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Seafloor Texture Classification with a Multiscale Discriminant Analysis on High Resolution Sonar Images

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Abstract

This paper presents a robust approach for the automatic classification of sonar pictures. The classification task deals with the segmentation of the sea-bottom thanks to the observations given by a high resolution sonar antenna. The originality of our approach consists in describing the seabed features with statistic multiresolution parameters. The obtained statistic parameters form a feature vector corresponding to a scale parameter description. A discriminant analysis allow us to significatively decrease the size of the vectorial space corresponding to the feature vectors and to generate an optimal subspace. A training set of 300 sonar observations has been used to reduce the feature space. This method has been validated on real world sonar pictures, with strong speckle noise.

Keywords: Sonar image segmentation, Noisy texture classification, Discriminant analysis, Multiresolution analysis, Multilayer perceptron, K-nearest-neighbors

1 Introduction

This article deals with the segmentation problem of high resolution sonar images. We propose a parametric method, with rotation invariance property, to classify different kind of seabeds observed with a high resolution sonar antenna. This approach has for originality to use together a discriminant analysis on the feature parameters and a multiscale analysis on the sonar images. This method is supervised in the sense that it needs a training set allowing to generate an optimal subspace from the original feature space by favoring decorrelated parameters. Each sonar image is described by a set of feature parameters called feature vector. These parameters are extracted from a multiresolution analysis on a wavelet basis. The main difficulty in this sonar image segmentation problem approach lies in the presence of a strong speckle noise [13][7][12]. The paper will be organized as follows. In the following section, major features of the high resolution sonar images are presented. In the same part, a compilation of the main approaches used for texture classification is briefly pointed out. In section 3, we specify the multiresolution parameter extraction, based on statistic properties of the wavelet coefficients. This parameters have the good property to be invariant for rotation transformation as we will see. Finally, in section 4, we will illustrate on some examples, the benefit we can get from our method associated with a K-NNA (K Nearest Neighbors Algorithm).

2 Seabed classification

Nowadays, high frequency sonar are performing systems, able to generate accurate picture of the sea-bottom. These sonar images are obtained with an antenna composed of hydrophones measuring pressure variations. On the pictures thus generated , one can observed sea bottom reverberation and shadow zones. The last ones correspond to areas acoustically masked by the objects lying on the sea-bottom or by the relief of the seabed. Here we focus on the automatic classification of the sea-bottom into 4 classes: pebble area, dune area, ridge area and sand area (cf. figure 1). The sonar frequency is approximately of $500KHz$, and the images are of large size, typically 6000 by 2000 pels. The sonar resolution allows, for these frequencies, to obtain a resolution cell near from $100cm^2$. It means that the classification of the four textures should be done at different scales. This paper aims to propose such an automatic and robust classification processing chain.

Texture analysis in image processing is a complex problem. Nevertheless, texture modelization and analysis framework can be approached under structural or statistic approaches [16]. In fact, one

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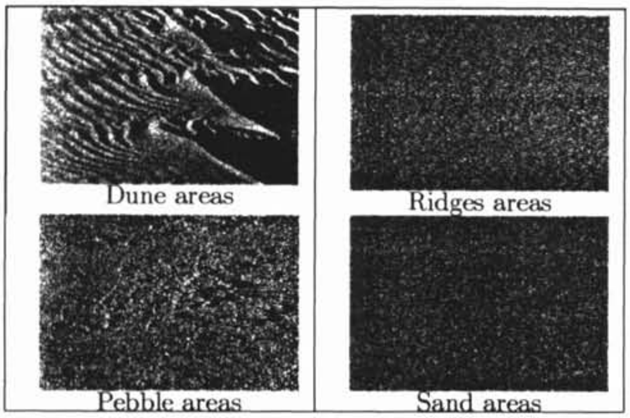

Table 1: Sonar pictures of the seabed obtained with a high resolution sonar. The size of each picture is 768 by 512 pels

can distinguish three main approaches for parametric description of textured pictures in the literature: 1) the statistic approach providing an image description according to its stochastic properties [1][4]; 2) frequency approaches, or more generally all representations including a space change allow to transpose the problem toward a well-fitted space [3][8]; 3) geometric approach permits an explicit description of the shapes the authors are looking for in textured images [11]. Both type of analysis have advantages and drawbacks. In our case, information at different scales appears on the sonar images. For instance, in the case of dunes of sand, the shadow shapes are spreading on few meters; whereas for areas with ridges of sand the shadow shapes are three order of magnitude smaller. We firstly define in the next section, the way we adopted to extract statistic multiresolution parameters (cf section 3) before to present the results obtained on real high resolution sonar pictures (cf section 4).

3 Multiscale approach

Multiresolution approach has been motivated by the difficulties we faced with, about the size of the shape composing the texture: in a area dunes of sand, large shadow zones succeed to large reverberation areas that should be locally classified as sand class. Otherwise, for small analysis windows, it is difficult to distinguish pebble areas from ridge areas. Last but not least, the managing of the boundary between zones involves analysis widows of small sizes. All these arguments imply to decompose the observations in scale in order to be able to increase the robustness of feature extraction. Finally, the presence of a strong speckle noise [5] at full resolution decreases for coarser levels, because of low pass filtering.

3.1 Multiresolution Analysis

Wavelets produce a natural multiresolution of every image, including the all-important edges. For more details about the mathematical theory, the reader will find an interesting compilation in [10]. A beautiful connection between wavelets and filter banks was discovered by S.Mallat [9] in 1988. The discovery, by I.Daubechies, of discrete orthogonal wavelets of finite length [14], having good properties (in term of smoothness, symmetry, inner product, accuracy of approximation, number of vanishing moments...), opened then new perspectives for image representation.

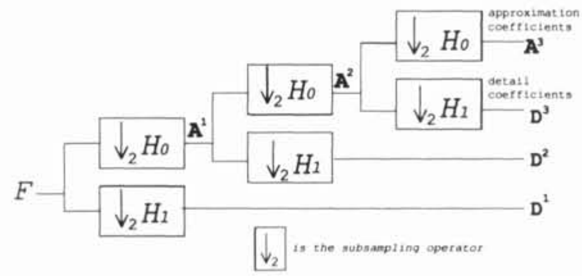

Figure 1: Scaling fonction and wavelets from iteration of the lowpass filter. H_0 stands for the lowpass filter, while H_1 is the highpass filter. In the case of biorthogonal filters, we have a perfect decomposition allowing a perfect reconstruction : $F \equiv A^1 + D^1 \equiv A^2 + D^2 + D^1 \equiv A^3 + D^3 + D^2 + D^1$

Scaling function and wavelets have remarkable properties. They inherit orthogonality or biorthogonality, from the filter bank. Because of the repeated rescaling that produce them, wavelets decompose an image into details D^l at all scale l for $l \in [1, L]$. In figure 1, we show the decomposition of an image F with analysis filters, up to the third scale level. We have compared the quality of the decomposition on three biorthogonal basis : coiflets, symlet and daubechies basis[14]. The choice of the best basis has been estimated on real sonar image by using a compression scheme. The best compression rates are compared according to the following Mean Square Error criterion : $MSE = \frac{1}{mn}\sum_{i=1}^{m}\sum_{j=1}^{n}(f_{ij}-g_{ij})^2$where f_{ij} stands for the original signal and g_{ij} is the reconstructed signal after compression (on the detail $(D^L, D^{L-1}, ..., D^l, ...D^1)$ and approximation (A^L) coefficients). Best results are obtained, according to the MSE criterion, with the coiflets coefficients and a size $N = 29$ for the discrete filter lengths. We will note c^l_{ij} the coefficients of the image projection onto this coiflet basis.

$$c^l_{ij} = \{D^l(i,j)\} \text{ if } 1 < l < L$$
$$\text{and } c^l_{ij} = \{\{D^l(i,j)\};\{A^l(i,j)\}\} \text{ if } l = L$$

In this multiscale framework, we obtain a set of coefficients that corresponds to the image projection toward different wavelets, in a fine to coarse scheme. At each scale, all the information is preserved: it means that the initial image may always be reconstructed (cf figure 1). We propose to extract statistic properties of these coefficients c^l_{ij} up to the third order, in order to describe the image features at different scales.

3.2 Multiscale Statistic Approach

Let the following attributes be extracted beyond the approximation and detail coefficients c^l_{ij}, at the resolution l :

1. Let H^l be a measure of the entropy:
   $H^l = -\sum_{i,j} p(c^l_{ij}) \log p(c^l_{ij})$ where $p(c^l_{ij})$ stands for the probability to have a coefficient of value c^l_{ij};
2. Let $\max^l$ be a measure of the highest coefficient value: $\max^l = \max_{i,j}(c^l_{ij})$
3. Let μ^l be a measure of the average:
   $\mu^l = \frac{1}{nm}\sum_{i=1}^{n}\sum_{j=1}^{m} c^l_{ij}$
4. Let σ^l be a measure of the standard deviation:
   $\sigma^l = \left(\frac{1}{nm-1}\sum_{i=1}^{n}\sum_{j=1}^{m}(c^l_{ij}-\mu^l)^2\right)^{\frac{1}{2}}$
5. Let $Skew^l$ be a measure of the third moment::
   $Skew^l = \frac{1}{nm}\sum_{i=1}^{n}\sum_{j=1}^{m}\left[\frac{(c^l_{ij}-\mu^l)}{\sigma^l}\right]^3$
6. Let $Kurt^l$ be a measurement of fourth moment:
   $Kurt^l = \frac{1}{nm}\sum_{i=1}^{n}\sum_{j=1}^{m}\left[\frac{(c^l_{ij}-\mu^l)}{\sigma^l}\right]^4$

where $n.m$ is the size of the c_{ij} coefficient images at resolution l.

The pels of the observed picture are zero-mean and reduced in order to improve the robustness of the classification scheme towards experimental conditions. One can note the rotation invariant property of the extracted multiresolution features. The feature vector describing an image i is decomposed on L resolution level: $x_i = \left(D^1, ..., D^l, ..., D^L, A^L\right)^t$ with $D^l = \left[H^l, \max^l, \mu^l, \sigma^l, Skew^l, Kurt^l\right]$ and $A^L = \left[H^L, \max^L, \mu^L, \sigma^L, Skew^L, Kurt^L\right]$. In our application, we consider $L = 3$. Then, we obtain 24 multiresolution statistical parameters for each image i. The parameter vector associated to each image i is then of size 24 : $x_i = (x_{i,1}, x_{i,2}, ..., x_{i,24})^t$

3.3 Discriminant analysis

The discriminant analysis consists in the description and then the classification of individuals, described by a large number of parameters, by means of a training set (individuals for which we a priori know the membership group). This supervised technic consists in searching the optimal linear projection generating class clusters in a subspace defined by the training images. This optimization task is made with a mean-square based criterion which is equivalent to the maximum likelihood criterion in the gaussian case[6]. Nevertheless, in practice, it is difficult to verify this last assumption and the feature parameters follow a priori any laws. However, the new feature parameters are more decorrelated in the subspace than in the initial space. Then the classification task will be easier, if the feature parameters remain discriminant. Of course the recognition rate is not always improved by using more features: if you add correlated features or non discriminant attributes, they obviously increase the noise within the feature space without increasing the performance.

The following section validates the processing scheme on a set of test images, providing by different sonar antennas, from real world seabeds.

4 Classification

On one hand, to generate the training set needed for the feature space reduction, we split the four images (cf figure 1). 300 windows of size 64 by 64 pels are thus obtained, on each of them a pyramidal decomposition is processed up to the third order $L = 3$. As mentioned earlier, 300 vectors x_i are deduced. The discriminant analysis on these feature vectors, associated to a trace criterion[15]; experimentally lead to a space reduction from $\mathbb{R}^{24}$ to $\mathbb{R}^3$. On the other hand, we generate a training set from large images, blocked 64 by 64 pels, that have to be automatically classified. We observe that the distinction between sand-ridge classes and between ridge-pebble classes will be difficult to realize because of their proximity (cf. Table 2).

The classification is based on the K-NNA (K Nearest Neighbors Algorithm)[2][17]. The distance between dots in the feature space is computed to find a set of K nearest neighbors. The decision rule is simple : one affects to one point, the class C_i being in the majority of the K nearest neighbors.

4.1 Results on noisy images from the real world

To show the general applicability of the method, we have tested the classification chain on 300 real sonar images, coming from a high resolution sonar

Classes	distance between center of gravity
$sand - ridges$	193
$sand - dunes$	527
$sand - pebbles$	344
$ridges - dunes$	605
$ridges - pebbles$	233
$dune - pebbles$	725

Table 2: Here we note that the distance between barycenters of ridge and sand classes are closed. Besides, the maximal distance is obtained between dune and ridge classes.

Classes	K-NNA recognition rate (K=30) in %
sand	100
ridges	63
dunes	100
pebbles	100

Table 3: Classification rate with multiresolution attributes. Results are significatively very good for all classes with the Kppv classifier, except for the ridges. In practice, on small pictures (64 by 64 pels), the shape of ridge shadow is of too small sizes and very noisy. This class is then very difficult to classify even with a multiresolution scheme.

system. The multiresolution features are extracted on each picture to labeled. Then the obtained coordinates in the subspace are presented to a K-NNA . In Table 3, the reader will appreciate the recognition rate.

5 Conclusion

This paper have presented a robust approach for automatic classification of high resolution sonar images. The multiresolution feature method described in this article provides reduced space for the classification step. The images to segment are splitted in windows which are projected onto a multiresolution basis of coiflets. Statistic features are thus evaluated and generate a feature space. We have developed a discriminant analysis in order to reduce the size of the space. In the most discriminant subspace, we classified sonar images using a K-NNA classifier. Good recognition rates have been obtained for large sonar pictures of the seabed. The extracted parameters are invariant for rotation transformations. Moreover, they are able to be discriminant for textures at different scales and thus, should be considered for other applications, where micro and macroscopic textures are mixed together. The processing chain has been validated on a number of high resolution sonar pictures, demonstrating the robustness and the efficiency of our approach, with an automatic processing of massive amounts of data.

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