Sidescan Sonar Imagery Segmentation with a Combination of Texture and Spectral Analysis

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***Abstract*— This paper deals with the seabed classification from textured sonar images and specially the potential of the combination of features extracted from co-occurrences matrices and directional filter bank (DFB) . The texture analysis based on the co-occurrences matrices is strongly dependant on the choice of parameter values (e.g. the distance and the angular direction for the estimation of the number of transitions). In most cases the choice is not trivial. To get representative features from textures with different spatial frequencies, a comprehensive set of co-occurrence matrices with corresponding displacements and orientation has to be computed. In this work, we investigate a non classical approach based on the DFB. The approach uses a decomposition of the Fourier spectrum into three spectral bands: low, medium and high frequencies. A subsequent analysis of the pattern isotropy is conducted by dividing the medium spectral band into small, overlapped, angular sectors. The features extracted from this process are assessed so as to determine their potential on the classification performances. First, a comparison with classification performances result given by texture features derived from grey level co-occurrences matrices (GLCM) is made. Finally the global performance of the segmentation is assessed using the spectral features, the features extracted from GLCM and the grazing angle. The Klein 5000 experimental data used in this study have been acquired by DGA/GESMA during BP 02 experiment conducted by NURC.**

Keywords*— *texture analysis, spectral analysis, directional filter bank (DFB), seabed classification, supervised, unsupervised.

I. INTRODUCTION

The notion of texture remains imprecisely defined in the literature despite the abundance of its use in image processing. It is a key problem in many application areas, such as remote sensing and object recognition. Texture analysis is a major step in texture classification and image segmentation. It is refers to a class of mathematical procedures and models that characterize the spatial variations within imagery as a means of extracting information. In image processing and vision, the notion of texture is often addressed by two approaches according to Haralick [1] a statistical and a structural approaches. Statistical methods analyze the spatial distribution of gray values, by computing local features at each point in the image, and deriving a set of statistics from the distributions of the local features. Depending on the number of pixels defining the local feature, statistical methods can be further classified into first order (one pixel), second-order (two pixels) and higher-order (three or more pixels) statistics. The second approach is suitable for structural textures in the periodicity of the patterns are evident. Others propose a synthesis of the two approaches by considering the texture as a spatial structure consists of organizing primitives each having a random aspect. The Grey Level Co-occurrence Matrix (GLCM) is a second-order statistical tool used for texture analysis of images proposed by Haralick [2]. It has been applied successfully on sonar images. The GLCM of an image is obtained by calculating the number of transitions for each pair of grey level (i; j) for a given distance (d) and angular direction (θ). Reference [3] points out that for the co-occurrence matrix estimation in texture recognition, "careful choice of specific sample d, θ values must be made: in most cases it is not at all obvious how such a choice should be made, and it is even more difficult to arrange for it to be made automatically".

In this paper, we investigate the ability of spectral features to discriminate between seabed textures. Spectral features are estimated from directional filter bank in the 2D-Fourier space. The directional filter bank (DFB) originally introduced by [4] and has been proven to be effective in processing image with directional information. The classical DFB shares its properties with the traditional Discrete Wavelet transform (DWT). In this work the Fourier spectrum is separated into three spectral bands: low pass, medium pass and high pass frequencies.

Seafloor classification and segmentation approaches could be categorized as either parametric or non-parametric. The parametric ones are based on modeling the probability distribution of the signal backscattered from the seafloor. These models take into account the conditions of acquisition, the properties of the seabed and the angular variations of signal backscattering. The nonparametric approaches do not consider the conditions of acquisition and physical properties of the backscattering signal. These approaches consider seabed backscatter as textured image. In this work the non parametric approach is used. The Haralick features based on the co-occurrence matrix and the proposed spectral analysis are computed for the features extraction step.

Several machine learning algorithms have already been applied to classify sonar images data such as decision trees, naïve Bayes [5], support vector machines (SVM) and self-organizing feature maps (SOFM) [6]-[7], hierarchical clustering etc.

In this work, to assess the potential of spectral features on the classification performances, supervised and unsupervised algorithms are tested on the data base created from the Klein 5000 experimental sonar data. Two algorithms for supervised classification are used: Bayes naives and Multilayer Perceptron. For the unsupervised technique, K-means and SOFM algorithm are used for the tests. First, we made a comparison with classification performances result given by texture features derived from gray level co-occurrences matrices GLCM. Then classification tests are made from spectral features. Finally, a combination of the two types of features with adding of grazing angle of the sonar is conducted.

The data used in our tests are sonar images acquired from Klein 5000 sidescan sonar. A data base of 400 images of 128x128 pixels is created to conduct the experiment tests. The data base consists of four types of sediment: ripples, rock, sand and posidonia oceanica.

This paper is organized as follows. In section 2, the different texture features used to discriminate the seabed are detailed. In section 3, the supervised and unsupervised classification step is presented. Section 4 provides experimental results of the classification accuracy conducted on data base created from real sonar images are compared and discussed. Finally, the last section concludes this paper.

II. METHODOLOGY

A. Features extraction

In the literature several techniques for texture analysis are proposed. There are methods based on first order statistics, others on second order like co-occurences matrices and methods based on spectral analysis. In this work, the two techniques are combined, the first is based on the Haralick features computed from co-occurences matrices and the second based on features derived from the the spectral analysis of the texture.

1) Statistical features: Theoretical work and practical applications to sonar imagery by [10]-[11] and others have shown that the grey level co-occurrence matrices (GLCM) are the most adapted tools for sonar texture classification. In our case, the GLCM is calculated in 4 directions (0°,45°, 90°, 135°) and for three cooccurence distances (d=1,4,8). Then from normalized GLCM different Haralick features are computed. In this work the Haralick features calculated are listed in Table. 1.

2) Spectral features: Spectral analysis can be used to study the properties of textured scenes, for example the power spectrum reveals information on the periodicity and directionality of a texture. Texture directionality is preserved in the power spectrum because it allows directional and non-directional components of the texture to be distinguished. These observations have given rise to a powerful approach for extracting texture primitives from the directional filter applied to the Fourier power spectrum.

Mallat [12] is the first proposed the concept of decomposition spectrum technique for multi-frequency channel decomposition of image (Wavelet transform). The directional filter bank (DFB) originally introduced by [8] and has been proven to be effective in in processing image with directional information. The classical DFB shares its properties with the tarditional Wavlet transform (DWT). A new non uniform DFB (nuDFB) proposed by [9] divide the spectrum in one lowpass with one to four decimation factor and six highpass with one to eight decimation factor. The nuDFB offers better performances of Brodatz texture then traditional DFB [9].

Our approach for directional filter bank is similar to that applied by nuDFB which decomposes into lowpass medium pass and highpass frequency. The proposed DFB is presented in Fig. 1. An example of spectral decomposition into three spectral bands: low, medium and high frequencies for three type of sediment (ripples, rock and sand) is shown in Fig. 2.

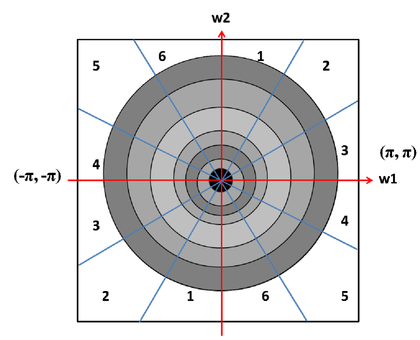

Fig. 1. The proposed directional filter Bank (DFB) with twelve (12) angular sectors and six (6) spectral bands.

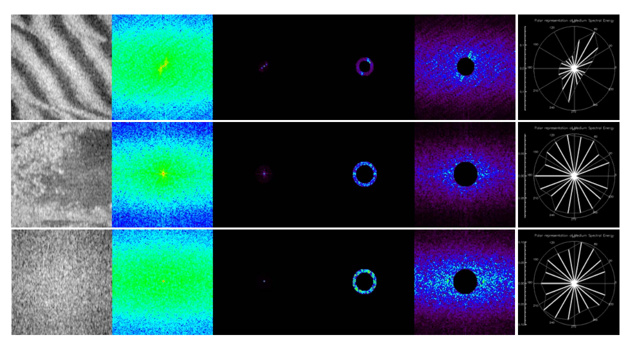

Fig. 2. column1: Ripples-Rock-Sand, column 2: The Fourier spectrum, column 3: Low pass frequencies, Column 4: Medium pass frequencies, column 5: High pass frequencies, Column 6: Representation in polar coordinates of the Medium low frequencies

3) Features vector: The features vector combines the statistical features computed from GLCM and spectral analysis. The images used in this work for features extraction

are 128x128 pixels size. On each image 121 features are computed, 96 of Haralick features using an analysis window of 64x64 pixels without overlapping and 24 spectral features. For the spectral features six are computed directly from the Fourier spectrum: Mean, variance and the power of magnitude, low pass frequencies, medium pass frenquencies and high pass frequencies. The others spectral features are computed by using proposed DFB presented in Fig. 1.
To take into consideration the incidence angle variations, grazing angle of sonar is inserted to the features vector. The features computed in this work are listed in the Table. 1

TABLE I. FEATURES COMPUTED FROM TEXTURE ANALYSIS AND SOECTRAL ANALYSIS.

Type of Feature	Number of Features
Texture Analysis (Haralick features)	
Kurtosis	12
Elongation Factor	12
Entropy	12
Contrast	12
Heterogeneity	12
Homogeneity	12
Correlation	12
Max. of probability	12
Spectral analysis	
Mean of magnitude	1
Variance of magnitude	1
power of magnitude	1
Low pass frequency	1
Medium pass frequency	1
High pass frequency	1
Mean of DFB	6 (six bands)
Standard deviation of DFB	6
Skewness of DFB	6
Grazing angle	1
Total	**121 Features**

III. CLASSIFICATION STAGE

For the classfication stage two techniques are used, supervised and non-supervised approaches.
Supervised classification predicts a discrete class label for a previously unseen instance from a model learned on labelled training instances. Many supervised techniques have been developed to tackle the problem of classfication. Neural networks and probabilistic classifiers have been frequently used in the litterature [13]–[15] and have been coupled with features extraction measures including, spectral analysis [16], fractal analysis [17] and co-occurrence matrices [18]. In this work, two classifiers are used for the supervised approach, the Naives Bayes [19]- [20] and Multilayer perceptron [21].

In the case of unsupervised learning, the principle of the this machine learning methods is to find an partitioning (i.e. clustering) of the data set. Cluster analysis is the organization of collection of patterns which are usually represented as vectors of features, into clusters based on similarities. Approaches to unsupervised learning include clustering (K-means, mixture models, hierarchical clustering, self organizing feature maps (SOFM), etc). In our case, two algorithms for unsupervised approaches are tested, the classical K-means [22] and the SOFM algorithm (Self Organizing features maps) [23]. For the supervised and unsupervised algorithms, the experiments were performed with the Weka machine learning package [24].

IV. EXPRIMENTAL RESULTS

The data used for our study were obtained during the BP'02 (Battlespace Preparation) experiments carried out by the SACLANT Undersea Research Centre in La Spezia, Italy. The system used is the Klein 5000 sidescan sonar operating at 455 kHz. The sensor can work on two modes of resolution. In low resolution mode, the along-track resolution is 20cm and the maximum range is 150m on each side of sonar which gives a swath of 300m. In high resolution mode, the along-track resolution is 10cm and the maximum range is limited to 75m (i.e. a swath of 150m). In both modes, the across-track resolution is 3cm. In our case we only use images acquired in high resolution mode. An example of sonar image is shown in Fig. 4. Three types of sediment can be distinguished: an homogeneous area representing sand and the other parts of image are more complex, we can distinguish ripples and rock.

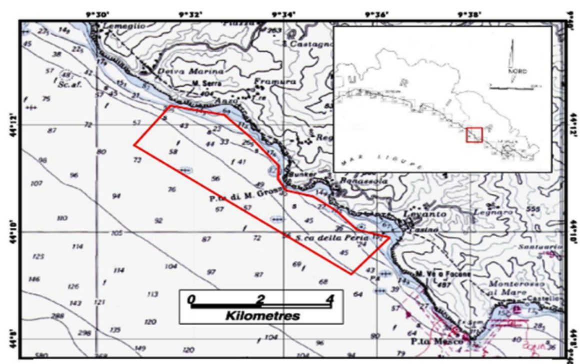

Fig. 3. Geographical location of the BP'02 experiment data acquired by Klein 5000.

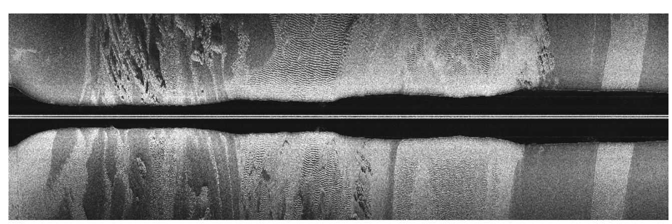

Fig. 4. Example of sonar image acquired by Klein 5000.

For experiment and to assess the contribution of spectral features for classification performances results, a data base of 400 images of four types of sediment (Posidonia oceanica, rock, ripples and Sand) is created from the sonar data images used. The data base is shown in Fig. 5.

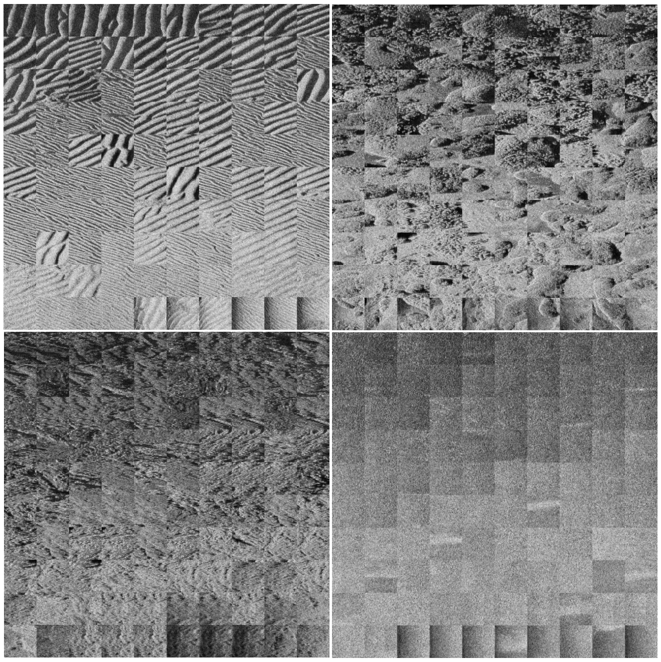

Fig. 5. Data base used for tests of 400 images for 4 types of sediment (ripples,posidonia, rock and sand) in different grazing angle of sonar.

A. Supervised classification

Two approaches are used in this work for the supervised classification of the data base shown in Fig. 5. The first based on the probabilistic technique is the Naïve Bayes and the second one is based on neural networks is Multilayer Perceptron. The comparison is made on the classification accuracy for each algorithm for three configurations: the first is to use only Haralick features, the second is to use spectral features then the last by using the combination of the two.

1) Naïve Bayes: The Bayesian classifier [19] is a well known probabilistic induction method. Bayes rule can be used to predict the class given the feature values. In a Bayesian classifier, the learning process builds a probabilistic model of the features and uses that model to predict the classification of a new example. Naive Bayes[19]-[20] simplifies probabilistic induction by making the assumptions that the features are independent given the class and all the probability estimations from the training sample are accurate.

2) Multilayer perceptron: A multilayer perceptron (MLP) is a feedforward artificial neural network model that maps sets of input data onto a set of appropriate outputs. An MLP consists of multiple layers of nodes in a directed graph, with each layer fully connected to the next one.

TABLE II. CLASSIFICATION ACCURACY FOR NAÏVE BAYES AND MULTILAYER PERCEPTRON APPROACHES IN THREE CONFIGURATIONS OF FEATURES USED: HARALICK, SPECTRAL AND THE COMBINATION OF ALL FEATURES.

Method of classification	**Features used**	**Correctly Classified Instances (%)**
Naïve Bayes	**Case1**: Haralick features	76.06
	Case 2: Spectral features	78.18
	Case 3: Haralick+Spectral+Grazing angle	**82.31**
Multilayer Perceptron	**Case1**: Haralick features	95.43
	Case 2: Spectral features	93.18
	Case 3: Haralick+ Spectral+Grazing angle	**99.06**

The confusion matrices for the two algorithms: Naïve Bayes and Multilayer Perceptron in the Case 3 presented in the Table. II are given in the Table. III and Table. IV.

TABLE III. CONFUSION MATRIX FOR THE NAIVES BAYES IN THE CASE 3 OF THE TABLE. II.

C_1	C_2	C_3	C_4	**← Classified as**
237	113	0	50	***C_1= Posidonia***
95	**305**	0	0	***C_2=Ripples***
1	0	**399**	0	***C_3=Rock***
19	3	2	**376**	***C_4=Sand***

TABLE IV. CONFUSION MATRIX FOR THE MULTILAYER PERCEPTRON IN THE CASE 3 OF THE TABLE. II.

C_1	C_2	C_3	C_4	***← Classified as***
394	2	0	4	***C_1= Posidonia***
1	**399**	0	0	***C_2=Ripples***
0	0	**400**	0	***C_3=Rock***
8	0	0	**392**	***C_4=Sand***

B. Unsupervised classfication (clustering)

For the unsupervised classification, we also used two algorithms. The first one based on classical K-means and the second is a competitive neural networks based on the SOFM (self- organizing feature maps).

1) K-means: K-means is an unsupervised learning algorithm; its purpose is to divide observations into K partitions or clusters in which each observation belongs to the partition with the nearest average.

2) SOFM: Self-organizing feature maps developed by Kohonen [23] is a competitive neural network algorithm based on the biological functioning of the cerebral cortex. SOFM algorithm is different from other artificial neural networks in the sense that it uses a neighborhood function to preserve the topological properties of the input space. This algorithm is applied successfully to the segmentation of raw sonar images [25].

TABLE V. CLASSIFIATION ACCURACY FOR K-MEANS AND SOFM ALGORITHM IN THREE CONFIGURATIONS OF FEATURES USED: HARLAICK, SPECTRAL AND THE COMBINATION OF ALL FEATURES.

Method of classification	Features used	Correctly Classified Instances (%)
K-means	**Case1**: Haralick features	63.06
	Case 2: Spectral features	44.00
	Case 3: Haralick+Spectral+ Grazing angle	**65.25**
SOFM	**Case1**: Haralick features	59.00
	Case 2: Spectral features	51.75
	Case 3: Haralick+ Spectral+ Grazing angle	**65.5**

Confusion matrices are computed for the two unsupervised algorithms, K-means and SOFM. The results for Case 3 (see Table. V) are given in Table. VI and Table. VII, respectively.

TABLE VI. CONFUSION MATRIX FOR THE K-MEANS CLASSIFIER IN THE CASE 3 OF THE TABLE. V.

C_1	C_2	C_3	C_4	**← Classified as**
375	17	8	0	***C_1= Sand***
21	**175**	99	105	***C_2=Posidonia***
1	166	**170**	63	***C_3=Ripples***
42	131	136	**91**	***C_4=Rock***

TABLE VII. CONFUSION MATRIX FOR THE SOFM CLASSIFIER IN THE CASE 3 OF THE TABLE. V.

C_1	C_2	C_3	C_4	***← Classified as***
275	0	125	0	***C_1= Rock***
29	**356**	6	9	***C_2=Sand***
11	24	**148**	217	***C_3=Posidonia***
0	29	102	**269**	***C_4=Ripples***

C. Analysis and discussion of results

From the Table . II the two supervised algorithms Naïve Bayes and Multilayer Perceptron give best results in the Case 3 respectively with classification accuracy of 82.31 % and 99.06 %. We note also, that the Multilayer Perceptron classify better the data base than the Naive bayes in the three cases of configuration. The Haralick features used alone with the Multilayer Perceptron give better result with 95.43 % comparing to 93.18 % for the spectral features. For the Naive Bayes, spectral features give better classfication accuracy with 78.06 % than Haralick features used alone with 76.06 % of good classfication instances.

From the Table. V the two unsupervised algorithm K-means and SOFM give best results in the Case 3, respectively with classfication accuracy of 62.25 % and 62.50 %. We also note, that the SOFM classify better the data base than the K-means in the the second and the third case of configuration (see Table. V). The Haralick used alone gives better classification results than spectral features in the two cases: K-means and SOFM.

The grazing angle feature improves the perfomances of classifiers for both supervised and unsupervised classification.

V. CONCLUSION

In this paper, we propose directional filter bank DFB for spectral features analysis. A combination of the proposed spectral features with the Haralick features derived from GLCM gives better classification results than the used only of GLCM features.

Both, supervised and unsupervised algorithms tested on the created sonar data base confirm the ability of DFB features to discriminate of seabed textures.

We also note that the grazing angle feature improves the classification accuracy.

The improvement of classification results on combined features show that GLCM and spectral features provide complementary descriptions of seabed textures. Further study will be conducted to analyze more deeply this complementarity.

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