Detection of Lofar Lines

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Abstract. The problem of extracting spectral lines from sonar images is treated using a complete scheme that combines an edge detector with a line tracking process. That is, the edge detection process allows filtering the sonar image and finding a region (zero-crossings of the second derivative of the sonar image) that includes a spectral line. The founded region is then used to initialize and to limit the extent of the line tracking process. Comparative performance results confirm the efficiency and the reliability of the proposed approach.

1 Introduction

The fundamental objective of a passive sonar system is to detect the presence of target-like signals in underwater acoustic fields. Signals emitted from the acoustic source are recorded by an array of hydrophones, beamformed and spectrum analysed. Narrow-band components of the signals' result provide an image of frequency power versus time, more commonly referred to as a "lofargram". Lofar is an acronym for LOw Frequency Analysis and Recording. Its main characteristics are:

- Signal to noise ratio is low due to the discreteness of the sources.
- A constant frequency tonal produces a darkening over time periods, which appears as a vertical line on the lofargram display.
- Multi-lines can be displayed on the lofargram depending on the spectrum band-width.
- Slanted lines or slightly curved lines can be shown on the lofargram. They are due to the Doppler effect.

By characterizing the spectral lines on a lofargram, one can determine the acoustic source of the sound.

Several methods have been proposed in the literature to extract lines from images. Our review is not intended to be exhaustive, but some of the related works represent important advances in this area, and we have experimentally tested some of them.

Abel *et al.* [1] perform a detection step using a statistical likelihood test. Then mathematical morphology operators are used to extract regions which encompass lines. This method, well tested on sonar images, requires however a priori information regarding the noise environment and the number and type of sinusoids present.

Other contributions in the field of curved line extraction are proposed by introducing perceptual considerations. All these methods rely on a two-step process [12, 10]. Globally, these methods give good results for constant curvature curves but they are not well adapted to fluctuating curves (curvature sign often changes) such as spectral lines.

Neural network approaches are also an important field of methods that have been proposed to deal with the line detection problem. However, these methods [5, 6], based on supervised learning neural networks, need a learning set that reduces their utility in real cases.

Line detectors, based on a differentiation operation [14] or on a local energy computation [4], can also be provided to extract spectral lines. Since the images are very noisy, these approaches require a smoothing stage. High smoothing removes noise and fine structures too. These approaches are not well adapted to lofar images because we need to restore very fine structures.

The work described in this paper is toward automatically processing lofargrams in order to suppress the noise and to detect the spectral lines. This process is very important because the quality of further automatic processing such as classification or tracing acoustic sources relies on the quality of the extracted spectral lines. Thus, we propose to combine an edge detector with a line tracing process. The edge detection process is used to initialize the tracing process.

2 Our approach

The different steps of our approach are described in figure 1. Spectral lines are extracted by the detection process in order to find surrounding regions. Then, a tracing step is executed in each region to find the lines accurately. We describe these three stages more precisely in the following sections.

Fig. 1. Approach scheme.

2.1 Detection process

The detection process consists of detecting and bridging spectral line contours in order to extract regions. The line detection, further described, is achieved in a two-step process: smoothing and differentiation.

Line detection

Smoothing. Noise in lofargram images is essentially characterized by high frequency components which can be reduced by a smoothing step. The Gaussian ensures an optimal compromise between the detection and localization errors: $g_\sigma(x,y) = \frac{1}{2\pi\sigma^2}e^{-\frac{1}{2}\frac{x^2+y^2}{\sigma^2}}$ where σ is a standard deviation.

Edge detection. The spectral lines in a lofargram can be modelled by peak profiles. To perform the detection, we run a detector based on steerable filters designed in quadrature pairs as described by Freeman and Adelson [4]. The method consists of calculating the response of an arbitrary linear filter by a linear combination of known filter responses, which will in general be significantly faster than computing the convolution of a rotated filter with the image (see [4] for more details).

The detection first computes in each image point a local dominant direction θ_d (the angle of maximum response of $E(\theta)$). This is performed by defining a local energy function $E(\theta) = [G^\theta]^2 + [H^\theta]^2$.

Once this is done, we can easily compute the second derivative of the image in order to enhance the lines and also to locate regions encompassing these lines. This is simply achieved by taking the appropriate combinations of the G basis filter outputs, and adaptively steering them along the local direction of dominant orientation. After finding, in the enhanced image, the 2D local maxima in the direction perpendicular to θ_d, the false contours are suppressed using an hysteresis threshold [2]. No additional filtering is required for this step and the whole process (*i.e.*, finding the local dominant direction and the derivation of the image) involves only one pass of the image.

Gap bridging Because of its local nature, the detection process is not able to provide continuity and coherence of image curves. In our case, the major drawbacks of this process result in:

- *gaps*, where weak but significant information is missed due to thresholding errors and intensity discontinuity stemming from various and complex physical phenomena ;
- *deviations in position and uncertainties of orientation* where local estimates of these quantities are adversely affected by noise.

Our aim is to restore continuous curves as long as possible. A linking process is first achieved on the thresholded image in order to obtain elementary curves, called tokens. Each token, defined by a linked edge points lying on the same curve, is characterized by a local dominant orientation at each end of the tokens and its main direction. The grouping step relies on two fundamentals concepts:

1) A strategy of association based on an iterative techniques of grouping by successive refinement [7, 13]. The process is iterated on a set of tokens and ends when no association is achieved at one stage.

2) A set of criteria that ensures a good robustness of the grouping process: proximity, curvature consistency and overlapping (see [13] for more details).

Discussion We have shown a global scheme to efficiently detect spectral lines embedded in a very noisy background. Nevertheless, even if they are well detected, fine structures are blurred by the smoothing step and so are not well localised. We propose to tackle this problem by first locating regions that encompass the contours and then using a tracing algorithm to accurately find the lines in each region.

2.2 Region locating

This process aims to provide the tracing process with a limited search space where we have a high chance of detecting lines. Such an approach enables us to avoid initialization and solution tree overlapping problems inherent in multistage decision processes. The main idea is to determine for each contour the boundaries of the smallest region it encompasses [13]. We first compute the zero-crossings of the second derivative of the image on each side of the contours (zero-crossings are detected in four direction scans). This information cannot be directly used as boundaries of regions because of effect of noise that can produce wrong zero crossings. Our solution consists of estimating each region width by calculating the mean distance from the curve it contains and its zero crossings. A mathematical morphology operator is thus ran to dilate each curve until we obtain the desired width. This method does not insure that a region contains only one curve. It is always possible that some closed spectral lines will be merged by the smoothing step into one contour. In our experiments, we have choosen the smoothing parameter σ equal to 3 in order to have good noise reduction and to be able to distinguish two curved lines 5 pixels from each other.

2.3 Tracing guided by contours

A multistage decision process [8, 3], based on the optimisation of an objective function Φ, is used to extract from each region R the spectral line going through it. The problem consists of finding an optimal path from a set of graph nodes defined by the pixels belonging to a region. This operation is achieved on the original image. The fundamental property underlying this method is that any optimal path between two nodes of a graph has optimal subpaths for any node lying on it. Thus the optimal path between two nodes P_A, P_B can be split into two optimal subpaths $P_A P_i$ and $P_i P_B$ for any P_i lying on the optimal path $P_A P_B$. The function Φ is chosen so that the values for a path increase as the path's total amplitude increases and as its global curvature decreases:

$$\Phi(C) = \sum_{i=1}^{N} a(P_i) - \alpha \sum_{i=2}^{N-1} |s(P_{i-1}, P_i) - s(P_i, P_{i+1})|$$

where $a(P_i)$ is the amplitude of P_i, $s(P_i, P_j)$ is the slope of the segment $[P_i, P_j]$. The gain coefficient α allows more or less local distortions to be obtained. In our experiments, its value was fixed to 3 in order to allow tracing very fluctuating lines.

3 Experimental results

Our method has been tested on a set of real lofargrams with different signal to noise ratios. The experimental results show that this method is well suited to detect spectral lines accurately, even with a low signal to noise ratio. Figure 2 shows the main steps of our method on a noisy image containing five spectral lines.

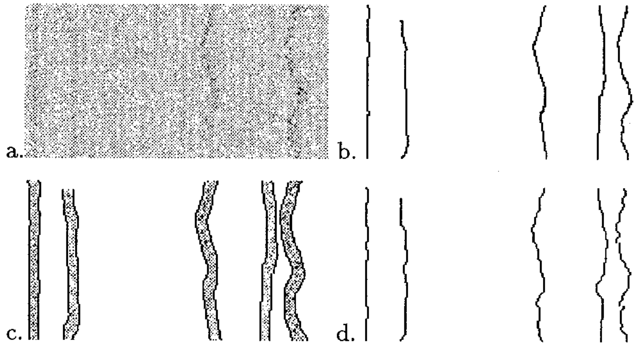

Fig. 2. Main steps of our line extraction method.

a) Real lofargram. b) Result of line detection. c) Regions encompassing the detected lines. d) Extracted spectral lines.

We have compared the location performance of the detection process (edge detector) and the detection combined with the tracing process (tracing guided by contours). Line location accuracy is assessed by the figure of merit proposed by Pratt [11] :$F = \frac{1}{max(I_I,I_A)} \sum_{i=1}^{I_A} \frac{1}{1+\alpha d^2(i)}$ where I_I is the ideal number of edge points, I_A is the actual number of edge points, $d(i)$ is the shortest distance of the ith actual edge point to an ideal edge point, and α is a positive constant. F is maximum (that is, $F = 1$) when $I_I = I_A$ and $d(i) = 0$ for all i. Table 1 shows results obtained from a set of images containing spectral lines with increasing spatial frequency (increasing fluctuation of the curves). We can see that, globally, our approach performs well, especially when the spatial frequency increases.

Spatial frequency	0.10	0.20	0.30	0.40	0.50	0.60
Detection process alone	0.90	0.90	0.89	0.85	0.82	0.81
Tracing process guided by contours	0.94	0.95	0.95	0.94	0.92	0.88

Table 1. Line-location figure of merit as a function of spatial frequency.

4 Conclusion and perspectives

We have proposed a complete scheme of processes to perform the spectral line extraction from lofargram images (sonar images). Our method is built on the cooperation of two techniques which are for our purposes complementary: the detection of contours and the tracing process. Comparative results are presented that show the performance of the tracing guided by contours versus the contour detection alone, especially when fine structures are to be detected (high spatial frequency). A set of experiments performed on images with different signal to noise ratios shows the robustness of our approach against noise. This method is currently applied to real lofargram images in a real-time situation.

At the present, the amount of smoothing, determined experimentally, is chosen to be high. The results is that very near spectral lines can merge after the smoothing stage and thus cannot be accurately localized by our tracing process, which supposes that a unique line belongs to each region. In other respects, our global schema of line extraction is not enterily automatic, due to the manual choice of the thresholding parameters. Further work will deal with these issues.

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