating different seabed types (e.g., sand, rock, pebble, mud) through texture analysis of mosaicked sonar images. Texture can result from one or several motifs repeated on a regular basis and is characterized by some homogeneity criterion. In other words, texture is a region where some statistical or structural properties are constant or change slowly. Two steps are generally required for texture analysis: information extraction and classification. Information elimination involves the computation of a characterization measurement (e.g., statistical property) from an image sub-area defined as a textel. cataloging then interprets those

dimensions and assigns a class type to the image textel. This operation, repeated on each image textel, leads to an image description in term of regions. In the purpose developed by TEI, information extraction is derived from co-occurrence matrices, and classification involves a neural network.

#### A. Information Extraction

In this first step the idea is to extract sub-areas with features relevant to the regions we intend to separate. Those features distinguish texture regions. In general, the classification algorithms work better and region identification is more accurate as the number of representative sub- areas selected increases. The textel detection schemes examined for this project included fractal dimensions, frequency analysis, and co-occurrence matrices. Fractals have received considerable attention in the field of underwater sediment characterization and sonar image analysis because of their ability to synthesize natural landscapes [5]. However, while a fractal dimension can quantify seabed roughness, it suffers from a lack of stability and is irrelevant as a unique feature for texture segmentation. Frequency analysis of type-regions proved to be efficient for sea-bed ripple detection [6] but was less successful for other bottom types. One foremost statistical representation for texture is the gray level co-occurrence matrix. Co-occurrence matrices estimate the joint probability density of the gray-level of two pixels separated by a given displacement  $D$  [7]. In other words, a co-occurrence matrix  $M$  is a  $n \times n$  array ( $n$  is the number of image gray levels) where each value  $M(i,j)$  represents the probability to find a pixel of level  $i$  and a pixel of level  $j$  separated by a displacement  $D$ . Many displacements can be used to generate several matrices. As a product of those matrices, Haralick proposed to compute several statistics that quantify some visual properties of textures. Those statistics include maximum probability, homogeneity, entropy, contrast, and correlation .

#### B. Classification

After information extraction and defining of textel properties, the classification step associates a region label (sand, rock, etc.) to each textel as described by its set of features. The TEI seabed classification application uses a multilayer perception neural network because it is robust and it possesses learning capabilities. Other classification tools examined during this project are summarized in.

Two modes characterize a perception neural network:

- A learning mode where the neural network tunes its own parameters. A “teacher” supervises this stage, providing the network with the solution to find for a given set of input features.
- Once the network has turned the identification parameters, it can perform classification tasks. For each input set of features, a class is assigned that represents the texture type.

#### C. Implementation

As noted above, TEI has developed and tested an automated SFC module. The SFC module uses mosaicked images (DDS\_VIF format) and produces an output vector file (DXF format) of the resultant region boundaries.

The information extraction step generates 44 parameters from co-occurrence matrices computed over four directions (0°, 45°, 90°, 135°). These multiple matrices enhance the robustness of the textel classifications through changing orientation. The neural network is a three-layer perception: the input layer uses the 44 computed parameters, the hidden layer has 50 nodes, and the output layer size depends on the number of regions requiring classification. The network learning stage is performed by a back-propagation algorithm. An intuitive GUI exists for assisting the user in selecting representative texture regions and for general SFC management. The network is built by selecting delegate regions or samples for each seabed type across a mosaicked survey area. Each selected sample is assigned to a seabed type or texture name (up to eight different textures can be classified). Sample size is user-definable. After all type regions have been selected, the classification parameters are computed. These parameters can be saved in a file or recomputed after adding or deleting textures or samples (e.g., if the classification results are not acceptable after the first pass). Such categorization is a local analysis of textures, and consequently a number of isolated regions may appear in the resultant creation. A post-processing stage has been added in order to reduce the number of small regions that may confuse the regional understanding of the survey area. This simplification stage merges small regions with larger neighbor regions according to a smallest state size (as specified by the user). The end product is a DXF file of region boundaries that may be overlain on the mosaic of the survey area.

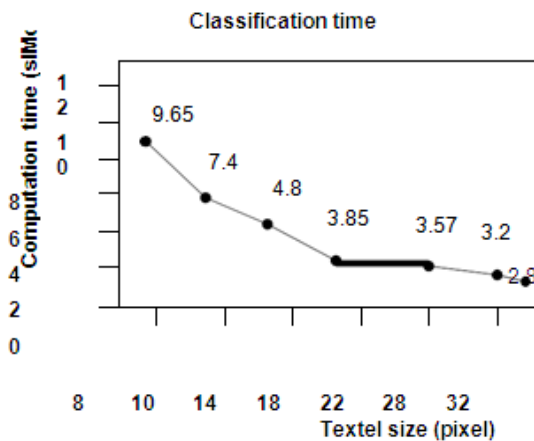


Fig.3. Classification processing time

Texture classification can be a time-consuming process because it is a local analysis repeated on each textel (i.e., on each sub-image). Additional time is consumed during the post-processing step of merging small regions into larger neighbor regions. Fig. 4 provides some control over the mean processing times required from SFC. These results were obtained with a standard Pentium III 800 MHz CPU. The x-axis of the graph represents the classification resolution and the y-axis represents the processing time required per Megabyte. Smaller textel sizes obviously require more processing time, but the primary contributor to the increased time lies in the post-processing stage as the greater numbers of isolated regions require more merging.

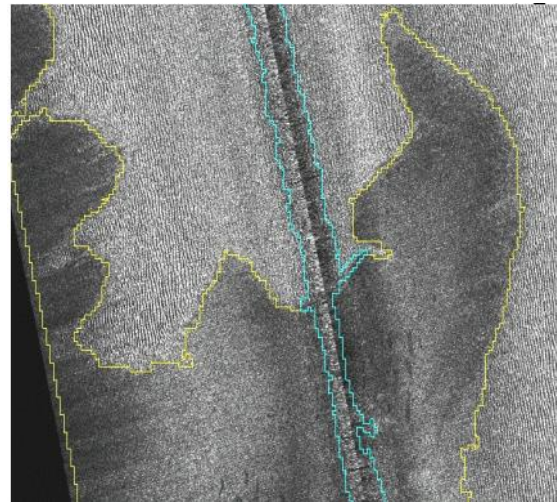


Fig.4. Automatic seafloor classification

#### IV. CONCLUSION

We have shown how classical image processing tools can be used toward robotic object detection, seafloor classification, and patch test completion. The applications developed by TEI are designed to assist processors and interpreters in quickly and easily manipulating and analyzing the vast volumes of sonar imagery ensuing from today's surveys. An added bonus is that fewer subjective decisions are made with these statistically based analytical procedures, thereby improving the consistency of interpretations from survey to survey. Our objective in the near prospect is to improve the accuracy and reliability of the ensuing data products through the use of other information tools such as databases or a GIS to store and display the information.

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