A High Frequency Approach for Seabed Vegetation Characterization

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Abstract

This paper focuses on the characterization of seabed vegetation, an interesting problem in a lot of Mediterranean sea coastal sites since water quality and pollution degree can be efficaciously solved by investigating the sea flora extents. The acquisition of the data about marine vegetation is accomplished by using a high frequency imaging sonar scanning the seabed. The proposed approach is based on a statistical feature-based description of the raw sonar data. A simple classifier attempts to characterize the acquired samples.

1. Introduction

1.1 The Shallow Water Surveying

The characterization of the sea bottom from acoustic data is an important problem with many applications in geophysics, biology, oceanography, geology and seismology. Acoustic characterization is made possible since the sea bottom material composition (either in or out of the bottom itself, e.g. sediments and vegetation) supports the excitation and propagation of acoustic waves [1].

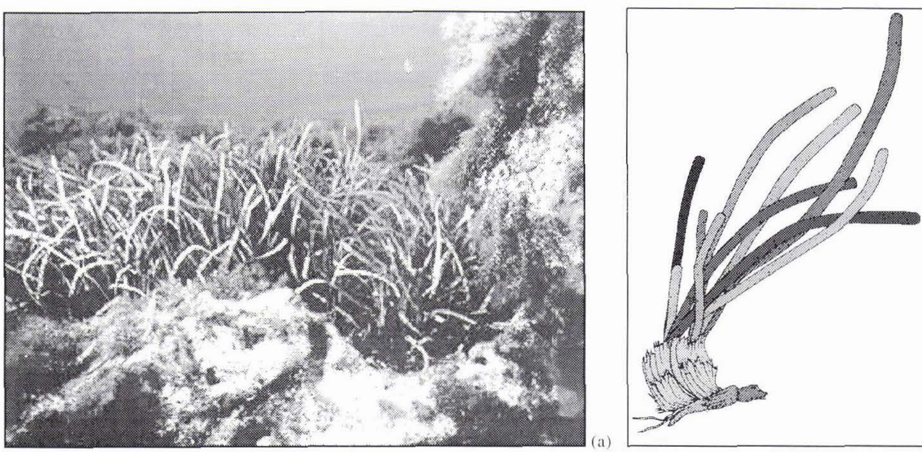
Acoustic waves (or pings) energy impinges the sea floor (or whatever material lying between the transmitting device and the sea floor) and it is scattered in all directions by all the interfaces between two mediums: in general, echoes from the interface between the water and the sea bottom, from the volume of the sea bottom and from the volume lying close to the bottom can be detected in the scattered signal [2][3]. Reflections due to particular interfaces can be in some way emphasized, despite of other interface contributions, by using particular range of frequencies. For example, in order to investigate the subbottom geological composition, low frequencies must be used (i.e., 100 Hz - 10 KHz), while high frequencies must be employed (i.e., 70 KHz - 2 MHz) in order to detect fish-bank.

Then, the returned echo pulses carry the information about the seabed characteristics from which the pulses have been reflected: for this reason, by analyzing the scattered intensity, it is feasible to develop appropriate techniques in order to extract measures from the echo signals and to detect and classify different areas responsible of scattering.

1.2 Posidonia Oceanica

The survey of the seabed is coming more and more important in several coastal sites since marine vegetation makes up a natural and specially meaningful sea state of health gauge [4]. Several species of plants and algae, each with different biological and morphological characteristics, populate the seabed. In this work, attention is focused on the endemic Phanerogam Posidonia Oceanica which extents along the French and Ligurian coasts and in several other Mediterranean sea continental shelf sites, playing a leading role in the global Mediterranean coastal ecosystem. This marine plant forms underwater meadows in littoral areas creating an irreplaceable environment for several fish species, marine mammals and other species of plants and algae [5]. Moreover, Posidonia Oceanica leaves contributes to limit the energy of the sea swells and current, and create natural barriers, thus strongly reducing the coastal erosion, Furthermore, through the photosynthesis process, its meadows produce big amounts of oxygen, being really a green lung for the submersed world. Unfortunately, Posidonia Oceanica is very sensitive to both natural (temperature rise, turbid water, strong competition with algae [6], etc.) and man-made changes (dikes, excavation, discharge of sewage and industrial waste, trawling): these factors often give rise to regression or quite disappearance of Posidonia beds. Nowadays, the survival of this plant depends not only on the pollution agents (chemical, biological, and physical) but also on the competitive growth of other species such as the tropical green alga Caulerpa Taxifolia. Therefore, the analysis of marine vegetation, and especially of this plant, assumes a scientific interest and also a practical importance to preserve the coastal water delicate ecosystems.

Posidonia Oceanica typically shows a great extent within a deep gradient from 1 to about 40 meters. It is organized in roots, a stem termed rhizome, and leaves (Fig. 1). The rhizomes can develop horizontally and vertically and act as anchors for the plant to the substrates by means of the roots in the lower part. The bright green leaves grow from the vertical rhizomes and are ribbon-like with rounded apices. They have a mean width of 1 centimeter and can be up to 1.5 meter long. Plants are arranged in six or seven number groups, organized in a fan-like structure. Older plant leaves, of greater length, are on the outside of the plant, whereas the smaller, younger leaves are on the inside of the sheaf-like arrangement. Posidonia leaves grow extremely slowly, up to 10 centimeters per year at the most, hence existing Posidonia meadows maintenance is essential.



(a) (b)

Figure 1: (a) Dense Posidonia Oceanica meadow; (b) drawing of the plant.

1.3 The Acoustic Survey

The only means to carefully analyse such small targets as represented by plant leaves consists in a high resolution acquisition of measures near to the seabed, and this operation can be performed by a high frequency acoustic device able to detect the response of low strength plant reflections and to perform a dense and accurate sampling of the sea bottom where the plants live.

Sector-scanning sonars carried by autonomous [7] or remotely operated vehicles are usually considered as one of the most efficient methods for object detection, identification and recognition in marine environment, where optical visibility is often limited and underwater cameras cannot be employed even at low ranges [8][9]. They generally provide noisy 2D range-vs.-bearing images of the insonified 3D scenes. The signals received by the sonar transducer are related to the insonified objects surfaces presented to the sonar head: hence, sonar acquisitions supply a distorted representation on a 2D space of the volume under inspection. Moreover, troublesome effects, such as clutter between the seabed and the surface, noise, reverberation and multipath, are generally present in sonar images, making them difficult to interpret [10].

If the purpose of our research had simply been the detection of vegetation presence, a side-scan sonar could have been sufficient [11]. In side-scan sonar images, vegetation is often recognizable by large dark areas, and meadows upper and lower limits are easily detectable. But, by using this type of sensors, only the detection and sometimes a macro-characterization is possible since spatial resolution is generally very poor [12]. Instead, our target is somehow more complex and ambitious, being to detect marine plants and trying to characterize them by supplying both quantitative and qualitative characteristics. Hence a high resolution survey is necessary. It is accomplished by a mechanically scanned, 2 MHz narrow pencil beam monostatic sonar, scanning a vertical sector towards the sea bottom: this sensor is used for insonifying the seabed, acquiring the backscattered signals and for the imaging process. The high frequency acoustic device assures a suitable resolution capability and a high sensitivity to low strength targets present upon the sea bottom.

2. The Technical Approach

2.1 Methodology

An autonomous or a remotely operated vehicle carrying the sonar head navigates at a very low speed with an almost constant distance from the sea bottom: while traveling, the head rotates around its axis of a variable sector, thus acquiring data about a strip-like area of the seabed. Hence, data referring to a strip-like area can be acquired and stored on the vehicle on-board digital memory or on a remote computer connected to the sonar by a standard serial link. The received echoes can be considered either as a sequence of raw scanline signals and processed in a one-dimensional space, or as correlated series of scanlines. In this second instance, a kind of image can be generated by placing side by side the sequence of scanlines.

The vegetation analysis is considered as a problem of pattern recognition [13] by using a statistical classifier. The basic concept at the basis of every classification sonar-based system is that the backscattered signals are in some way highly correlated with the characteristics of the area or the volume which return the signals. Therefore, the received echoes can be processed in order to extract significant features [14][15] and to identify different seabed areas in terms of vegetation presence and characteristics. The high frequency employed in our survey does not let penetration of the sonar signal in the subbottom, while allowing the backscattered echoes to be essentially referred to the low-strength vegetation leaves and to the water-bottom interface. This consideration shows the effectiveness of the chosen acoustic sensor.

2.2 Data Acquisition

A Tritech ST2000 2 MHz narrow pencil beam sonar, scanning a vertical sector towards the sea bottom was employed for the data collection. The sonar measurements result from the combination of a sequence of individual measurements made while it sweeps its nominal sensor axis through a defined sector spanning an area of interest. The sensor can generate scans containing 800 individual measurements at equally spaced intervals of 0.45° over a full 360° panorama. The sonar operates by transmitting an outgoing pulse (i.e., ping) of duration depending on the range of the target to be insonified, by listening the received signal up to the time corresponding to the selected range, and finally, by reorienting the transducer for the next ping cycle.

In order to better visualize the acquired data, the image of the observed underwater scene is build by placing side by side, in a vertical arrangement, each received scanline without any kind of pre-processing or compensation operation. The raw sonar signal can be mapped into a 8-bit image with standard range 0÷255 corresponding to the head dynamic range 0÷80 dB.

Figure 2 shows a sonar image acquired in a laboratory acoustical tank at 1 meter distance from the bottom. All the images presented in this paper were acquired in a tank where both real Posidonia Oceanica and flat plant leaves were fixed over a synthetic lawn, while the sonar scans variable sectors always at the best angular (0.45°) and spatial (1 sample every 6.4 μs in time, 4.8 mm in range) resolution. Low contrast and a preferred vertical direction are relevant factors that must be taken into account for the selection of suitable processing algorithms.

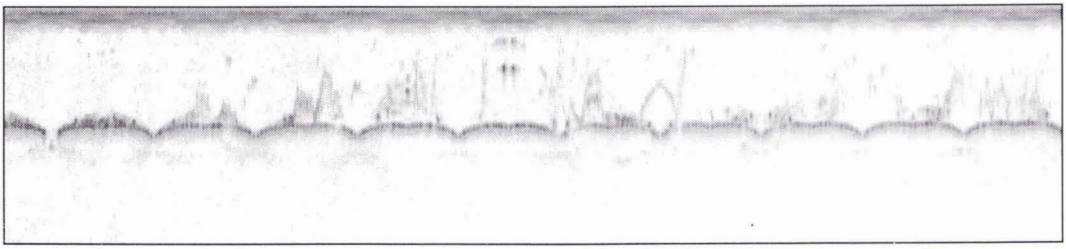


Figure 2: Sonar image of real plant leaves on a nearly flat bottom.

Vertical and horizontal resolutions are not a-priori fixed and this kind of image representation is effective only when a sufficiently high spatial resolution on the sea bottom really exists. The vertical resolution is influenced by the transmitted pulse length and the ratio between the selected range and the number of acquired samples: by sampling the backscattered echoes at the highest possible rate, a nominal range resolution of 4.8 mm is assured. However, the AD converter inside the sonar head can handle only 1500 samples per each scanline at the most and this characteristic involve a limitation about the maximum available range in order to maintain the best resolution. This limit is fixed at about 7 meters from the targets. But, the highest is the number of acquired samples and the vertical resolution, the longer is the time spent to acquire the scanline data and the worst is the horizontal resolution on the bottom, since while the head keeps silent to transfer the backscattered echoes to the processing unit, the vehicle moves forward along its path. The result is an image in which each columns is poorly related to its adjacent ones. Therefore, a balance between the desired vertical resolution and the sampling interval on the seabed has to be reached, otherwise only a 1D analysis can be carried out.

2.3 Data Preprocessing

Before analyzing the acquired signals to extract features and to attempt the seabed classification, a preprocessing phase is applied in the 2D domain by using essentially image processing algorithms. They aim at filtering the received noisy signals and at focusing the attention on significant parts of each scanline, that correspond at isolating interesting areas within the corresponding image. This second objective is particularly important since most of the feature extraction algorithms to be successively applied, are time consuming and great improvement in computational burden can be drawn by considering a small portion of the signal instead of its wholeness.

The first operation applied to the raw scanline signals is a compensation for the local bottom slope: the information about the distance between the acoustic receiver and the bottom is supposed as a known variable, being either directly measurable from the raw data (if the acoustic pulse is not absorbed by the overhanging plant leaves) or provided by an external sensor such as an ecosounder.

Image processing techniques basically consist in a combination of non-linear [16] and morphological filters [17]. Figure 3 shows an acquired sonar image and the result obtained at the end of the preprocessing phase. The bottom lower limit and the upper bound of targets are clearly observable.

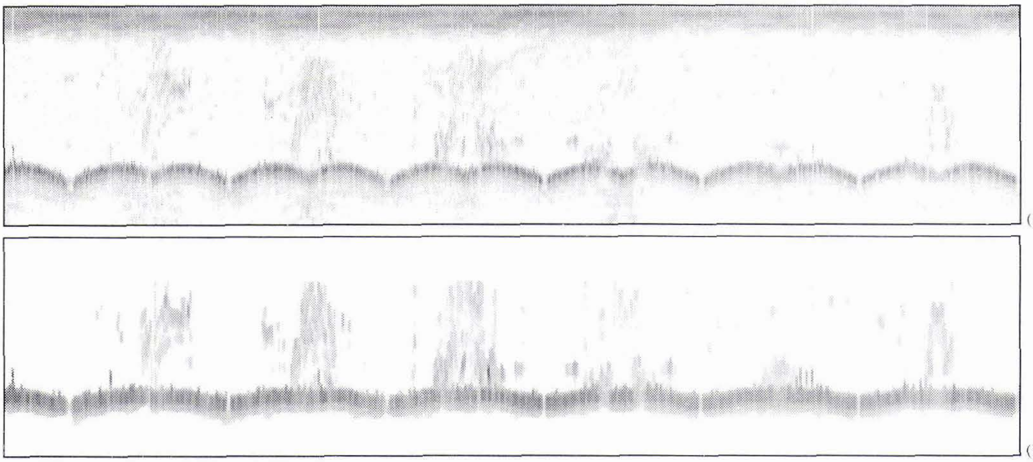


Figure 3: (a) An original sonar image and (b) the focused sonar image as it appears after the image preprocessing.

2.4 Feature Extraction

The first step of the proposed statistical classification consists in the extraction of feature vectors from the acquired and preprocessed data. This is a fundamental operation since only by considering features suitable for separation of different vegetation types, the successive classification phase can guarantee satisfying performances. In fact, the classifier's capability to discriminate between different information classes relies on how well the different classes are separated in the feature space [13].

We have directly access to the sampled backscattered data, hence methods examining echoes shape and strength appears suitable. Thus, several features based on backscattered strength, texture content and scanline shape analysis are extracted on the basis of the mentioned 2D representation. Each feature is extracted from the selected part of the original scanline signal: this corresponds to compute the feature value only within the portion of the signal that was preserved during the image preprocessing. This technique allows to reduce the required operations by saving time.

The following features were extracted from the focused data: mean value, standard deviation, mean deviation, skewness, kurtosis, distance between the bottom and the upper bound of the plants, number of maxima and minima of the signal, and several quantiles (from 0.1 up to 0.9) [14].

Most of the above mentioned features are related to the distribution of a random variable. Especially the quantiles can be useful to describe a distribution, being the pth quantile of a set of values defined as the mean value Q_p of the subset $\{x_i\}$ of values satisfying the following condition $P(x_i < Q_p) \leq p$ and $P(x_i \geq Q_p) \leq 1-p$.

Moreover, also the texture content was quantified in terms of energy, entropy, contrast and homogeneity, by supposing that variations in acoustic reflectivity may correspond to different structures (i.e., plant types) present over the seabed. Texture features were calculated by defining the gray-level spatial co-occurrence matrix (GLCM) for small strip-like subsets of the whole image composed by 10, 15, and 20 successive pings (corresponding to angular sectors 4.5°, 6.75°, and 9.0° wide). The GLCM is a symmetric matrix of relative frequencies P_{ij} with which two neighboring pixels separated by a fixed distance d along a fixed direction θ occur in the image, one with gray level i and the other with gray level j. Within the defined area, several tests of the distance parameter value d were performed for all the four principal direction θ (0°, 45°, 90°, 135°).

Figure 4 shows four different normalized training features (standard deviation, skewness, lower and upper quartiles) derived from the images above corresponding to the three classes to be identified: seabed without any plant (left), and bottom with dense (center) and sparse (right) vegetation meadows.

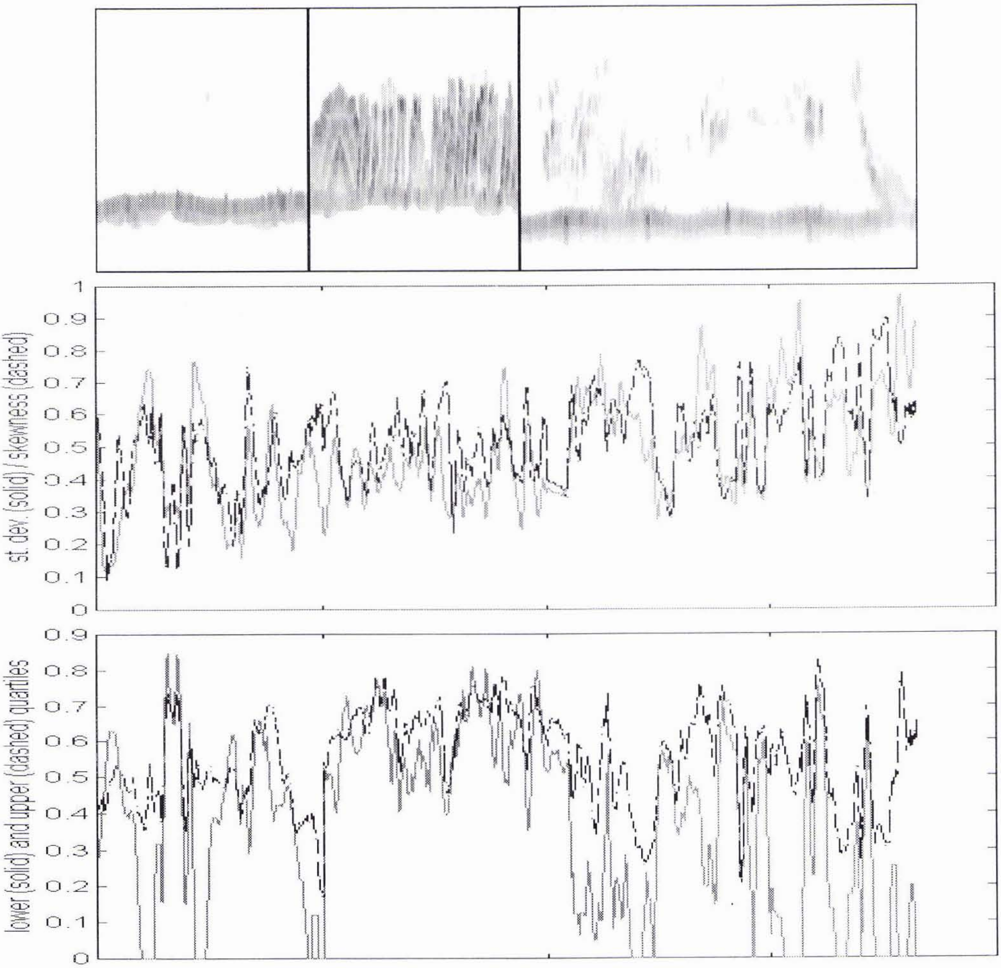


Figure 4: Some normalized feature values related to the corresponding scanlines from which they were extracted.

By carefully analyzing the plots contained in figure 4, it is evident how not even the most significant features are able to powerfully discriminate between different plant types since a lower differentiation is already present for dense and sparse plant arrangements.

About 78 features were extracted from the training data set (X) organized into a MxN matrix, being $M=78$ the dimensionality of the feature space and $N=20000$ the number of training scanlines, quite equally divided into the three classes: bottom, sparse Posidonia leaves and dense flat plant leaves. The feature space dimension is surely too large to be envisaged, giving rise to insurmountable computational and visualization difficulties. Furthermore, only a finite amount of information is contained in the data, hence, many features are likely to contribute no useful information, being noise sensitive, redundant or intrinsically not significant.

These are the main reasons to perform a feature space reduction consisting in mapping the full feature vector to a reduced feature vector with a very small dimension. This operation is performed by a principal component analysis (PCA) [18]. The statistics of the data are analyzed to determine a set of orthogonal axes in feature space along which the data varies at the most. Data principal components (PCs) are obtained by an eigen analysis of the data covariance matrix: the obtained eigenvectors provide the directions in which the data arrangement in the feature space is stretched most. Projections of data on the eigenvectors e_i (i=1, 2, ..., M) are the PCs. The corresponding eigenvalues λ_i give an indication of the amount of information the respective PCs represent: PCs corresponding to large eigenvalues represent much information in the data set and must be preserved, while other PCs may be discarded carrying much less information.

Table 1 shows the eigenvalues, the amount of variance associated to each eigenvalue and the cumulative variance: the corresponding first 7 ($P=7<M$) eigenvectors account for about 89.3 % of the total variance from the data set with 78 features. Hence, by reducing the original data set from 78 features down to only 7 vectors, there has only been a loss of 10.7 % of the total variance.

i	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15-78
λ_i	0.953	0.415	0.184	0.117	0.069	0.056	0.044	0.022	0.019	0.017	0.015	0.014	0.012	0.011	-
Var. σ_i^2	46.24	20.14	8.94	5.70	3.36	2.76	2.18	1.09	0.94	0.86	0.73	0.71	0.59	0.55	-
Cum. Var.	46.24	66.38	75.32	81.02	84.38	87.14	89.32	90.41	91.35	92.21	92.94	93.65	94.24	94.79	100.0

Table 1: Eigenvalues amount of variance.

PCA provides with a set of reduced feature vectors containing most of the covariance energy. Since the covariance within the same class is expected to be less than the covariance between different classes, the reduced feature vectors should be clustered around location corresponding to a class in the reduced feature space.

The clustering method is a k-means algorithm based on the minimization of a performance index which is defined as the sum of the squared distance from all the points in a cluster domain to the cluster center [13]. This method is extremely simple but it is not a refined technique, since it is necessary to specify the desired number of clusters and it is sensitive to the choice of initial cluster centers and to the order of the training samples.

Figure 5 shows two views of the three clusters as obtained after several tests with different initial cluster centers by considering only the first three eigenvalues (corresponding to the 75.32 % of the total variance): a really good separation between the classes cannot be observed.

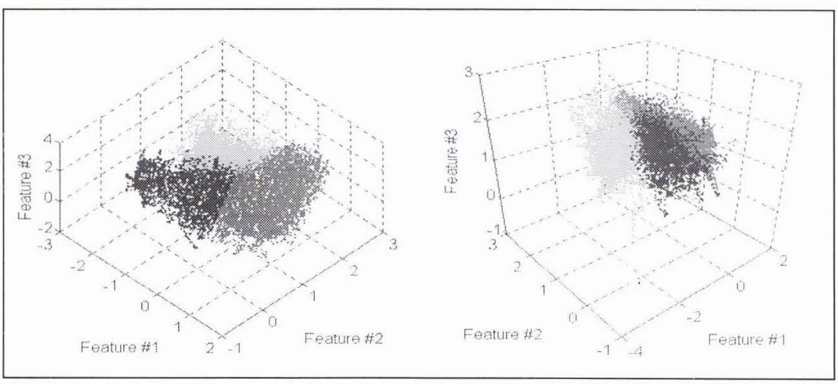


Figure 5: Two views of the clustering of the reduced feature vectors with the first three principal components.

2.5 Classification

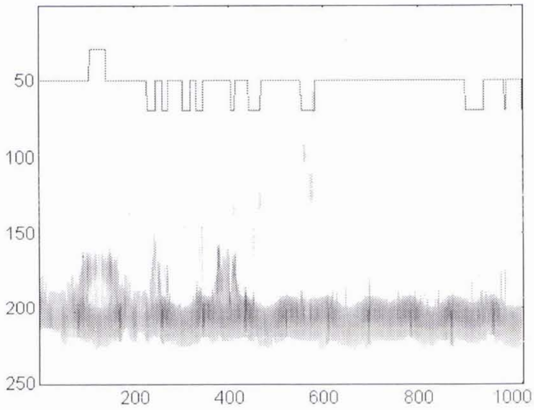
In the presented application, classification consists in labeling each new ping (i.e., each column in the image domain) in view of its characteristics as individuated through its feature values to a pre-defined class, being the employed method a supervised classifier.

Three classification stages, with increasing order of complexity, can be defined: the first consists in the decision about the presence or the absence of vegetation on the seabed; the second concerns the identification of dense or sparse plants on different bottom substrates, and the third, according to the descriptive power of the acquired data, relates to a more precise ,e.g., by distinguishing between Posidonia Oceanica and Caulerpa Taxifolia plants. Currently available results refer to the first two classification stages.

Moreover, two different levels of information can be associated to these three classification stages: the first and the second steps may supply with a quantitative information while the last classification result may provide a qualitative description of the surveyed area.

The employed classifier is the k-Nearest Neighbor (k-NN) classifier: it is a traditional non-parametric algorithm related to the Bayes decision rule: the most frequently represented class label among the k nearest training samples to the current samples x under examination is assigned to x. The vote is based on the Euclidean distance between the samples.

It is really impossible to provide precise performances for the classification algorithm on a ping-by-ping basis. Nevertheless, is it feasible to visually compare each acquired series of scanlines with the corresponding labels, by superimposing the labels on the scanlines image (Fig. 6).



Upper level: dense plant arrangements

Middle level: sea bottom without any plant.

Lower level: sparse plant arrangements.

Figure 6: Classification results limited to the discrimination about sparse or dense settlements for a test sequence.

3. Conclusions and Future Perspectives

In this paper we investigated a system aiming at characterizing marine vegetation on the seabed by means of a high frequency imaging sonar. The problem is considered as a pattern recognition application, hence, aquatic plants are characterized by extracting meaningful features based on signal shape, intensity and texture content from the acquired echoes.

Data about real Posidonia and common flat plant leaves were collected in a controlled environment and then used as training input to the developed system. Acquired data were organized as images and image processing techniques were employed for the first analysis phase consisting in the detection of plants upon the simulated sea bottom. The characterization process performed only on the meaningful portions of the acquired data series was detailed together with the feature selection methodology. A simple k-NN classifier was tested.

Preliminary results shown in the paper demonstrate the effectiveness of the selected approach for what concern the possibility of investigating marine vegetation with a high frequency sonar. Both the resolution of the analysis and the performances of the preliminary characterization final stage are in accordance with the desired and expected results. Good performances may be obtained if only a quantitative description of the data is requested: plant detection behaves satisfactory in almost all the acquired samples without being heavily influenced by changes of the acquisition parameters and discrimination about sparse and dense plant settlements is equally satisfactory.

However, system performances make worse with respect to the increasing desired qualitative description degree: different plant types classification strongly depend on several factors especially due to the random plant arrangement and to the poor information contained in the backscattered data. Hence, for a more accurate and robust characterization in terms of distinction of different plant species, further research is required. Some changes in the sonar head characteristics parameters (i.e., transmission pulse duration, and head sensitivity) are necessary in order to increase the spatial resolution within each scanline, thus by detecting morphological differences between different plant types. Moreover, an intensive experimental activity at sea is going to be carried out along the Ligurian coast to collect more data about Posidonia Oceanica meadows.

4. Acknowledgments

This work was partially funded by the MAST-III programme of the Commission of the European Communities under contract MAS3-CT95-0036 "MAUVE".

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