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Lake-bottom recognition using a wideband sonar system and time-frequency analysis

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The work presented in this paper deals with the response of underwater bottom insonified with wideband ultrasonic signals. The aim of the study is to investigate the feasibility of the recognition of the nature of sediment layer using a wideband sonar system and time-frequency representations of backscattered echoes from the bottoms. The experiments have been performed in a natural environment, in Lake Geneva. Time-frequency representations of backscattered echoes based on the pseudo-Wigner distribution are realized. A method of feature extraction using the energy distribution of the time-frequency images associated with the echoes is presented. Two classification techniques have been applied to recognize the nature of the lake bottom: a classical discriminant analysis and a neural network approach using multilayer perceptron architecture. The average recognition rates for five different types of lake bottom and for both techniques are presented and compared. © 1995 Acoustical Society of America.

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INTRODUCTION

In the field of underwater acoustics, a great deal of research has been devoted to the study of the seafloor and objects lying on it. Indeed, acoustics is nowadays the only available remote method to explore underwater bottoms. A great part of these studies are concerned with detection and recognition of objects lying on the seafloor.¹ Earlier studies have been devoted to the recognition of the type of sea bottom. One of these studies is based on the use of standard echo-sounders and extraction of the echo time envelopes.² Another study deals with side-scan sonar and spectral analysis of the received signals.³ Both studies use monochromatic sonar. Nevertheless, there have been attempts to classify marine sediment using a wideband chirp sonar⁴ over the frequency range 2–10 kHz; this study is based on measurements of the output magnitude of the matched filter.

In this article, we present a part of a more general study whose aim is the detection and recognition of objects lying on the seafloor. The recognition of the nature of sea bottom can improve the detection of targets lying on it since the detection processing can then include the statistical properties of the concerned seabed type. Therefore it has been decided to perform a study on the recognition and characterization of lake bottoms using acoustics, and particularly using a wideband sonar system. The main purpose of this paper is the first step of the study: to investigate the feasibility of bottom recognition. Indeed, if it is possible to recognize the nature of bottoms, it will surely be possible to characterize them in a more physical way by means of the same acoustic devices. In the frequency range used (>20 kHz), it can be assumed that the main part of the energy received from the bottoms is due to the water–bottom interface: the frequency range does not permit deep penetration of the sonar signal in the sub-bottom. Thus the backscattered echoes will be essen-

tially characteristic of the upper sediment layer and of the interface roughness.

Data collection was carried out on Lake Geneva. This site permits underwater acoustic experiments to be carried out with many of the specificities due to a natural environment. Earlier studies have shown the interest of time-frequency analysis applied to wideband ultrasonic echoes.⁵ Thus in order to extract relevant information from the bottom echoes, time-frequency analysis of the backscattered signals is realized. Then parameters are computed from the time-frequency pictures to provide feature vectors for classification purposes. Finally, recognition results obtained by using neural network and discriminant analysis are compared.

I. EXPERIMENTS

A. Experimental setup

The experiments described in this paper were held on Lake Geneva, near the "Lacustrian station of hydrobiology" of INRA (National Institute of Agronomic Research), at Thonon-les-bains, France. Data collection was carried out on five different types of bottom: sand, silt, pebbles, rocks, and a mixture of fine gravel and silt. The experiments were performed in shallow water. Great care has been taken in the choice of these lake bottoms. The assistance of a diver and the use of an underwater camera were necessary. The diver was in charge of exploring, choosing the lake bottoms, and measuring their slope, to give a precise idea of their nature. Video pictures of the bottoms were taken. Samples of the bottoms were also collected by the diver. The samples and environmental information collected by the diver together with the video pictures have made it possible to determine with confidence the nature and slope of the bottoms (cf. Table I).

TABLE I. Bottom characteristics for each class.

Nature of the water-bottom interface	Slope of the bottom
silt	11°
silt and fine gravel (∅ some mm)	≈0°
sand	≈0°
pebbles (∅ 5–10 cm)	5°
rocks (∅ 20–40 cm)	5°

The sonar system includes a wideband constant beamwidth transducer (CBT) designed by Van Buren *et al.*⁶ This apparatus shows a constant directivity in its passband: 20–140 kHz, its aperture half-angle at –3 dB being 12°. This CBT has virtually no near field. The transducer was used for emission of the signal as well as for reception of the backscattered echo from the bottom: a monostatic configuration was used. The CBT is placed in order to obtain normal incidence of the ultrasonic signal on the bottom. A scheme of the experimental configuration is given Fig. 1. The transmitted signal is a “chirp,” a linearly frequency-modulated signal, between 10 and 150 kHz. A common frequency-modulation law has been chosen in order to simplify the interpretation of the time-frequency representation of the backscattered echoes. The band of the emitted signal is wider than the band of the transducer in order to obtain the flattest spectrum possible in the transducer frequency range. The duration of the chirp is 1 ms, which gives a high time-bandwidth (TB) product: TB=120.

The electric sonar signal and its power spectrum are shown in Figs. 2 and 3 (upper view). The sonar signal was produced with an arbitrary function generator Lecroy AFG 3100. The echoes were recorded with a digital oscilloscope Lecroy 9410, the sampling frequency being 1 MHz and the resolution 8 bits. Then the signals were stored onto a personal computer.

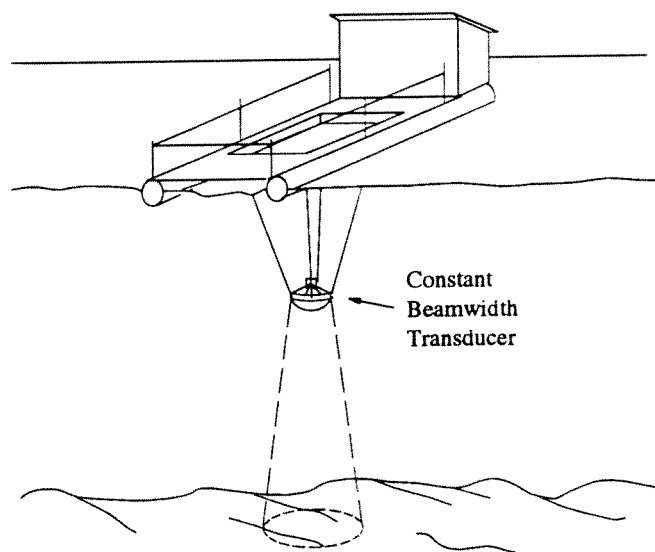


FIG. 1. Experimental configuration.

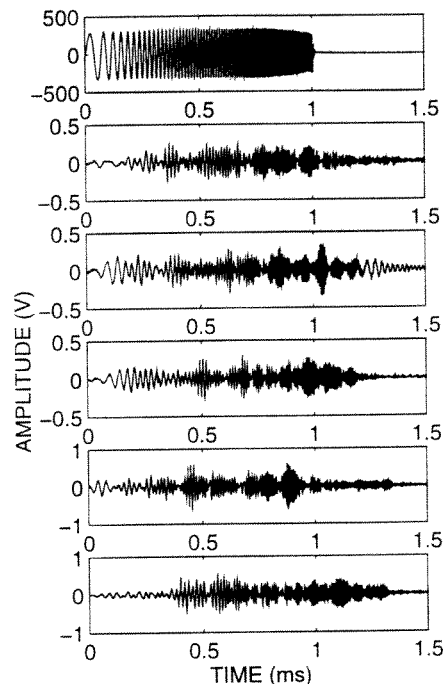


FIG. 2. From upper to lower. The transmitted chirp signal and the echoes of the five different bottom types: silt, silt and fine gravel, sand, pebbles, and rocks.

B. Experimental results

The data collection was carried out from 23, July 1993 to 26, July 1993. For each kind of lake bottom, 180 echoes were recorded over 2500 points, i.e., over 2.5 ms. The recording took place with a repetition emission period of 500 ms. Five sequences of 36 echoes per class are now analyzed. For each kind of bottom the signal-to-noise ratio (SNR) has been computed by

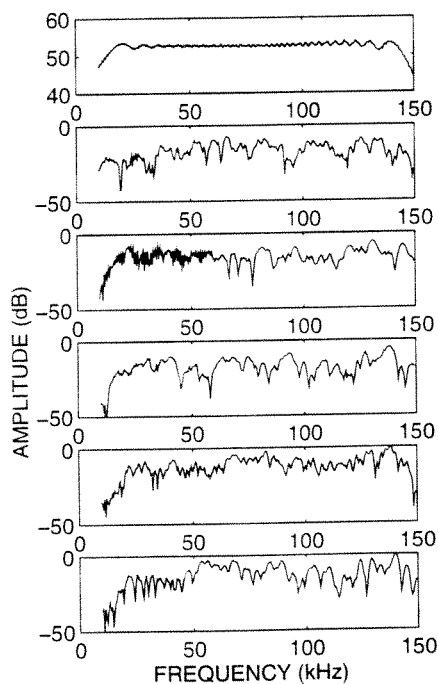


FIG. 3. From upper to lower. The spectrum of the transmitted chirp signal and the spectra of the five different bottom types: silt, silt and fine gravel, sand, pebbles, and rocks.

TABLE II. Mean SNR and mean standard deviation (variability) of the spectra ($\bar{\sigma}$) for each class.

Nature of the water-bottom interface	SNR (dB)	$\bar{\sigma}$ (dB)
silt	21	5.3
silt and gravel	21	5.4
sand	22	4.5
pebbles	24	4.6
rocks	24	5.3

$$\text{SNR}_i = 10$$

$$\times \log_{10} \left[\frac{(1/Ts) \int_{t_0}^{t_0+Ts} s_i^2(t) dt}{[1/(T-Ts)] [\int_0^{t_0} s_i^2(t) dt + \int_{t_0+Ts}^T s_i^2(t) dt]} \right] \quad (1)$$

where $s_i(t)$ represents the i th echo of the sequence, Ts the duration of the echo, t_0 the beginning of the echo signal, and T the duration of the recording. The mean SNR computed on the whole database is 22 dB. The average SNR for each kind of bottom is given Table II.

The echo variability from a same type is estimated through the mean standard deviation $\bar{\sigma}$ of spectrum on the band $f_1 = 20$ kHz to $f_2 = 140$ kHz:

$$\bar{\sigma} = 20 \log_{10} \left[\frac{1}{f_2 - f_1} \int_{f_1}^{f_2} \left(\frac{1}{N-1} \sum_{i=1}^N (|X_i(f)| - \overline{|X(f)|})^2 \right)^{1/2} df \right] \quad (2)$$

where N is the number of echoes (36), $|X_i(f)|$ the spectrum of the i th echo, and $\overline{|X(f)|}$ the mean spectrum. In Table II, $\bar{\sigma}$ is given for each kind of bottom.

The echoes show a great variability inside each class. This variability can be interpreted as the joint effects of the sonar directivity and of the movements of the barge. Indeed, due to the movements of the sonar the insonified surface is never exactly the same. In addition, the bottom is a highly scattering medium. Finally, the refraction and reflection of sound within the sub-bottom sediment layers depend on the incident angle of the ultrasonic wave. As we have seen, the insonified surface and consequently the incident angle are never exactly the same, so the ultrasonic signals will never show exactly the same behavior with the sediment layers.⁷ Thus it was necessary to collect a considerable database for each type of bottom, in order to determine their specific characteristics. Examples of the recorded echoes and their spectra are shown in Figs. 2 and 3, respectively.

II. TIME-FREQUENCY ANALYSIS FOR FEATURE VECTOR COMPUTATION

A basic processing method applied to signals is often spectral analysis. This kind of processing does not appear optimum for the type of signal analyzed in this work. The transmitted signal as well as the collected echoes are time-varying signals; therefore the time-frequency analysis yields

the information in a more revealing form.⁸ Time-frequency analysis seems to be well adapted to bottom echoes since this kind of transformation can display the evolution of frequency contents versus time, i.e., versus propagation distance. These evolutions do not appear when classical spectral analysis is applied. Time-frequency analysis is nowadays commonly used in the field of underwater acoustics. For example, the work of Yen *et al.*⁹ is devoted to the analysis of acoustic scattering from elastic objects by using time-frequency analysis and has shown the advantages of such a representation.

A. Time-frequency representations

Several methods are devoted to time-frequency analysis. Among them, the Wigner distribution (WD) provides with no doubt a high resolution and has been successfully applied to solve a lot of applications. For example, the Wigner distribution shows a better resolution than the spectrogram and does not imply the hypothesis of local stationarity needed for the short-time Fourier transform.¹⁰ Moreover, frequency resolution and time resolution are not linked. On the contrary, with the spectrogram, an increase of spectral resolution risks compromising the local stationary hypothesis in the shifting window. The Wigner distribution is defined as

$$\text{WD}_s(t, \nu) = \int_{-\infty}^{\infty} s(t + \tau/2) s^*(t - \tau/2) \times \exp(-j2\pi\tau\nu) d\tau \quad (3)$$

where $s(t)$ is the analytic signal associated with the original signal.

Though the Wigner distribution provides high time and frequency resolution, the existence of cross components can lead to difficulties of interpretation.¹¹ These cross terms are a direct consequence of the bilinearity of this class of distribution (Cohen's class). Among several new improvements devoted to cross-term reduction, a modified version of the Wigner distribution called the pseudo-Wigner distribution (PWD) has been implemented. This version of the Wigner distribution has already been used for broadband signal analysis because of its good mathematical properties.¹²

The PWD in the continuous domain is given by

$$\text{PWD}_s(t, \nu) = \int_{-\infty}^{\infty} s(t + \tau/2) s^*(t - \tau/2) h(\tau/2) \times h^*(-\tau/2) \exp(-j2\pi\tau\nu) d\tau \quad (4)$$

where $h(\tau)$ is a sliding window.

The PWD in the discrete domain is given by

$$\text{PWD}_s(t, \nu) = 2 \sum_{\tau=-N+1}^{N-1} h^2(\tau) s(t + \tau) s^*(t - \tau) \times \exp(-j4\pi\tau\nu) \quad (5)$$

where $h(\tau)$ is a real symmetrical window centered at $\tau=0$. This function has been implemented for the discrete time-frequency analysis of the echo signals of the present work.

The introduction of the window leads to a smoothing of the cross components in the frequency domain. The most

relevant property to notice about the Wigner distribution is that the representation can be interpreted as a function that indicates the distribution of the signal energy over time and frequency.^{13,14} A study to determine the best parameters and window for the PWD has been performed. During the computation process of the PWD the fast Fourier transform (FFT) is used. Thus the PWD of the present work has been processed with a Hamming sliding window with a length of 61 points (122 μ s), and FFT is performed over 128 points.

It is necessary to determine with accuracy the beginning of every echo; therefore the cross correlation between the transmitted chirp signal and every echo is performed in order to determine accurately the beginning of the echoes. This preprocessing is important for further classification since the PWD has the property of time shift. At the same time, the signals are undersampled to 500 kHz vs 1 MHz originally. This, jointly with the detection of the beginning of every signal, provides signals over 1024 points versus the 2500 originally recorded. The undersampling processing is justified by the PWD algorithm: the frequency range of the PWD is $0-f_s/2$, where f_s is the sampling frequency of the signal. Thus f_s has to be reduced in order to avoid unnecessary computations. Then every echo is normalized: it is divided by the square root of its energy, so only the time-frequency characteristics will be taken into account but not the total amount of energy reflected by the bottom. Therefore the pseudo-Wigner distribution will provide one time-frequency digital image of size 128×1024 pixels associated with every bottom echo.

PWD images associated with the transmitted chirp signal and to each bottom-type echo are presented in Fig. 4. Only the parts containing information have been kept, so the size of the images is reduced to 90×750 pixels. (On the color images the values under a chosen threshold of the PWD have been set at zero value in order to increase the legibility. These low values of the PWD representations correspond to cross components and may lead to difficulties in the visualization of the images. The ratio between the informational values of the PWD and the highest suppressed values is greater than 34 dB. Negative values of the PWD have also been discarded for visualization but have been kept for computation.)

B. Feature vector computation

The next step of the method is to compute feature vectors derived from the time-frequency image. Indeed, classification methods were not able to accept data as large as a whole picture for feature vector. And, furthermore, this would not be suitable since the value of a single pixel of the PWD image cannot be interpreted directly. Thus the information contained in the time-frequency representation has to be compressed, but in a way that would keep the time-frequency characteristics of the backscattered echoes. The idea applied here is to cut the picture in slices with time versus frequency in order to obtain cells. Then the function of the energy corresponding to each cell is calculated with the double integral of the PWD along the borders of the cell, by using the properties of the PWD concerning the energy distribution. The value of the computed energy is then asso-

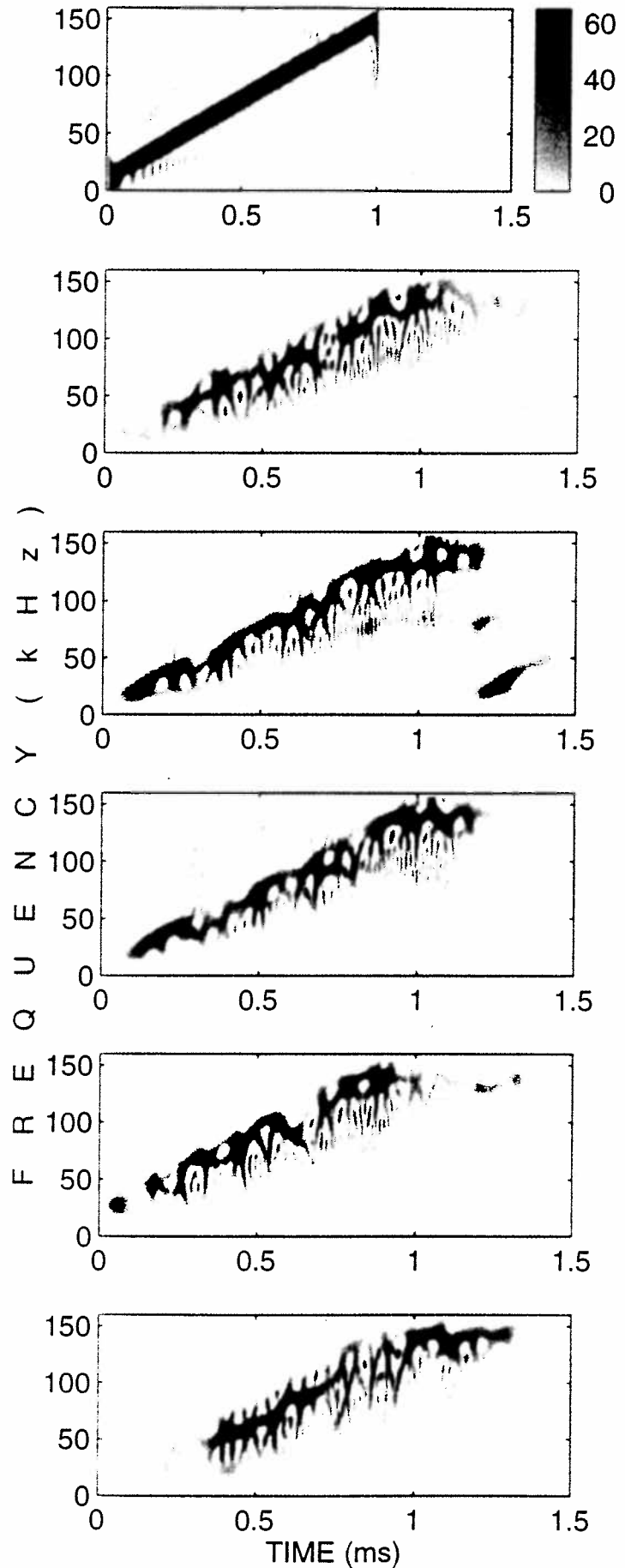


FIG. 4. From upper to lower. The time-frequency representations of the transmitted chirp signal and of the five different bottom types: silt, silt and fine gravel, sand, pebbles, and rocks.

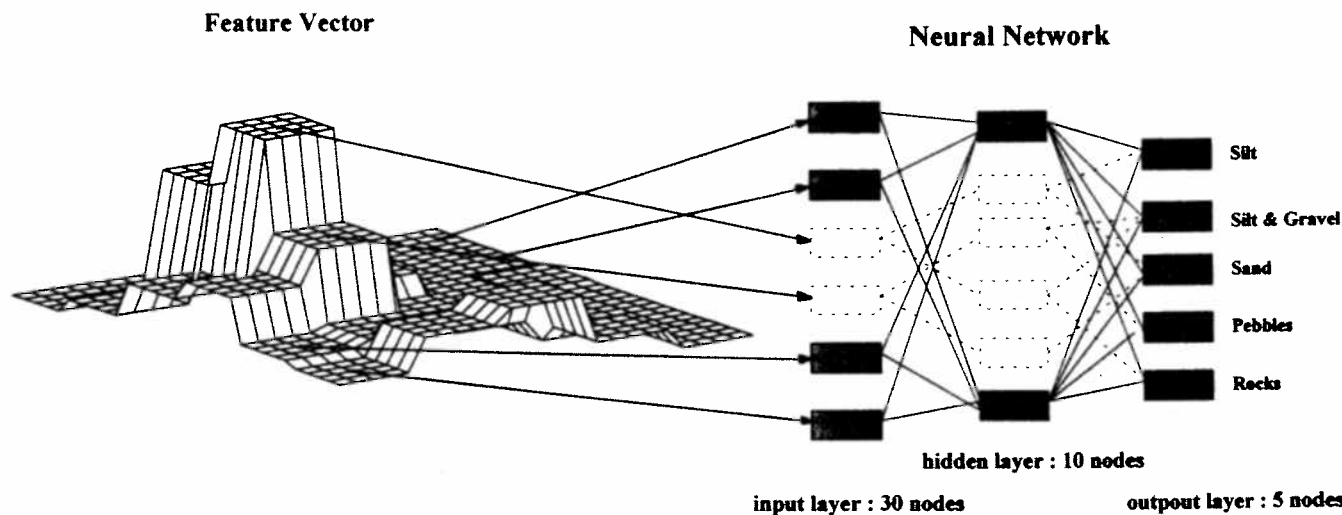


FIG. 6. Sending the feature vector to the neural network.

cal analysis exist nowadays (nearest neighbor, discriminant analysis,...). For the past few years new methods based on neural networks have appeared. These methods tend to be very attractive in underwater acoustics each time a classification or recognition is required. These neural approaches have been already experimented to recognize biological impulse noises¹⁵ from five different classes. A neural networks method has also been used in order to classify shadow of objects lying on the sea bottom produced by a sonar.¹⁶ Finally, a recent study has been performed in order to recognize five different underwater targets using a sonar and a neural network as a classification tool.¹⁷

It was then decided to experiment two different methods in order to classify the bottom echoes. The first method chosen is a statistical one: the now classical discriminant analysis.¹⁸ The first step of the method leads to the extraction of the most discriminating parameters among those initially available. Thus the size of the feature vector is reduced from its initial value to the number of parameters selected by the first step of the method. The second step is the computation of the linear discriminant function with the selected parameters. The third step is the classification itself. The linear discriminant function computed above is then applied to the echoes to be classified. This is the test phase.

The second method investigated is based on a neural approach. The network used is a three layer perceptron with 30 input nodes corresponding to the 30 parameters of the feature vector, 10 nodes in the hidden layer and 5 output nodes corresponding to the 5 different bottoms. Every output node correspond to a bottom type. The way the feature vectors are presented to the network is shown Fig. 6. For a given feature vector the network determines the values (activity) of its five outputs. These outputs are in the range of 0–1. Thus, if the output node corresponding to the silt shows an activity of 1 and the others an activity of 0, the associated bottom echo will obviously be identified as a silty bottom. The network was trained using the backpropagation technique. In

the learning phase, feature vectors are presented to the network and the outputs are calculated. Then the quadratic difference between calculated and expected outputs is calculated. This error is then backpropagated in the upper layers of the network. The aim of the backpropagation algorithm is to decrease the mean output quadratic error on the whole database. For the recognition phase the following rule is applied: If the activity of the output node corresponding to the bottom type of the feature vector tested is higher than 0.5 and the other output activities are lower than 0.5, then the associated bottom echo is assumed to be recognized. The number of nodes on the hidden layer has been briefly studied. Results have shown that the recognition rates are not better when the number of nodes is increased. In all cases, we tried to respect a general rule concerning the hidden layer: too many nodes could lead to a fall in the recognition rate for the echoes not involved in the training sequence.

IV. RESULTS

Recognition of the five different types of bottom is achieved by using both classification techniques. For both methods, the database has been separated in two groups: the first is used for the training sequence of the technique (learning base) and the second is used for testing the results of the method on echoes not involved in the training sequence (testing base). On the whole database, one half was devoted to the learning phase and the other half to the test phase. It is important to notice for the interpretation of the results that every processing applied was exactly the same for each kind of bottom and of course for both classification techniques.

The training of the neural network for the five class problem consists of approximately 360 000 iterations; the three class problem converges after about 30 000 iterations, whereas the training steps are rather long (1 h to several tenths of hours), the recognition step is very fast (a few mil-

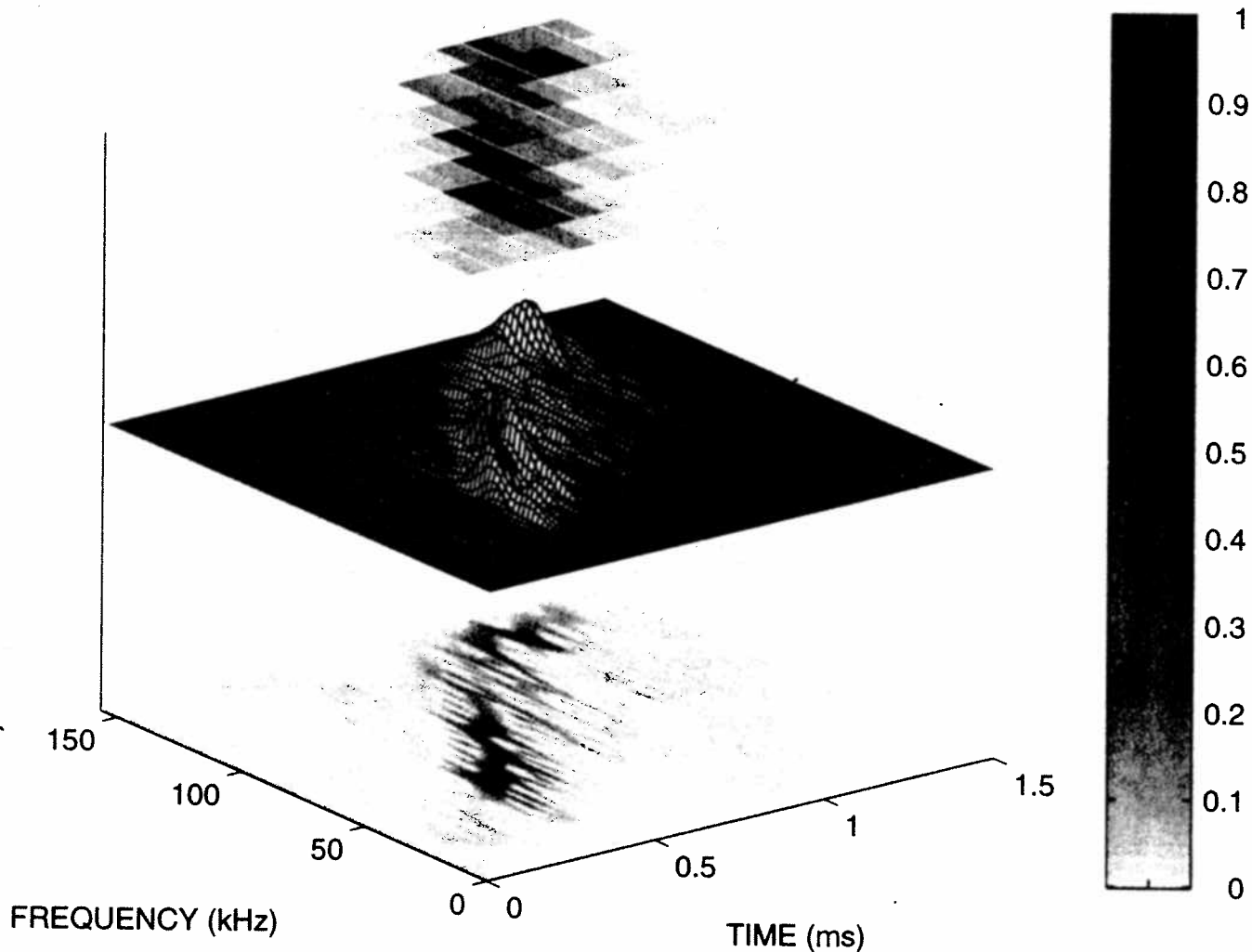


FIG. 5. Feature vector computation. Lower view: Choice of the useful parts of the PWD image associated with the echo of rocks. Middle view: 3-D mesh of the PWD. Upper view: result of the partitioning.

ciated with each cell. Cutting the picture into m frequency slices and n time slices will provide $m \cdot n$ cells whose values will be the elements of the feature vector. This processing obviously leads to an averaging versus time and frequency of the time-frequency pictures. This solves the problem of the local interpretation of the PWD representation.

Every echo is associated with its time-frequency representation. It can easily be seen on the time-frequency images that all the information is concentrated on the modulation slope of the chirp. More precisely, if one compares the time-frequency image of the chirp with any of the images associated with the bottom echoes, one observes that all the information is concentrated in a time strip during several hundredths of ms on the right side (i.e., toward increasing times) of the modulation slope. This fact can easily be related to physical properties of the sediment layer of the bottom. The major part of the acoustic energy of the signal is reflected at the water-bottom interface; a part of the energy is transmitted in the sediment layer and may be reflected later by a deeper sediment layer. These reflected parts of the

signal are then represented on the right side of the modulation slope since they are received later by the CBT. Therefore, only the parts of the representations in the time strip of interest will be kept for further processing. Obviously, the frequency limits of the useful parts of the images will be 20–140 kHz. Determining the width in time led to investigating every type of echo. The maximum time lengthening was found in silt with 500 μ s. For a mean value of sound in the sedimentary bottom, this lengthening corresponds to a sound penetration of 20–50 cm for most of the echoes. The selected parts are cut into six slices in frequency (20 kHz each) and five slices in time (100 μ s each). This provides a 30 element feature vector per echo. Figure 5 shows the choice of the useful parts on the lower view, and the result of the partitioning for a rocky bottom echo on the upper view.

III. CLASSIFICATION METHODS

The following step of the work is to implement an efficient classification method. Many methods based on statisti-

TABLE V. Results of the neural network method for three classes.

Nature of the bottom	Recognition rate: Learning phase	Recognition rate: Test phase
sand	99%	95%
pebbles	99%	87%
rocks	84%	77%
Average recognition rate	94%	86%

liseconds). Recognition rates concerning the discriminant analysis are presented in Table III and results of the neural network are given in Table IV.

The average recognition rate is higher for the neural network than for the discriminant analysis: 68% vs 60% in the test phase. The recognition rate for the learning phase is quite satisfying for the neural network (89%) but rather less (62%) for the discriminant analysis. Nevertheless, it can be assumed that the results of the test phase for the neural networks are good considering the difficulty of the problem: it has to be remembered that the original echo signals show a great variability inside each class. Furthermore, results of recognition for a three class problem using the neural network are presented in Table V. These results are satisfying and better than the ones for the five class problem. The geophysical properties of the three bottom types are, respectively, more different and the average recognition rate reaches 94% and 86% for the learning phase and the test phase, respectively. We obtain 95% of good recognition for sandy bottoms.

V. SUMMARY AND CONCLUSIONS

This study has shown the feasibility of lake-bottom recognition using a wideband sonar system and time-frequency analysis. The feature extraction emphasizes the time-frequency characteristics of the backscattered echoes. Indeed, the bottom responses to a broadband ultrasonic wave have been the basis of this study. The time-frequency representation of the echoes provides useful information concerning the localization of echo energy along time for each frequency range. This can be linked to the penetration of ultrasonic waves in the upper sediment layers. Meanwhile, identification of geophysical parameters from such a representation is under study and the present work is limited to the classification of bottom echoes without *a priori* information concerning the acoustical response of the bottom. The neural network method has given better classification results than the discriminant analysis for both learning and test phase.

TABLE III. Results of the discriminant analysis.

Nature of the bottom	Recognition rate: Learning phase	Recognition rate: Test phase
silt	68%	61%
silt and fine gravel	56%	56%
sand	54%	47%
pebbles	59%	57%
rocks	74%	78%
Average recognition rate	62%	60%

TABLE IV. Results of the neural network method.

Nature of the bottom	Recognition rate: Learning phase	Recognition rate: Test phase
silt	87%	71%
silt and fine gravel	87%	59%
sand	91%	76%
pebbles	90%	74%
rocks	91%	61%
Average recognition rate	89%	68%

Thus the three layer neural network seems to be well adapted to the recognition problem described in this paper. The results, although not perfect, are encouraging. The most relevant recognition rate is the test phase rate. The recognition rate of 68% for five bottom types and 86% for three bottom types on the whole test database for the neural network can be seen as a good result facing the great variability of the original echoes and also the small difference between the different types of bottom. Furthermore, some improvements can be made in the data collection step in order to improve the results. Preprocessing of the echoes could include a selection of the echoes whose signal to noise ratio exceed a fixed threshold. Indeed, it would be useful to take into account the transfer function of the transmitter-receiver sonar since this transfer function leads to a higher sensitivity to high frequencies than to low frequencies. Thus it would be useful to perform the deconvolution of every echo signal by the transfer function of the whole sonar system. This would lead to investigating the impulse response of the bottoms.

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