

## Improved Segmentation Method for Sonar Images

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*Abstract- Conventional image segmentation methods cannot be accurately applied in side looking sonar (SLS) because that makes the shadow as the segmentation target. Even if they use different and various texture features, are mainly stated as the optimization of a criterion evaluating punctual pixel likelihoods or similarity measure computed within a local neighborhood. These approaches require sufficient dissimilarity between the considered texture features. An additional limitation is the choice of the neighborhood size and shape. In this paper, we study the different characteristics of SLS image and the shadow interference. An improved level set segmentation method is proposed. The algorithm constructs a multi resolution representation of the input image using the forward and inverse wavelet transform. To overcome the shadow negative effects, we prefer the selective segmentation. This method does not require re-initialization and does not make any a priori assumption on the nature of the input image.*

**Keywords:** Level Set, Sonar, Texture, Classification

### I. INTRODUCTION

Underwater images obtained by the acoustic camera, side looking sonar (SLS), bathymetric sonar, synthetic aperture sonar (SAS), incoherent sonar, parametric sonar, etc., are used in different fields to realize seafloor task, such as navigation, seabed mapping, fishing, ocean drilling barrier, oil exploration, mine detection, and so on [1]. As they are characterized by their very high performance resolution, images provided by SLS are of great interest for the detection and classification of objects lying on the seabed or buried in the sediments. In the context of mine warfare, detected objects can be classified from their cast shadow or their high intensity reflection of the wave on the object. But for the reason of the complexity of oceanic environment, image obtained from sonar is polluted by the noise [2]. Therefore, it became an important research field to remove the noise of sonar image before the application of various approaches of image processing. Furthermore, according to the operated approach, pre or post processing are generally used to make each step of processing more robust. This paper discusses the methods of pre processing sonar images. Further, the principle, utility and the different approaches of sonar image textural analysis are cited. Finally, segmentation and classification methods for underwater objects are represented.

### II. SONAR DATA PROCESSING

The analysis of textured images plays an important role in image processing, pattern recognition and particularly in sonar images classification [4]. As part of mine detection, the distinction between the image of a mine and an object that physically resembles a mine is very complex and is relied on the recognition in shapes and textures. This method is developed for the quantification and recognition of acoustic textures. In this work only six parameters are used: homogeneity, contrast, entropy, correlation, uniformity and directivity. Many segmentation methods are based on statistical model using first and second order statistics. It is based at first on using local statistical proprieties of sonar images. The large data amount to process, the exploitation of the collected data has to be achieved with an automatic processing chain [5]. The Figure.1 shows the sonar angular variation.

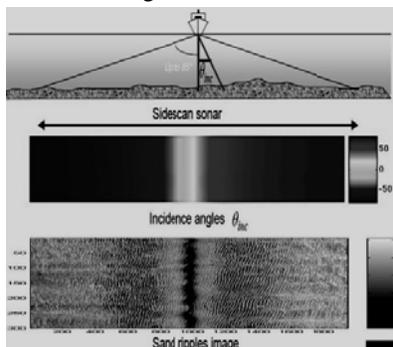


Figure.1 Sonar Angular Variation

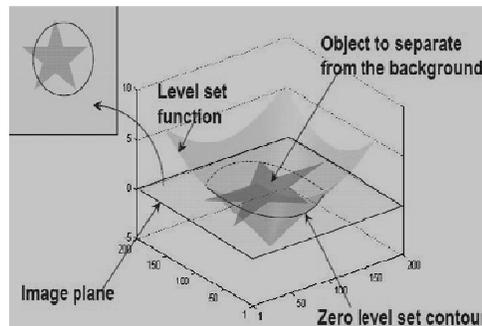


Figure.2 Typical Level Set Method

The detection of objects located on the sea bottom and then their classification (as wrecks, rocks, man-made objects, etc.) is also based on the extraction and the identification of their associated cast shadows. Thus, before any classification step, one must segment the sonar image between shadow and seabottom reverberation areas [6].

### III. LEVEL SET METHOD

It process sonar images and divided into classes depending on the type of seafloor. The method lies on a set a experts-classified images, which allowed to create a knowledge database [7]. In this way, sediments and seabed types are reliably characterized as shown in Figure.2. On sonar images, sediments are characterized using their texture like sand, ripples and rocks. The texture is extracted in cutting the images in tiles and calculating parameters on them. However, the main drawback is its lack of accuracy, due to the division of the whole image in tiles. In general, correlation and contrast are noisy. In addition, uniformity and homogeneity give the same kind of information in matter of segmentation, but uniformity seems attenuated. In order to optimize the time of processing, this parameter won't be taken into account. The parameters of the present work are homogeneity, entropy and directivity. Each image is firstly segmented into 4 levels using Fisher segmentation. This reduces the number of level sets to be created during the segmentation, and enhance the accuracy in highlighting. In order to perform the segmentation, the amplitudes of matrix must be found in the same zones. It is indeed reverse for some parameters, and homogeneity and contrast matrix have high levels where entropy matrix is minimum. Level sets are used to search for forces evolution in images, and especially discontinuities [8]. It allows to automatically finding zones of minimal discontinuity and creates close shapes. The more iterations, the sharper the borders. This number must thus wisely be chosen, and may be considered as a filtering step [9]. It allows to accurately and quickly determining the zones of great changes in the image. This smoothing will then be used as input to get the final borders.

### IV. EXTENDED LEVEL SET

The objective is to select a whole set of parameters from the wavelet coefficients of any pixel of the image analyzed and to compute a distance between this set of parameters which characterizes a specific region of the image. If this distance is sufficiently small, the current pixel will be associated with the considered region. If not, another specific region will be considered. This is a vector composed by some local values of statistical moments computed in a neighborhood centered in the current pixel. For example, the features vector can be formed by the local mean and by the local standard deviation of the current pixel computed in a rectangular neighborhood [10]. Some of the most popular texture extraction methods for retrieval are based on filtering or wavelet-like approaches. Essentially, these methods measure energy at the output of filter banks as extracted features for texture discrimination. The basic assumption is that the energy distribution in the frequency domain identifies a texture. Besides providing acceptable retrieval performance from large texture databases, those approaches are partly supported by physiological studies of the visual cortex. The features which will be used for segmentation are the mean and the standard deviation of the magnitude of the transform coefficients in each detail subband from each decomposition level [11]. Computing the distance between the vector of features of the current pixel and the vector of features of each center and selecting the region at which corresponds the minimum distance, we can make the segmentation [12]. The features which can be selected for segmentation in regions are: the preferential direction (indicated by the subband in which belongs the current wavelet coefficient), the decomposition level, the local mean of the wavelet coefficient (which indicates the level of brightness of the corresponding pixel) and the local standard deviation (which show if the considered pixel belongs to a region with rapid changes). The first processing of the images is the feature calculation (mean or variance of gray scale values in a area around a pixel). The result of the feature calculation is feature vectors, one vector per pixel of the original image. The features are calculated as a statistics in the neighborhood of a point in the image.

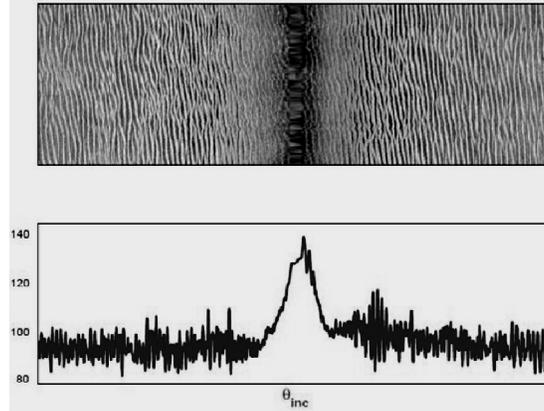


Figure.3 Mean variation of Sand ripple

The size of neighborhood varies, and in the case of the trawl track detector the neighborhood it is quite large. Algorithm enhancing connected dark regions is applied to the image. This image is then threshold and searched for connected regions. All connected shadow regions within a specified size are then assumed to be cast by stones. Finally the density of stones is calculated locally. If the resulting density is above a threshold the type “scattered stones” is assigned. A crucial point in the seafloor classification is the selection of a proper set of features. First, we want to have as few different features as possible, since the number of calculations needed for a classification grows with the number of features. Further, introducing redundant or irrelevant features introduces both statistical and systematic noise to the decision making. Secondly, we need to have enough features to be able to see a difference between the different seafloor types. As a rule of thumb we need a number of features equal to the number of seafloor types that we are interested in. The feature selection is actually the most important step in the whole process. Finding good features for our special purpose involved close examination of the data. It turned out, that for each of the seafloor types under consideration; we were able to find a feature that could distinguish that seafloor type from the rest. All features are calculated setting options in the program feature. After the calculation of features, classes are assigned using a simple threshold classifier as shown in Figure.3. In the first stage of the segmentation algorithm a set of texture features from the sonar image is extracted. The texture descriptors used here are the Haralick features based on the estimation of co-occurrence matrices within a window surrounding each pixel in a lattice in the sonar image. This feature set is well known to be a good descriptor of the textures present in sonar data. To improve computational efficiency the feature extraction algorithm implemented here uses the sum and difference histograms approximation method [13]. The model is robust to noise and has good regularization properties, as a result of the velocity dependence on the global region statistics and the curvature of the contour. This is numerically approximated through a first order monotone scheme. One of the problems when working with texture features is feature selection. Identifying a set of features able to discriminate between the textures present in all images of a data set is not always possible. One of the novel features of our implementation is an automatic feature selection step which has been integrated in the evolution scheme. The basic idea is to embed the planar-curve in a 2D scalar function  $\varphi(x, y, t)$  such that the original curve is retrieved by intersecting the surface with the xy plane. Since  $z = 0$  on the plane, the extracted contour is called the zero level set. Over the rest of the plane  $\varphi(x, y, t)$  is defined to get the distance between the plane and the surface, where sign is defined to be positive for points outside the curve and negative for points inside. Now instead of evolving the curve in the 2D plane we move the surface-function  $\varphi(x, y, t)$  with respect to the xy plane and retrieve the new contour as the zero-level-set of the function. Getting back to the image world,  $\varphi(x, y, t)$  can also be seen as a distance map that for each pixel  $(x, y)$  gets the value of the  $\varphi(x, y, t)$  function. Since the evolving front  $C(t)$  is a zero level set of the scalar function  $\varphi$  for every time  $t$ , we get for the evolving contour

$$\phi(C(t), t) = 0 \quad (1)$$

Derivation with respect to  $t$ , using the chain rule we get

$$\phi_t + \nabla \phi \cdot C_t = 0 \quad (2)$$

Let  $F$  be the speed in which the contour propagates in the direction normal to the curve. Hence

$$F = C_t \cdot n \quad (3)$$

Where

$$\mathbf{n} = \frac{\nabla \phi}{|\nabla \phi|} \tag{4}$$

Therefore

$$\phi_t + F|\nabla \phi| = 0 \tag{5}$$

And we get a PDE on  $\phi$  with an initial condition  $\phi(\mathbf{C}, t = 0)$ . This equation can be solved using finite differences approximations for the spatial and temporal derivatives. To account for regularization, a curvature dependant speed  $F = F(k)$ , for example,  $F = -k$  (concave points go faster in the normal direction. To get an inflation force we add a constant term  $F_0$  :

$$F(k) = F_0 - k \tag{6}$$

And so we are left with the edge-stop term. To multiply the above speed by the function

$$g(x, y) = \frac{1}{1 + |\nabla G_\sigma * I(x, y)|} \tag{7}$$

This function behaves as an inverse of a gradient detector. It therefore approaches zero in the vicinity of an edge, bringing the velocity to a stop. Smoothing by a Gaussian filter helps skipping weak edges.

$$\phi_t + g(x, y)(F_0 - k)|\nabla \phi| = 0 \tag{8}$$

Incorporating the classical equation for the curvature  $k$

$$k = \text{div}\left(\frac{\nabla \phi}{|\nabla \phi|}\right) = \frac{\phi_{yy}\phi_x^2 - 2\phi_x\phi_y\phi_{xy} + \phi_{xx}\phi_y^2}{(\phi_x^2 + \phi_y^2)^{3/2}} \tag{9}$$

and changing the sign  $F_0$ , we get the final Extended Level Set flow as a PDE:

$$\phi_t = g(x, y) |\nabla \phi| (F_0 + \text{div}\left(\frac{\nabla \phi}{|\nabla \phi|}\right)) \tag{10}$$

The Figure.4 show the Matrices computed for Sand for different parameters

### V CONCLUSIONS

In this paper, we presented an automatic segmentation approach based on level set method for classification of sonar images. The preliminary results show the progress that can be performed in this field The bottom of the sea may thus be fully automatically classified. In addition, considering the real-time aspect of this method, one may hope an easy implementation directly on a sonar system. Those results are not good enough yet to constitute a final system, but they may be opening gates for future researches. One may hope to be able to both merge the good performance of sea floor characterization with accuracy of its borders. This work gives a preview for further researches.

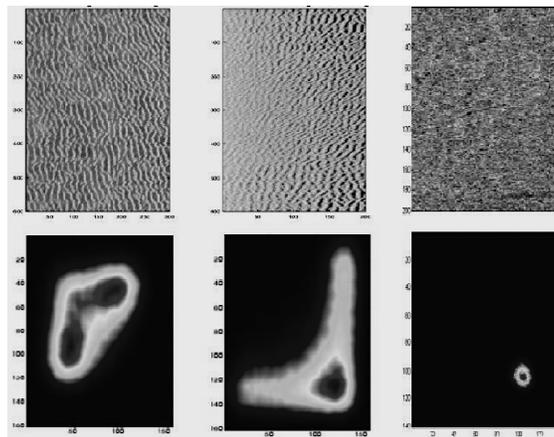


Figure.4 Typical matrices of Sand for different parameters

Finally, we would conclude saying that an expert is still mandatory for the learning phase. Those experts are giving advices about their level of confidence on images, and that could be used as a weight for supervised approaches.

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