A 2-D FILTER SPECIFICATION FOR SONAR IMAGE THRESHOLDING

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Abstract - We propose a new image sonar segmentation by combining two complementary competencies. On the one hand, following an image processing approach, we aim at partitioning raw image data to provide a binary image. On the other hand, we take advantage of technological knowledge such as the principle of sonar image formation.

For sonar images, grey-level histogram generally presents a single mode which entails a poor separation of two theoretical modes related to reverberation and shadow subpopulations of the image. The separation of these two modes is of critical interest in a further description of objects from their cast shadows. In this paper, an optimal filter is specified by a criterion which aims at changing the statistical properties of each area while making threshold value selection from the histogram easier. While minimizing the output pixels variance, pixel values in each region concentrate around the respective average value while, simultaneously, two distinct modes appear on the histogram of the filtered image. The minimum value found between the two modes in the smoothed histogram leads to the searched threshold. In addition, we show how filter aspect depends as well on the image sonar resolution as on sonar parameters.

Keywords – sonar image, optimal filter, variance, correlation, histogram, threshold

1. Introduction

A high resolution sonar provides high-quality acoustic images of the sea-bed, allowing the classification of objects from their cast shadow. The first step called segmentation consists in partitioning the image into homogeneous regions. Beside the sea-bed reverberation area, each image presents an echo corresponding to the detected object and the cast shadow on the sea-bed characterized by a lack of acoustic reverberation. To obtain binary from grey-level image, we aim at giving the label zero for pixels belonging to the shadow and the label one elsewhere.

Several segmentation methods have been proposed (Pal and Pal, 1993). A classical technique is based on thresholding (Sahoo et al., 1988). Thresholding can be done from global information, e.g. grey-level histogram or statistical values of the entire image. Nevertheless as far as sonar images are concerned, threshold selection is not trivial. For example, we can compute a threshold value from the estimation of the reverberation mean level but this technique is only valuable under precise conditions such as a given contrast between the two areas of interest (Jan, 1987). Given that the image contains a distinct object on a background, the histogram would be likely to be bimodal, and threshold selection at the valley easier using the mode method technique. Unfortunately, sonar images are corrupted by strong speckle noise generally modelled by a Rayleigh's law. This is what we can observe on the left histogram of Fig.3 where distribution of pixels belonging to the shadow area intermingles with distribution of pixels belonging to the reverberation area. This phenomenon affects class separability. Various methods allow threshold selection but not in case of Rayleigh distributions. In that way, Otsu's method based on the optimization of discriminant criterion measures seemed to be a promising solution. Applied to sonar images however, Thourel obtained too large threshold values (Thourel, 1996) (Otsu, 1979).

To facilitate the use of the mode method, values of local properties can be used to improve the shape of a bimodal grey-level histogram (Weszka, 1978). But, it is not adequate for a sonar image's grey-level histogram which is generally unimodal. To make it bimodal, a criterion is proposed to minimise pixels variance by spatial filtering. In the resulting histogram, peaks represent shadow and reverberation regions (differing in average grey-level) while the single valley represents shadow edge. The optimal filter designed for such an image does not look like a known low-pass filter but strongly depends on the principle of the sonar image formation in terms of size and coefficient values.

The paper is organized as follows. In Section 2, we give bases of the proposed method. Sections 3 describes respectively a full and a low resolution processes. In section 4, experimental results obtained on real sonar images are provided. Finally, the conclusion of our study is given in Section 5.

2. Optimal Filter Definition

Given the contrast between the two regions of interest, we were interested in grouping pixel values of each region around the respective average value. This can be done by minimizing pixels variance. This optimization criterion is applied to estimate a filter whose size has to be preliminarily specified. This problem is tackled by analysing sonar data acquisition.

Sonar data are related to the received signal scattered back to the sonar, amplified and recorded in the slant plane. Resolution power depends on sonar parameters and data processing. Sonar parameters set the image sonar resolution, that is to say the minimal distance between two objects to be distinguished (Blondel and Murton, 1997) (Somers, 1993). On the one hand, the range resolution is determined by the bandwidth of the transmitted signal B. On the other hand, the azimuth resolution mainly depends on the wavelength λ and the antenna length L. Fig. 1 gives the parameters of the resolution cell without any ulterior treatment.

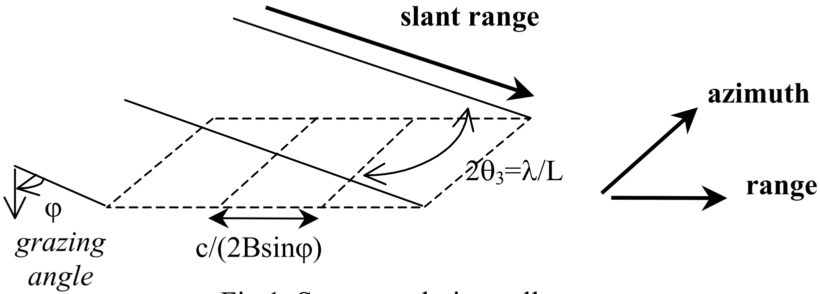


Fig.1. Sonar resolution cell

Data processing is the transformation of the raw data to usable image characterized by an intensity variation that is proportional to the acoustic backscatter signal strength. Generally pixel size is chosen to be smaller than the resolution cell and the insonified area is differently oversampled along the two axes. But, if oversampling aims at improving image presentation and usefulness of the data, it also entails pixels correlation.

Sonar parameters as well as data processing provide us a useful means to fix the minimal size of the filtering mask which corresponds to range and azimuth correlation distances (d_r,d_a). Given the statistical criterion stated at the beginning of this section, and provided that the sum of the filter coefficients is set to one, we have to find optimal values of the $(d_r+1)\times(d_a+1)$ filter $H=(h_{i,j})_{i,j\in[0,d_r]\times[0,d_a]}$ that solve:

$$H = Arg\min_H VAR(H * I_R),$$

where VAR stands for the 2-D variance operator,

and I_R is the image extracted from the reverberation area in the observed sonar image,

subject to $\sum_{i=0}^{d_r}\sum_{j=0}^{d_a} h_{i,j} = 1$

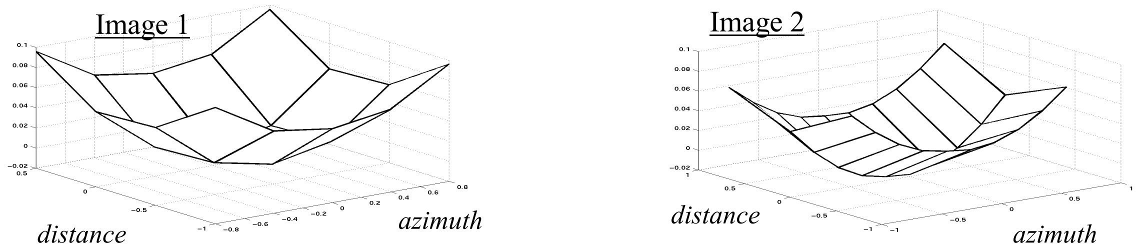
starting at the values $h_{i,j} = 1\big/(d_r+1)\times(d_a+1)$, ∀i,j, i.e. an averaging filter.

This constrained optimization is performed using a nonlinear programming method called Sequential Quadratic Programming method implemented in the Matlab Optimization toolbox (Fletcher, 1980) (Coleman and al., 1999).

Actually, the function of the acquisition system operates as a convolution operator on raw data. In this way, we are close to image deconvolution, already applied to restoration of satellite images or denoising of nuclear medicine images (Kalifa and al., 1999) (Jammal and Bijaoui, 1999). In our case, data processing entails range-azimuth information redundancy. For such correlated pixels, instead of the classical preprocessing which consists in low-pass filtering, we rather use a specific shaped filter with smaller values at the centre of the mask so as to average uncorrelated pixels while filtering. Table I and Fig. 2 clearly display the link between the optimal filter size and image formation. We can verify that the more correlated are pixels, the larger the minimal filter size is. Nevertheless, other degradations (as calibration of the antenna, side lobes of its directivity function,…) can occur and modify the theoretical size of the resolution cell (Urick, 1983). It entails a larger minimal filter size as in the case of these real images.

Table I

Image formation	Sonar resolution (in accordance with the sonar parameters)		Pixel size (in accordance with data processing)		Number of correlated samples per resolution cell	
Image	*distance*	*azimuth*	*distance*	*azimuth*	*distance*	*azimuth*
Image 1	6.25cm	3.7cm	3.15cm	1.25cm	**≈ 2**	**≈ 3**
Image 2		9.5cm				**≈ 8**



Filter of size [4 5]   *Filter of size [3 10]*

Fig. 2. Examples of optimal filters

Given these observations, two processes can be applied. At full resolution, according to sonar image formation, values of a well-fitted filter can be optimized as explained above and applied on the observed sonar image. At low resolution, another solution consists in decimating the image first according to pixels correlation and simply applying a gaussian filter.

3. Full and low resolution processes

According to pixels correlation, we synthesize the optimal filter which minimizes pixel variance. While filtering, the histogram of the output image changes such as a deep valley appears between the two peaks. Maximum values of these peaks are the average values related to the two main areas, the shadow and the reverberation areas. Consequently, selection of threshold using the mode method becomes possible for shadow-background separation (see Fig. 3).

An alternative consists in firstly decimating the image according to pixels correlation and so, information redundancy. For such uncorrelated pixels, a gaussian filter is a suitable low-pass filter to minimize pixels variance while preserving spatial localization of the contour (Marr and Hildreth, 1980). This is a less computational method but, resulting segmentation is much coarser because binarization is performed at low resolution. The effective segmented shadow is conversely provided after duplication.

Fig. 4. briefly displays the successive steps of these two possibilities.

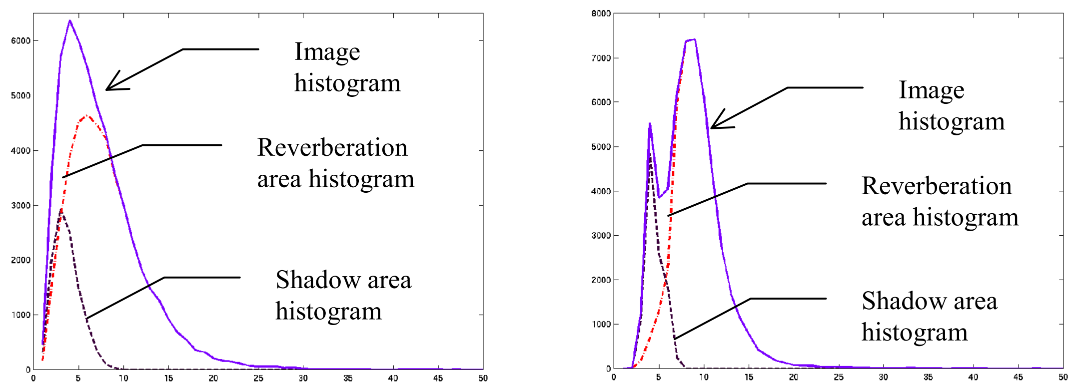


Fig. 3. Sonar images grey-level histograms:
without any treatment (left column) and after optimal filtering (right column)

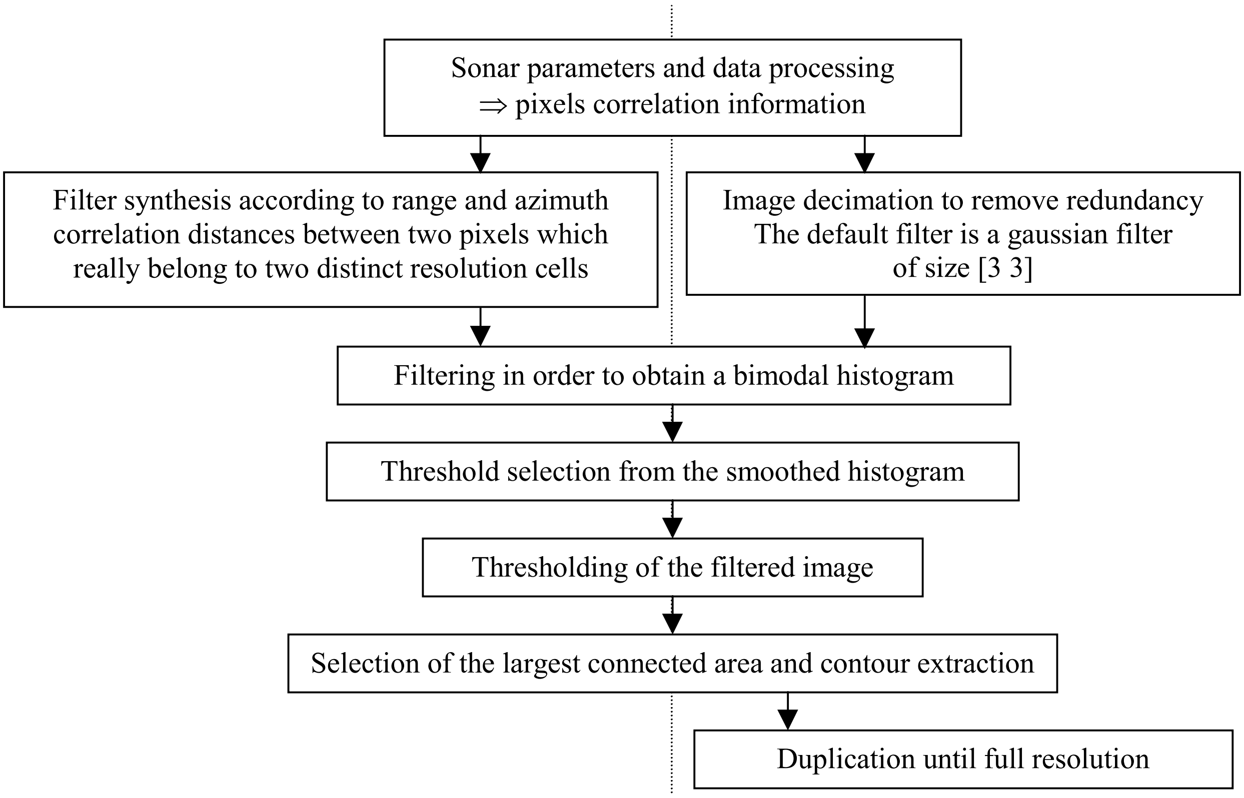


Fig. 4. Segmentation schemes: at full resolution (left column), at low resolution (right column)

4. Experiments

Both segmentation schemes have been tested on real synthetic-aperture sonar images (Billon and Fohanno, 1998). The corresponding sonar parameters and filter aspects are given in table I and fig. 2. On each picture of the Fig. 5., the contour of the segmented shadow overlapped the sonar image. This allows to appreciate segmentation accuracy.

At full resolution, the extracted contour divides raw image data into two homogeneous areas supplying an accurate segmentation. But this method suffers from computational time that filter optimization involved. Nevertheless, provided that images are acquired in similar conditions, sonar parameters, data processing and then the optimal filter remain identical.

As expected, contours are coarser when binarization occurs at low resolution. Such a technique can then be inapplicable if low resolution does not preserve global shape information. This can be detrimental for next steps especially for features extraction designed for shape recognition. Nevertheless, this second method is the fastest.

Hence, depending on segmentation aim and operational conditions, a compromise has to be found between computational time and accuracy.

5. Conclusion

In this paper, a novel approach was proposed for image sonar thresholding. In the context of mine warfare, objects can be classified from their cast shadow to be extracted during the segmentation step. Such typical image presents two main areas: a dark one related to the cast shadow caused by the detected object, and the sea-bed reverberation area.

Threshold selection from the grey-level histogram is performed after a specific image filtering. Based on modification of image statistics, this technique also includes parameters derived from image data acquisition. Indeed, the minimal size required for the filter is closely linked to image sonar parameters and data processing involved in sonar image formation. Filter coefficients are then optimized in order to minimize pixels variance. Under this criterion, the grey-level histogram becomes bimodal making the mode method usable.

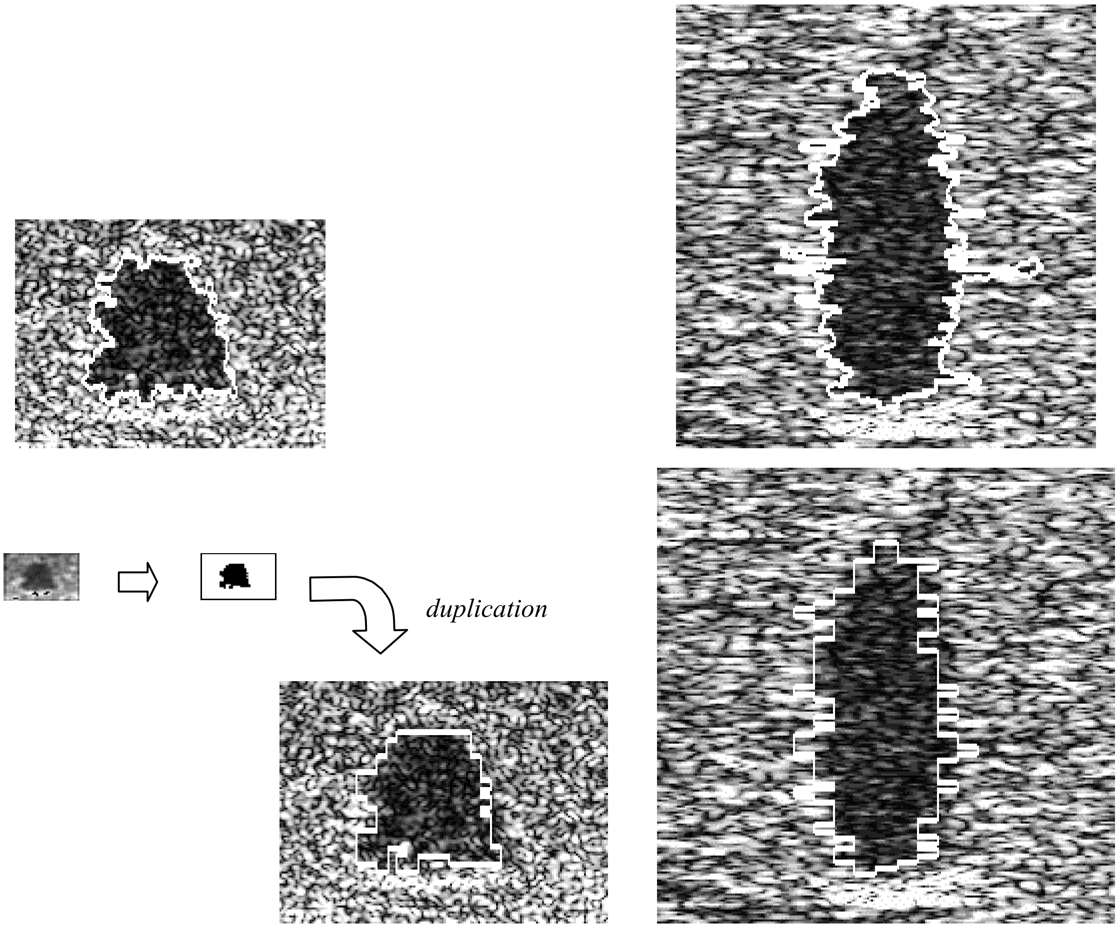


Fig. 5. Segmentation results: at full resolution (at the top), at low resolution (at the bottom)

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