SonarClass: A MATLAB TOOLBOX FOR THE CLASSIFICATION OF SIDE SCAN SONAR IMAGERY, USING LOCAL TEXTURAL AND REVERBERATIONAL CHARACTERISTICS.

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Abstract: *A Matlab toolbox for the acoustical classification of Side Scan Sonar imagery has been created and is presented in the current paper. SonarClass is based on a methodology that concerns extraction and analysis of local textural and reverberational characteristics and consists of 3 main stages: 1) selection of training samples, 2) feature selection and calibration according to the training samples so that the bottom classes are optimally discriminated into the feature space and 3) supervised classification of the SSS image using the selected features and a variety of classifiers. Second order (or textural) statistical parameters are derived from the well known Grey Level Co-occurrence Matrices (GLCMs) and the two-dimensional Fourier spectrum whereas first order (or tonal) statistics are simple calculations of elementary statistical features and central moment estimations. The originality of the method lays on the fact that 1. it applies automatic selection of the best combination of parameters, through an iterative optimization process and 2. it performs calibration of the offset (d) and theta (θ) parameters that control the GLCM efficiency. The main target of this methodological scheme is to ensure that the researcher has maximum supervision over the classification process and generalized classification rules can be straight forward realized. The created Matlab toolbox and the graphical interfaces are particularly comprehensible and the user has full control over the classification process. The options of overall image classification or individual bottom type detection are feasible on user's demand and unsupervised classification abilities are also apparent.*

Keywords: *Sidescan sonar, texture analysis, image classification, SonarClass, GLCMs optimization*

1. INTRODUCTION

Sidescan sonar has been an important tool for seafloor survey over the past few decades. Due to the highly textured appearance of sonar images, texture analysis techniques become natural choices for sidescan sonar image analysis. Grey level cooccurrence matrices (GLCMs) and Fourier Transform approaches are among the methodologies that have mostly been used for textural analysis and image classification. Statistics over GLCMs are very powerful texture descriptors but they need a sufficient amount of input parameters to be specified a priori. In works of Ph. Blondel et.al these parameters are specified by performing repeated tests until optimal separation between textural units is observed [1], while R.Jobanputra et. al. have arbitrarily set standard values [2]. G.Y. Ojeda et.al extracted various image description features using both textural and grey level first order statistical parameters and investigated their ability to differentiate classes by plotting diagrams between most of the feature combinations [3]. John Preston extracted a vast amount of features concerning many first and second order statistical parameters and then reduced the data dimensionality to only three components by using PCA [4]. Xiaoou Tang et.al. proved that Fourier Transform magnitudes contain enough texture information, if the right feature extraction algorithm is used [5].

In this study we have proceeded to three innovations: 1) grey level first order (tonal), second order (textural) and Fourier transform methodologies were all together used to extract a variety of image description features, 2) optimal feature selection is ensured through a computerized process that tests the discrimination ability of all the possible combinations between the features and 3) numerous GLCM input parameters (offsets, directions and other special treatments) are used to produce different feature values and the optimal ones are selected via innovation no 2. Tests upon artificial textures and case studies [6] showed that the proposed methodological scheme provides optimal separation between bottom classes and thus reliable classification seafloor maps can be produced.

2. METHODOLOGY OVERVIEW

The process of pattern recognition in the context of the SonarClass software involves five main steps: 1. manual selection of a limited number of small characteristic regions from each desired sea-bottom class (training samples), 2. extraction of a large number of first order (tonal) and second order (textural) statistical parameters from each training sample, 3. automatic selection of the combination of parameters that provide the highest discrimination between the acoustic types (optimization process), 4. extraction of these parameters from sub-regions throughout the whole SSS image and 5. supervised classification of the image. In practice, steps 1 to 3 compose the Calibration module while steps 4 and 5 the Classification module of the SonarClass software. SonarClass can be considered a sea bottom classification software that parallels the methodologies adopted by the broadly used TexAn [1] and QTC [4] softwares, but through a more explorative way. Five GLCM properties, four simple first order gray statistics and two 2D FFT spectrum descriptives are in use by the SonarClass software.An in depth description of them can be found in [6]. Fig. 1 describes in brief the methodological scheme adopted by the SonarClass software.

A key feature of SonarClass toolbox is the emphasis that has been given to the way that GLCM features are calculated. In particular, only the 5 more popular features out of the 12 that Haralick [8] introduced are considered. Symmetrical and normalized cooccurrence matrices are used so that matrix elements refer to joint probability densities. Averaging the GLCMs by using four angular directions (0^o,45^o,90^o and 135^o) is an established method to ensure insensitivity to pattern rotation [1]. In our study a new approach is developed, according to which more angular directions are analyzed and the maximum statistical values of the θ directions are recorded apart from the averages ones. These treatments of angular directions will be referred in the text as “max θ” and “average θ” treatments. In [6] it has been proven that the “max θ” treatment very often gives much better results than the classic “average θ” treatment.

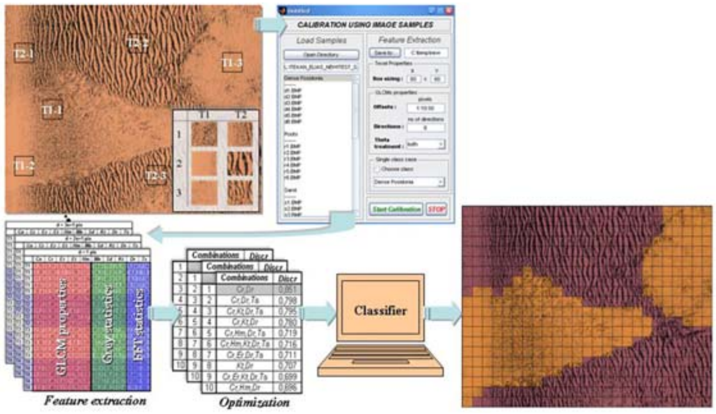

Fig.1: An overview of the methodological scheme adopted by SonarClass.

2.1. THE CALIBRATION MODULE

Using a large amount of features for classification purposes is not always efficient as some of them may be correlated or may reduce the discrimination of the classes within the features’ space. Data reduction methods such as Principal Component Analysis is a common technique [4] but the components that are created have no particular physical meaning and they cannot be used to train a classifier that will be applied to a different data set, thus making them applicable only for unsupervised classification purposes. Taking the previous into account, careful selection of the features is always important to optimize a classifier’s efficiency. The methodology followed in SonarClass involves 3 stages: 1) feature extraction from the training image samples, 2) estimation of the discrimination power for all the possible combinations (not only per two) between the n features and finally 4) selection of the combination that provides the highest discrimination power score. The calibration practice is firstly applied to the GLCM features, estimated for a variety of d and θ values and for both ‘max’ and ‘average’ ‘θ treatments’, as requested by the user. After the GLCM properties (d, θ and θ treatment) and the combination of GLCM features that provide the best possible discrimination power have been found, the process is repeated including the rest of the features. Finally the top combinations of all the features are shown to the user who can decide which suits him best. The motivation for this methodological approach is that as far as we know the d and θ values are usually selected either arbitrarily by setting d = 1 pixel and θ = 4 angular directions, or by performing protracted manual tests to specify the best ones. When dealing with a large amount of features, possible combinations between the features are too many to be tested out manually. For example the possible combinations between 8 features are 255 and between 11 variables are 2047. Notwithstanding, finding out the features that provide the best between classes discrimination is vital for the optimization of the classification process. Consequently, in SonarClass, a computational procedure is employed that automatically tests all the possible combinations between the n features and decides which one provide the higher score. Then, this combination is considered as an appropriate one for the classification process.

Discrimination power measure is provided by the cluster silhouette values. The silhouette value for each sample point is a measure of how similar that point is to points in its own cluster (class) compared to points in other clusters, and ranges from -1 to +1. The sensibility of the discrimination power to changes of the offset, θ and θ treatment properties can be very clearly seen in experiments that have taken place in [6] making their careful selection an issue of importance.

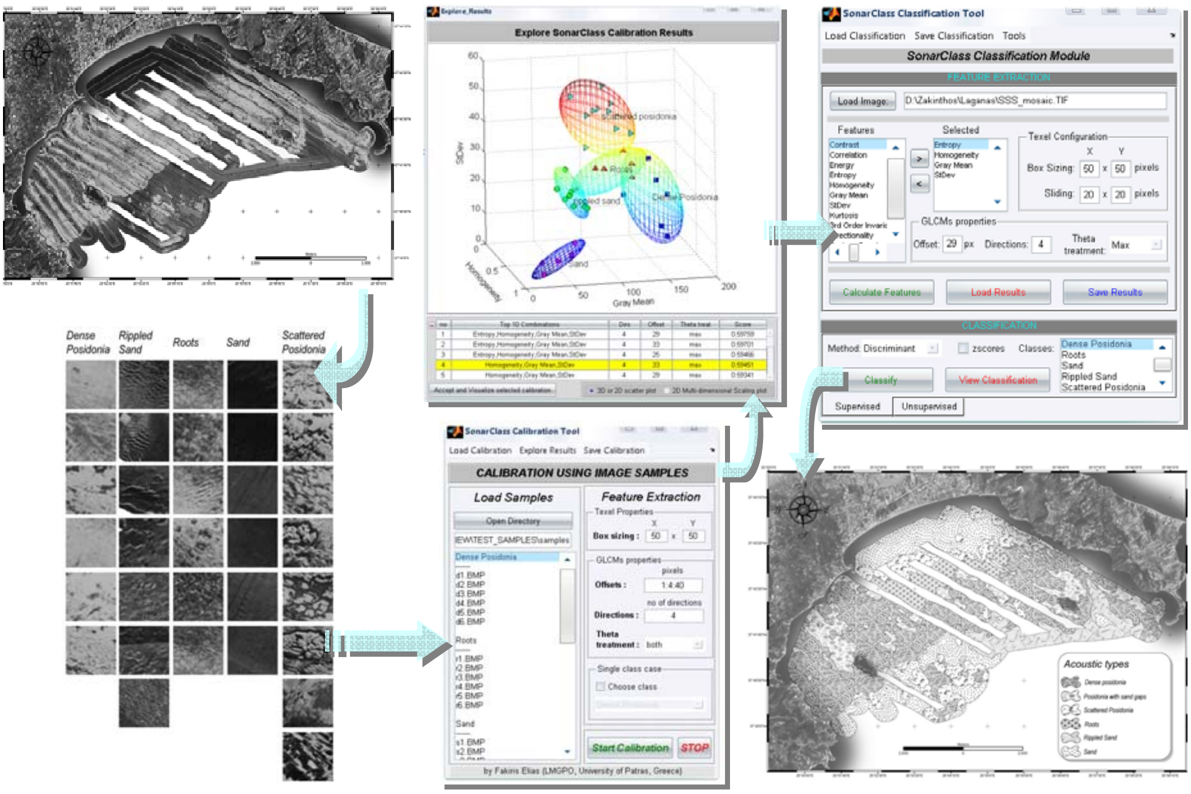

Fig.2: The SonarClass software as used for creation of a bio-habitat map in Laganas Gulf, Zakinthos Island, Greece [7].

The "Calibration module" of SonarClass is responsible for the implementation of the above mentioned procedure. It has a graphical user interface (Fig 3) that allows the user to control the number of offsets and directions to be included in the process and the theta treatments to be considered. In addition, each class can be analyzed individually so that different feature combinations are to be used for the classification of every bottom type (Fig 4). The top ten combinations of features and all their characteristic parameters can then be visually explored via the "EXPLORE RESULTS" tool (Fig 3). The preferred combination of features can then be selected to be used in the "Classification Module" for the classification of the raw SSS image, into as many classes as reported by the training samples.

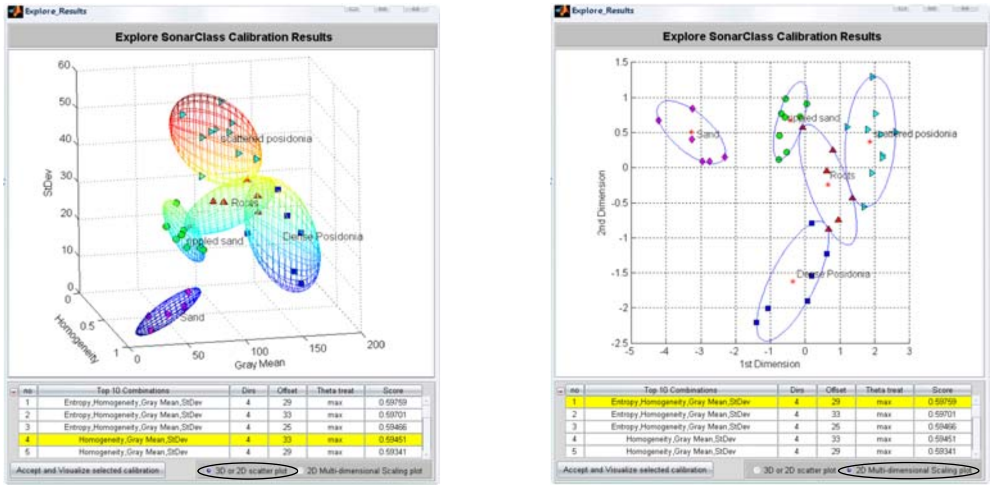

Fig.3: The "Explore Results" tool and the options that it offers.

2.2. THE CLASSIFICATION MODULE

At this point we have extracted GLCM, first order and Fourier statistical features from the sample data set and we have concluded in which features to use in order to provide optimal categorization between classes. The training of the classifier is done using the selected features as extracted from each sample region. Then the sidescan sonar image is divided into either distinct or sliding windows (sub-regions or texels), and each one is classified according to the decision rules created by the classifier. If a window consists of more than 50 % white or black areas it is considered as 'no data' area and is excluded from the analysis.

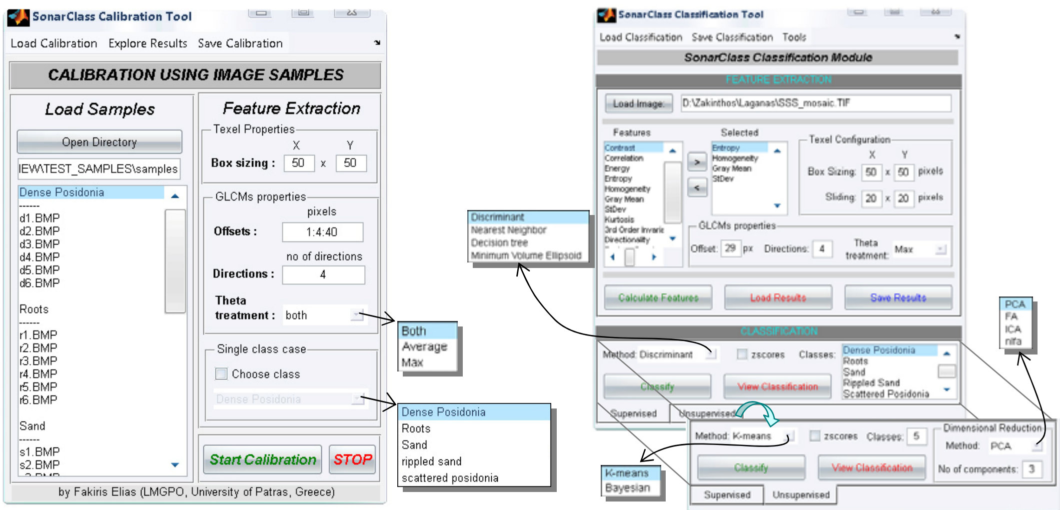

Fig.4: The options that are given to the user by the SonarClass Calibration and Classification modules.

The Classification module gives the option of supervised or unsupervised classification (Fig 4). In the first case the features to be included in the analysis are supplied by the calibration module whilst in the second the features are manually selected as well as the GLCM properties. In the "unsupervised" case, the data can be dimensionally reduced using a variety of data reduction techniques. In each case the user can choose between a number of classifiers and decide whether the data will be standardized or not. Finally, the user selects the SSS imagery to be classified, the window sizing (in pixels) and the overlapping window area if sliding windows are desired. The results can be viewed and stored in comma delimited matrices and indexed-color georeferenced classification images.

3. CONCLUSIONS

In this paper a fully developed MATLAB toolbox for side scan sonar imagery classification has been presented. The implemented methodology involves three image analysis approaches (first order statistics, GLCMs and simple Fourier Transform approaches) and a computerized GLCM calibration and feature selection procedure. We have introduced a methodology that automatically compares all the possible combinations between the features and finds those that provide the best seperability between the various sea bottoms classes, based on collected image samples. The same samples are used to train a classifier. The simultaneous use of a variety of feature extraction methodologies in combination with the calibration process has been proved to be a promising aspect. The SonarClass MATLAB toolbox and its convenient graphical interface have already been successfully used for the classification of SSS records from a variety of sea bottom environments.

4. AKNOWLEDGEMENTS

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