MULTISCALE SEGMENTATION OF TEXTURED SONAR IMAGES USING COOCCURRENCE STATISTICS

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ABSTRACT

A new method for the segmentation of textured backscattering strength (BS) sonar images is presented.
The method is based on the analysis of joint wavelet statistics by using the whole information brought by co-occurrence distributions. After the wavelet transform of the image, on the most informative frequency bands of the wavelet transform, we discriminate between textures by directly measuring the similarity between co-occurrence statistics. Then, we fuse the different segmentations according to the weighted voting rule.
Results on real sonar images and textures from the Brodatz album illustrate the effectiveness of the scheme. Finally, performances and results are discussed.

1. INTRODUCTION

Many marine activities (marine geology, commercial fishing, offshore oil prospecting and drilling, cable and pipeline laying and maintenance, and underwater warfare) need tools and methods to remotely characterize the seafloor. Modern swath-mapping sonars are well designed for this task; they have quickly evolved upwards over the last 40 years, they begin to meet most of the requirements needed to reliably characterize the seafloor. Among the existing acoustical mapping systems, multibeam echo sounders are currently the main focus of attention because of their ability to provide both a bathymetric map and a backscatter image of the surveyed area.
Typical example of (BS) image with a good resolution (Fig.2) shows various textures and spatial organizations of pixels that are clearly related to variations in the nature of the seafloor. In addition to its average level, the BS variability within subareas makes it possible to improve seafloor characterization using statistical techniques [1]. Techniques using textural information [2][3] and hierarchical Markov model were proven to be the more efficient for the segmentation of textured sonar image[4].
Recent studies on the texture analysis and synthesis [5][6] [7] showed the relevance of the textural information especially parameters extracted from co-occurrence matrices[8]. Besides, the contribution of multiresolution analysis to reduce speckle noise sonar images was stressed in[4].
Here, we aim at combining both a statistical co-occurrence based characterization and a multiresolution analysis. Unlike the usual methods that use features derived from co-occurrence matrices, such as entropy, energy… [8] as entries in a classification scheme (discriminating analysis, neural network…), the evaluation of texture similarity is issued from a statistical distance computed between co-occurrence distance. To benefit from multiresolution analysis, we evaluate co-occurrence statistics of wavelet coefficients. The fusion between the segmentations obtained within different wavelet sub bands improves final result.

This paper is organized as follows: in section 2, we detail the segmentation method. Then, we present the fusion scheme between the segmentations, carried out at different resolutions and different bands. After that, we expose the obtained results and briefly discuss the performances of the method.

2. WAVELET SUBBAND SEGMENTATION

2.1. Wavelet sub band segmentation

After the image decomposition with a Daubechies wavelet transform, we choose a set of wavelet filtered images, according to their Shannon-Weaver entropy value:

$$\eta(x) = -\sum_i p_i \log(p_i), \quad p_i = \frac{|x_i|^2}{\|x\|^2}.$$

We retain the images of the wavelet coefficient that have an entropy superior to a threshold. The threshold is fixed according to the average entropy value of the set of the filtered images.

2.2. Measure of texture similarities

Instead of measuring texture similarities as metric distance between texture features extracted from co-occurrence matrices [2], we aim at exploiting the whole

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information carried by these statistical distributions. Therefore, we rely on a probabilistic distance between these distributions.
The co-occurrence matrices have mainly been devoted to texture feature analysis of a whole image for the classification of the textured regions. These statistical distributions are related to regional properties. Consequently, they are computed on a neighborhood. In order to reliably estimate these statistical distributions, the neighborhood should be large enough to characterize primitive elements of the textures, but small enough not to cross texture boundaries. Thus the neighborhood size is generally limited. To compensate the lack of data for the computation of co-occurrence matrices on the analysis window, we use a non parametric Parzen density estimation method [9], with a Gaussian kernel. The parameters are set to minimize the mean square error [10].
In figure 1, we present the co-occurrence distributions of a real sand ripples texture, computed for various analysis window sizes, using an empirical estimation (on the left) and the Parzen estimation (on the right).

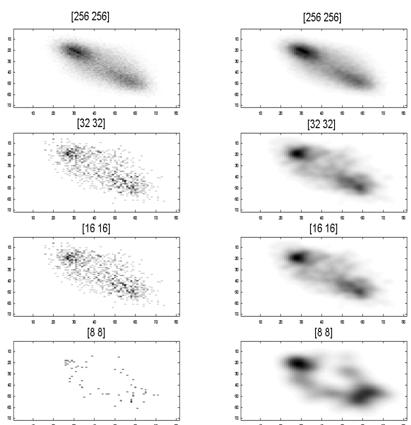

Fig.1. Co-occurrence distribution estimations computed on windows of sizes from 256x256 to 8x8 pixels

To measure the similarity between co-occurrence distributions, the Kullback-Leibler divergence called also cross-entropy, is an adequate measure of the difference between two statistical distributions $p(x)$ and $q(x)$:

$$K(p,q) = \int p(x) \log \frac{p(x)}{q(x)} .$$

To keep the texture models to a manageable size, we reduce the quantization level of each of the three texture images to L levels, L<<256. Moreover, it is desired to accomplish this histogram reduction with as little as possible change in the texture appearance. This means that we wish to minimize the change in gray levels for every pixel. To this end, the K-means clustering algorithm [11] is used to select the L quantization gray levels for the new histogram.

2.3. Segmentation of filtered wavelet image

For each retained filtered wavelet image, the segmentation method consists in measuring the similarity between the Parzen estimation of observed co-occurrence distributions and the training distribution ones. The training samples are visual homogeneous regions interactively delimited by geologists from the image itself.
The segmentation proceeds as follow: for each pixel, we assign the texture class corresponding to the minimum Kullback measure.
We segment these images with variable size of the analysis windows: smallest windows for finest scales to precisely localize region boundaries, and larger windows at coarsest scales to better characterize texture information. The window size depends on texture granularity, but for a given texture, we use reduced sizes, compared to traditional approaches [2]. For our examples we use sizes from 17x17 to 9x9.

3. FUSION METHOD

As shown in figure (3), the quality of the segmentations depends on the resolution; at low resolution, we have a larger immunity to the noise but less precision on the detection of the borders between homogenous regions, whereas at finer resolutions, we have a better precision but more badly classified pixels. In addition, depending on texture orientations, some wavelet segmentations are better than others. The fusion scheme is the most important stage of the segmentation method. It must benefits of the quality of the original and the wavelet filtered image segmentations.

3.1. Method 1

First, we have experienced a classical fusion scheme that assigns to each point of the image a set of windows from the original image and the retained filtered ones. Then a set of estimated cooccurrence distributions is computed from the different analyzing windows. This set is used as vector feature to discriminate between textures.

3.2. Method 2

Second, as the performances of the different bands depends on the type of the textures, we try to exploit the superiority of each band on the discrimination of certain textures, so to each pixel we assign the class given by the weighted voting rule. The weights are calculated for each pixel, and they depend on the texture class. For each pixel (i,j), the contribution of each subband k is weighted according to the normalized Kullback divergence values by $w_k^l(i,j)$, $k = 1,...K$, $l = 1,...,L$. K is the number of retained wavelet subbands and L is the number of the textures in the image.

If for a pixel (i,j), we note $d_k^l(i,j)$, the vector corresponding to the subband k formed by Kullback divergence values between the distribution of the test window and the l^{th} texture class training one,

$$w_k^l(i,j) = \frac{\operatorname{var}iance(d_k^l)}{d_k^l - mean(d_k^l)}.$$

The class of pixel (i,j) is given by the following expression: $\hat{l}(i,j) = \arg\max_l \left(\sum_{k=1}^{K} w_k^l(i,j)\right)$.

4. RESULTS AND DISCUSSION

As proven in Table I, the segmentation accuracy is greatly improved by the Parzen estimation of the co-occurrence. Besides, this scheme also permits to use smaller analysis window. In table I, we report the good classification rates of the segmentations made on a Sonar mosaic with various analysis windows. We show the results for segmentations using co-occurrence distributions issued from the Parzen or empiric estimation schemes.

Window sizes	Empiric estimation	Parzen estimation
32x32	97.66	100
16x16	98.73	99.70
8x8	45.21	89.99
4x4	25	76.59

Table.I. Classification rates for a Sonar mosaic

Experiments have also been carried to evaluate the relevance of the Kullback divergence compared to the Euclidean distance. Results reported in Table II demonstrate that the latter is significantly outperformed by the probabilistic similarity measure.

Window sizes	Euclidean distance	Kullback
32x32	95.31	98.83
16x16	89.75	90.92
8x8	71.07	71.63

Table.II. Classification rates for the two similarity measures

In Table III, the quantization scheme is proven at not to affect the segmentation accuracy, while drastically reduces the computing time by decreasing the size of co-occurrence matrices.

Level quantization	Segmentation ratios
32	87.11
5	98.83
10	98.82

Table III. Classification rates for different quantization level for 16x16 analysis windows.

Here, we present experimental results obtained on both a real sonar image and on a mosaic of textures from the Brodatz album (figures 2,3).

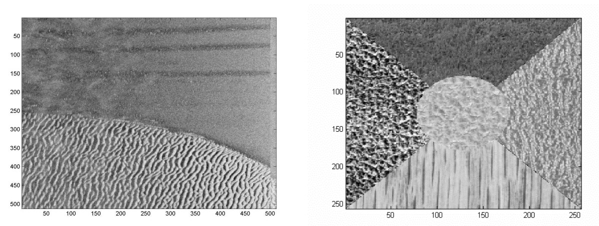

Fig.2. A textured sonar image (on the left), a Brodatz mosaic (on the right)

In figure 3, we present the segmentation results obtained for the images retained from the wavelet analysis: the original image (I0), the scale coefficient image of the first level of the wavelet decomposition (LL1), the LH wavelet of the first level of the wavelet decomposition (LH1) and the scale coefficient image of the second level of the wavelet decomposition (LL2). On the left we show the segmentations corresponding to the sonar image and on the right, we present those of the Brodatz mosaic.

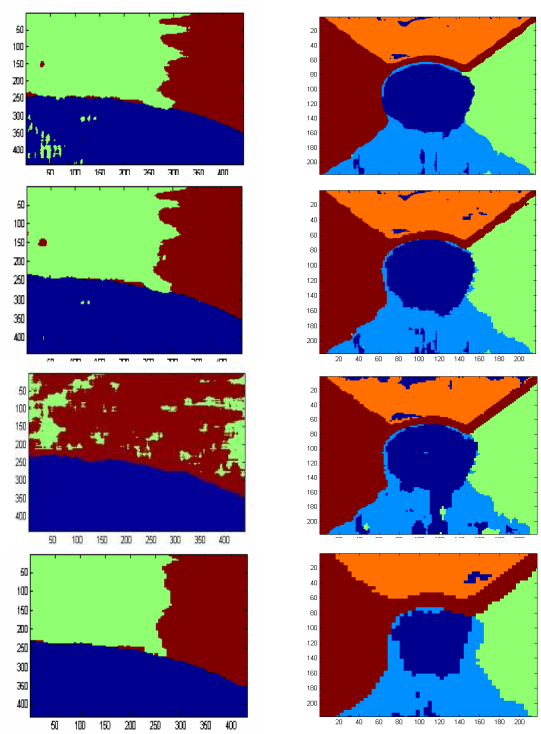

Fig.3. Segmentations of the wavelet subbands

The classification rates for the segmentations of the Brodatz mosaic are given by table IV:

	I0	LL1	LH1	LL2
Ratio	91	85.27	79.37	82.51

Table.IV. Classification rates for segmentations of the 10 levels quantized Brodatz mosaic

Compared to methods using parameters computed from co-occurrence matrices [2], we notice that we get better results when we use the whole co-occurrence distribution. We also notice that the segmentations carried out on the scale coefficient images, succeed in identifying all the classes of the image, whereas the segmentations made on the wavelet coefficient do not distinguish between classes having similar textures even with different gray level values. This is due to the fact that the scale coefficient images unlike, wavelet coefficient images, contain at the same time information concerning the texture and also the average gray levels values.
In figure 4, we display the final segmentations using the fusion between the wavelet filtered images. On the left, we show the segmentations corresponding to the sonar image. On the right, we show those of the mosaic of textures from Brodatz album. Upper images correspond to the segmentations that use the first fusion method, while the lower ones are those using the second fusion method.

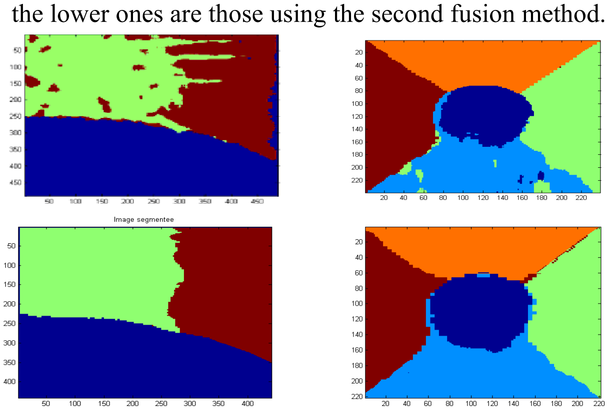

Fig.4. Segmentations after fusion

For the first fusion method, the segmentation rate of the Brodatz mosaic is of 94%. The segmentation boundary regions, when detected, are precisely localized but there are more misclassified pixels. The second fusion method has nearly the same segmentation rate (96%) but the quality of the segmentation is visually better. In fact this segmentation gives homogenous regions and allows globally separating the different textures.
Compared to the full resolution image segmentation, the use of the first fusion method does not improve the results for both sonar and Brodatz images especially when the textures are nearly similar. The second fusion method regularizes boundaries and removes smallest areas but sometimes, it fails to keep good boundaries localization. The weighted voting rule, we have used, takes into account the particularities of each segmentation. That is why the final segmentation is always better than all others retained wavelet filtered image segmentations.

5. CONCLUSION

This paper shows that sonar image segmentation with directly using the co-occurrence distributions estimations is promising. The multiresolution fusion scheme, by using the normalized Kullback divergence as weights for the wavelet filtered image segmentations improves the final result.

6. REFERENCES

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