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Time-frequency transform techniques for seabed and buried target classification

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ABSTRACT

An approach for processing sonar signals with the ultimate goal of ocean bottom sediment classification and underwater buried target classification is presented in this paper. Work reported for sediment classification is based on sonar data collected by one of the AN/AQS-20's sonars. Synthetic data, simulating data acquired by parametric sonar, is employed for target classification. The technique is based on the Fractional Fourier Transform (FrFT), which is better suited for sonar applications because FrFT uses linear chirps as basis functions. In the first stage of the algorithm, FrFT requires finding the optimum order of the transform that can be estimated based on the properties of the transmitted signal. Then, the magnitude of the Fractional Fourier transform for optimal order applied to the backscattered signal is computed in order to approximate the magnitude of the bottom impulse response. Joint time-frequency representations of the signal offer the possibility to determine the time-frequency configuration of the signal as its characteristic features for classification purposes. The classification is based on singular value decomposition of the time-frequency distributions applied to the impulse response. A set of the largest singular values provides the discriminant features in a reduced dimensional space. Various discriminant functions are employed and the performance of the classifiers is evaluated. Of particular interest for underwater under-sediment classification applications are long targets such as cables of various diameters, which need to be identified as different from other strong reflectors or point targets. Synthetic test data are used to exemplify and evaluate the proposed technique for target classification. The synthetic data simulates the impulse response of cylindrical targets buried in the seafloor sediments. Results are presented that illustrate the processing procedure. An important characteristic of this method is that good classification accuracy of an unknown target is achieved having only the response of a known target in the free field. The algorithm shows an accurate way to classify buried objects under various scenarios, with high probability of correct classification.

Keywords: Time-frequency transform, sediment classification, buried target classification

1. INTRODUCTION

The problem of pattern classification has been addressed in many contexts and different disciplines. Among the most complex and challenging pattern recognition problems are sediment classification and underwater and under-sediment target classification.

The underwater classification problem involves finding a classification algorithm that improves the classification performance over that of standard algorithms. There are many techniques employed to solve this problem among which pattern recognition ones play an important role. The goal of pattern recognition is to build classifiers that automatically assign measurements to classes. The basis of these techniques is to represent the signal in a favorable space by one or more projection methods; feature vectors are then obtained in this space, usually followed by dimensionality reduction methods. The next step is to use a classification method for determining the class that the signal belongs to; this can be either supervised classification or unsupervised classification (i.e. clustering), depending on the nature of the data. In supervised classification, the given labeled patterns (training data) are used to learn the descriptors of classes which in turn are used to label new patterns. In the case of clustering, the problem is to group a given collection of unlabeled patterns into meaningful clusters. In a

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sense, labels are associated with clusters also, but these category labels are data driven. The classification can be carried out in different ways, depending on the application, the nature of the signal and the final objective.

In recent years, interest in and use of time-frequency tools has increased and become more suitable for sonar and radar applications,[1],[2] and[3] . Major research directions include the use of time-frequency analysis for target and pattern recognition, noise reduction, beamforming, and optical processing. In this paper a novel technique is proposed that allows efficient determination of seafloor bottom characteristics as well as underwater buried target classification. The new approach is based on time-frequency techniques that give a better representation of the signal that leads to a good discrimination of the patterns.The method introduced in this work employs the Fractional Fourier Transform (FrFT)[4] in order to compute the impulse response of the seafloor. The FrFT is better suited for chirp sonar applications because it uses linear chirps as basis functions. Singular value decomposition of different distributions (e.g. Wigner, Choi-Williams[5]) applied to the impulse response is then performed. In this way, discriminant features for classification are obtained due to the fact that the singular value spectrum encodes the most relevant features of the signal. The features thus obtained are mapped in a reduced dimensional space, where various classification approaches are considered and their performance are compared.

In this paper we begin by presenting the essential concepts and definitions related to the Fractional Fourier transform, time frequency distribution, singular value decomposition and acoustic scattering model for elastic cylinders. The overview is followed by a description of the proposed method and the applications of the time-frequency transform technique with emphasis on sediment classification using sonar data and buried target classification for simulated data. The experimental results are shown and an evaluation of them is carried out to present the performance of the proposed technique. The last section of the paper gives a summary of the presented work, conclusions, future work, and recommendations.

2. THEORETICAL ASPECTS

2.1. Fractional Fourier Transform

The Fractional Fourier Transform (FrFT) is a generalization of the Fourier Transform and provides an important tool in time-frequency domain theory for the analysis and synthesis of linear chirp signals. The traditional Fourier transform decomposes a signal by sinusoids whereas the Fractional Fourier transform corresponds to expressing the signal in terms of an orthonormal basis formed by chirps. Since the FrFT uses linear chirps as the basis function, this approach is better suited for chirp sonar applications.

There are several ways to define the FrFT; the most direct and formal one is given[4] :

$$f_\alpha(u) = \int_{-\infty}^{\infty} K_a(u, u') f(u') du' \tag{1}$$

where

$$\alpha = \frac{a\pi}{2} \tag{2}$$

$$K_\alpha(u, u') = A_\alpha \exp[i\pi(\cot\alpha \cdot u^2 - 2\csc\alpha \cdot u \cdot u' + \cot\alpha \cdot u'^2)] \tag{3}$$

$$A_\alpha = \sqrt{1 - i\cot\alpha} \tag{4}$$

when $a \neq 2k$,

$$K_\alpha(u, u') = \delta(u - u') \tag{5}$$

when $a = 4k$, and

$$K_\alpha(u, u') = \delta(u + u') \tag{6}$$

when $a = 4k + 2$, where k is a integer and $A_\alpha$is a constant term and the square root is defined such that the argument of the result lies in the interval $(-\frac{\pi}{2}, \frac{\pi}{2}]$.

Due to periodic properties, the a range can be restricted to $(-2, 2]$ or $[0, 4)$. The Fractional Fourier transform operator, Fa, satisfies important properties such as linearity, index additivity, commutativity, and associativity. In the operator notation, these identities follow[4] : $F^0 = I; F^1 = F; F^2 = P; F^3 = FP = PF; F^4 = F^o = I$; and $F^{4k+a} = F^{4k'+a}$, where I is an identity operator, P is a parity operator, and k and k' are arbitrary integers. According to the above definition, the zero-order transform of a function is the same as the function itself $f(u)$, the first order transform is the Fourier transform of $f(u)$, and the 2^{nd} order transform is equal to $f(-u)$.

The definition can be understood as a multiplication by a chirp, followed by the Fourier transformation, followed by another chirp multiplication and finally a complex scaling.

2.2. Time-Frequency Analysis

Time-frequency methods are powerful tools for studying variations in spectral components. The spectrum's time dependency of the return signal could be a strong indicator of the seafloor's acoustic signature.

The generalized time-frequency representation can be expressed in term of the kernel $\varphi(\theta, \tau)$, which determines the properties of the distribution[6] :

$$C(t, \varpi) = \frac{1}{4\pi^2} \int \int \int f^*(u - \tau/2) f(u + \tau/2) \varphi(\theta, \tau) e^{-j\theta t - j\tau\varpi + ju\theta} du d\tau d\theta \tag{7}$$

The Wigner distribution can be derived from the generalized time-frequency representation for the value of the kernel $\varphi(\theta, \tau) = 1$:

$$W(t, \varpi) = \frac{1}{2\pi} \int f^*(t - \tau/2) f(t + \tau/2) e^{-j\tau\varpi} d\tau \tag{8}$$

The Wigner distribution function is a time-frequency analysis tool that can be used to illustrate the time-frequency properties of a signal, and it can be interpreted as a function that indicates the distribution of the signal energy over the time-frequency space. The Wigner distribution is symmetric with respect to the time-frequency domains, it is always real but not always positive. The Wigner distribution exhibits advantages over the spectrogram (short-time Fourier transform): the conditional averages are exactly the instantaneous frequency and the group delay, whereas the spectrogram fails to achieve this result, no matter what window is chosen. The Wigner distribution is not a linear transformation, a fact that complicates its use for time-frequency filtering.

One disadvantage of the Wigner distribution is that it sometimes indicates intensity in the regions where one would expect zero values. These effects are due to cross terms and can be minimized by choosing a kernel that has the form $\varphi(\theta, \tau) = e^{-\theta^2\tau^2/\sigma}$, and in this case the distribution becomes the Choi-Williams distribution:

$$C(t, \varpi) = \frac{1}{4\pi^{3/2}} \int \int \frac{1}{\sqrt{\tau^2/\sigma}} f^*(u - \tau/2) f(u + \tau/2) e^{-\sigma(u-t)^2/\tau^2 - j\tau\varpi} du d\tau \tag{9}$$

Choosing this kernel, the marginals are satisfied and the distribution is real. In addition, if the σ parameter has a large value, the Choi-Williams distribution approaches the Wigner distribution, since the kernel approaches one. For small σ values, it satisfies the reduced interference criterion.

2.3. Singular Value Decomposition

A decomposition of joint time-frequency signal representation using the techniques of linear algebra, called singular value decomposition determines a qualitative signal analysis tool. Singular value decomposition (SVD) is an important factorization of a rectangular matrix with several applications in signal processing and statistics. Singular value decomposition provides an acceptable approximation with a minimum number of expansion terms. The set of representations of singular values is called singular value spectrum of the signal, which has a high data reduction potential. It encodes the following signal features: time-bandwidth product, frequency versus time dependence, number of signal components and their spacing. The SVD spectrum is invariant to shifts of the signal in time and frequency and is well suited for pattern recognition and signal detection classification tasks[6] .

The concept of decomposing a Wigner distribution in this manner was first presented by Marinovich and Eichman[7] . One motivation for such decomposition is noise reduction because when keeping only the first few terms most of the noise is lost; the other motivation for this decomposition is for the purpose of classification[5] . The basic idea in the latter case is that singular values contain a unique characterization of the time-frequency structure of a distribution and may be used for classification.

The singular value decomposition of a matrix A is given by:

$$A = UDV^T = \sum_{i=1}^{N} \sigma_i u_i v_i^T, \tag{10}$$

$$\|A\|_F^2 = \sum_{i=1}^{N} \sigma_i^2 \tag{11}$$

where superscript T denotes transpose, $D = diag(\sigma_1, \sigma_2, ..., \sigma_N)$ with singular values $\sigma_1 \geq \sigma_2 \geq \ldots \geq \sigma_N$, U and V are matrices that contain singular vectors, and $\|A\|_F$ is the Frobenius norm matrix.

Permutations of the rows (columns) or unitary transformation of A lead to similarity transformations of AA^T and A^TA. The singular values are invariant under this transformation and also invariant to time and/or frequency shifts in the signal. The number of non-zero spectrum coefficients equals the time-bandwidth product of the signal. Because singular values of the time-frequency distribution encode certain invariant features of the signal, the set of singular values can be considered as the feature vectors that describe the signal, and used for classification purposes.

2.4. Acoustic Scattering Model

The analysis presented in this paper is based on the acoustic scattering model for elastic cylinder presented in[8] . In order to estimate the scattered field due to a cylinder of finite length, the volume flow per unit length of the scattered field of an infinitely long cylinder is integrated over a finite distance. Many scatterers posses elastic properties, so conversion of compressional waves into shear waves has to be taken into account. The assumption made for the infinite cylinder is that there is no absorption, dispersion, or nonlinearity in the cylinder or the surrounding medium[8] . The scattering from ends of the cylinder is ignored, and the receiver-target separation must be great enough to be in the first Fresnel zone (i.e, $L << 2\sqrt{r\lambda}$, where L is the length of the cylinder or of the insonified "spot" of a longer cylinder, λ is the acoustic wavelength and r is the range from the axis of the cylinder to the receiver or field point). Stanton[8] shows that taking into account arbitrary transmitter direction, receiver position and cylinder orientation, and assuming that $r >> L$, the expression of the scattered pressure is given by (12):

$$P_{scatter}(k) = -P_0 \frac{e^{ikr}}{r} \left(\frac{L}{\pi}\right) \frac{\sin(\Delta)}{\Delta} \sum_{m=0}^{\infty} \varepsilon_m \sin(\eta_m) e^{-i\eta_m} \cos(m\phi) \tag{12}$$

where k is the acoustic wavenumber; P_o is the amplitude of the incident plane wave; r is the source-target separation; $\Delta = \frac{1}{2}kL(\overrightarrow{r_i} - \overrightarrow{r_r}) \cdot \overrightarrow{r_c}$, $\overrightarrow{r_r}$ the unit direction of receiver, $\overrightarrow{r_i}$ the unit direction of incident plane wave, $\overrightarrow{r_c}$ the unit direction of cylinder axis; ε_m is Neumann's number: $\varepsilon_0 = 1, \varepsilon_{m>0} = 2$; η_m is scattering phase angle; and ϕ is the azimuth angle of the arbitrarily oriented cylinder. In equation (12), $\frac{\sin(\Delta)}{\Delta}$ represents the beam pattern. If it is assumed to be Gaussian, the effective length insonified is given by $\widehat{L} = \sqrt{2\pi}\sigma e^{-s_0/2\sigma^2}$ where s_0 is the distance from the maximum response on the bottom to the closest point of approach of the cylinder. The following considerations have to be incorporated in the model: spherical spreading by replacing P_o by P_1/r, and the bottom effects. Assuming a flat bottom comprising a homogeneous lossy half-space with sound speed c_s and density ρ_s, (c_w is sound speed in water and ρ_w is density in water) the pressure is reduced by $T_{ws}T_{sw}e^{-2\alpha_s z_s}$. Here, $T_{ws} = 2\rho_s c_s/(\rho_w c_w + \rho_s c_s)$ is the normal incidence plane wave transmission coefficient from water to sediment and $T_{sw} = 2\rho_w c_w/(\rho_w c_w + \rho_s c_s)$ is the normal incidence plane wave transmission coefficient from sediment to water; α_s is the attenuation coefficient in sediment, and z_s is depth of the cylinder below surface. The scattered pressure becomes:

$$P_{scatter}(k) = -P_1 T_{ws} T_{sw} \frac{e^{i(k_w r_w + k_s r_s(1+i\delta_s))}}{(r_w + r_s)^2} \left(\frac{\widehat{L}}{\pi}\right) \sqrt{2\pi}\sigma e^{-s_0/2^2} \sum_{m=0}^{\infty} \varepsilon_m \sin(\eta_m) e^{-i\eta_m} \cos(m\phi) \tag{13}$$

where k_w and k_s are the wavenumbers in the water and sediment, respectively, r_w and r_s define the path lengths in water and in the sediment, and $\delta_s = \alpha_s/k_s$. The solution is for continuous wave signals of infinite duration. For a band-limited, finite duration pulse, a time series can be created from Fourier synthesis of solutions over a discrete range of wavenumbers k_n, $n = 0, 1, ..., N$. The impulse response for the jth sample of the time series is given by:

$$h_{scatter}(t_j) = \frac{2\pi f_s}{N^2 c_s} \sum_{n=n_{\min}}^{n=n_{\max}} P_{scatter}(k_n) e^{2\pi i(j-1)(n-1)} \tag{14}$$

where $n_{\min}$ and $n_{\max}$ are determined from the upper and lower frequency band.

3. TIME-FREQUENCY TRANSFORM TECHNIQUE

Our proposed technique for sediment and buried target classification is based on the Fractional Fourier Transform in order to determine the impulse response. The signals that need to be classified are represented in time frequency space and then projected into a favorable space that allows feature extraction for supervised classification. The acoustic data are discriminated into classes via a supervised classification, based on their most relevant features. Our technique efficiently classifies sediment types or buried targets using the acoustic backscattered signal.

The following steps are performed in the proposed technique[9] and illustrated in Figure 1:

1) Compute the impulse response using the FrFT for each beam

2) Determine the time-frequency distribution of the impulse response (for each beam)

3) Compute the SVD of the time-frequency distribution

4) Capture the first few SV's (for each beam) as features

5) Perform supervised classification using the selected features in the new reduced dimensional space.

The FrFt which produces the most compact support for a given linear chirp is defined as the optimal fractional Fourier transform of that signal[10] .

The optimum order of the transform can be estimated based on the properties of the chirp signal: the rate of change, sampling rate f_s, and the length of the data segment N[11] :

$$a = \frac{2}{\pi} \tan^{-1}\left(\frac{f_s^2/N}{2\lambda}\right) \tag{15}$$

The bottom impulse response is given by the magnitude of the Fractional Fourier transform for optimal order applied to the bottom return signal[12] :

$$|h(t)| \approx |fa| \tag{16}$$

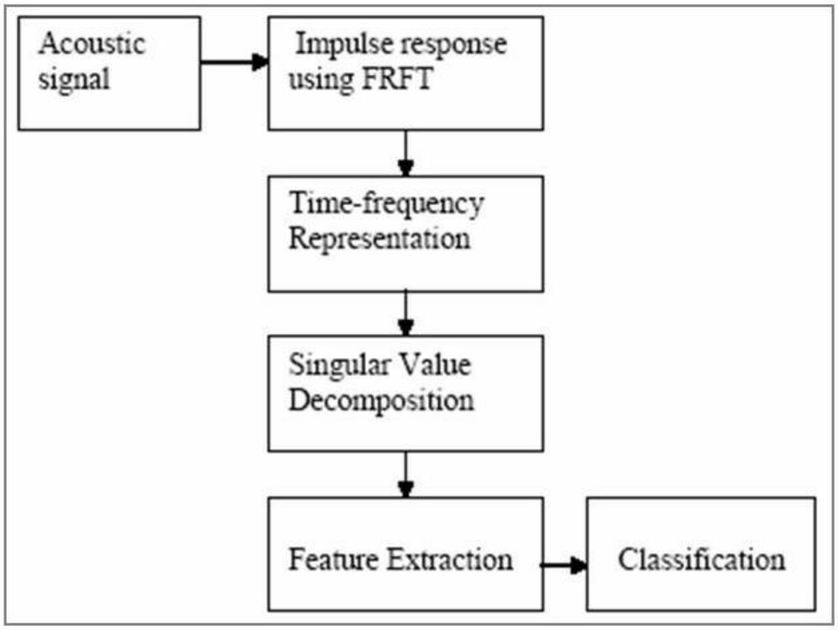

Figure 1. Block diagram of the proposed technique.

The classification procedure has been implemented based on the singular value decomposition of the time-frequency distribution of the obtained impulse response corresponding to each beam and each sediment class. Because feature analysis involves dimensionality reduction, we consider the first two singular values for sediment classification and the first three singular values for target classification from the SVD spectrum as relevant features.

4. EXPERIMENTAL RESULTS

4.1. Sediment Classification

In this chapter, the authors present experimental results using sonar data collected in a field trial, and processed using the proposed technique introduced. The data were acquired by Volume Search Sonar (VSS), one of the AN/AQS-20's sonars during a mission in the Gulf of Mexico. Two sediment types were present and therefore considered for classification: mud and sand. The data set sizes are presented in Table 1. The first four data sets include data extracted from the response of the seabottom sediments corresponding to nadir beams only, and the last three data sets contain data from ten central beams per ping, five beams fore and five beams aft. In all data sets equal size subsets of mud and sand data are considered. In addition, the testing data sets are chosen from slightly different geographical locations than the training data sets. Two methods are employed to compute the impulse response of the sediment: the standard deconvolution method, implemented in the frequency domain and the Fractional Fourier Transform method. The impulse response is then represented in the time-frequency domain using the Wigner distribution and the Choi-Williams distribution. The singular value decomposition of these distributions are computed next. In this way, important discriminant features for classification are obtained because the singular value spectrum encodes the characteristic features of the signal. The features thus obtained are mapped in a reduced dimensional space, by discarding all except the first and second singular values. Three classification approaches (linear classifier, quadratic classifier and Mahalanobis classifier) are then applied to the resulting features, and their performances compared.

In this section, the authors discuss first the results obtained only for nadir sets (sets 1 through 4) and then for central beam sets (sets 5 through 7). The results are consistent for nadir sets and for central beam sets, respectively, and can be summarized as follows.

Table 1. Data sets size for sediment classification.

Data sets	Training set	Testing set
Set 1	60 nadir beams	22 nadir beams
Set 2	60 nadir beams	30 nadir beams
Set 3	60 nadir beams	40 nadir beams
Set 4	40 nadir beams	40 nadir beams
Set 5	300 central beams	200 central beams
Set 6	260 central beams	102 central beams
Set 7	260 central beams	142 central beams

In sets 1 through 4, only nadir beams (fore and aft) are used. Applying the linear discriminant function, the standard deconvolution performs better than the FrFT (by almost 5%) when the Wigner distribution is employed as shown in Tables 2, 3, 4 and 5. When the Choi-Williams distribution is used, both methods (standard deconvolution and FrFT) achieve on average, almost the same accuracy for linear discriminants. Further, when the quadratic discriminant function is used for classification based on the Wigner distribution, the FrFT method gives a better accuracy than the standard deconvolution method by about 7% as illustrated in Tables 2, 3, 4 and 5. Using the Choi-Williams distribution, the standard deconvolution method performed the best for quadratic discriminants, with the highest accuracy of 90%, also shown in Table 2. When the Mahalanobis discriminant function is used, the FrFT method leads if the Wigner distribution is used, as illustrated in Tables 2, 3, 4 and 5, and gives the best overall performance of 100% accuracy (Table 2). For the last discriminant function discussed, the FrFT method gives similar (as shown in Table 2) or better classification results (Tables 3, 4 and 5) than the standard deconvolution method when the Choi-Williams distribution is employed.

Table 2. Classification results for data set 1 (sediment classification).

Discriminant Function	Accuracy			
	Standard deconvolution method		FrFT method	
	Wigner	Choi-Williams	Wigner	Choi-Williams
Linear	**86%**	**86%**	81%	**86%**
Quadratic	77%	**90%**	86 %	86 %
Mahalanobis	86%	95%	**100 %**	95%

Table 3. Classification results for data set 2 (sediment classification).

Discriminant Function	Accuracy			
	Standard deconvolution method		FrFT method	
	Wigner	Choi-Williams	Wigner	Choi-Williams
Linear	**83%**	**83%**	80 %	**83 %**
Quadratic	76%	**86 %**	83 %	83 %
Mahalanobis	80%	86 %	**93%**	90%

The best combination, that gives the highest accuracy, for nadir data, using only two singular values is the FrFT/ Wigner/ Mahalanobis.

The data sets 5 through 7 consist of 10 central beams per ping. The training and testing data set sizes are

Table 4. Classification results for data set 3 (sediment classification).

Discriminant Function	Accuracy			
	Standard deconvolution method		FrFT method	
	Wigner	Choi-Williams	Wigner	Choi-Williams
Linear	**82%**	**82%**	77%	**82%**
Quadratic	75%	**85%**	82%	**85%**
Mahalanobis	80%	90%	**95%**	92 %

Table 5. Classification results for data set 4 (sediment classification).

Discriminant Function	Accuracy			
	Standard deconvolution method		FrFT method	
	Wigner	Choi-Williams	Wigner	Choi-Williams
Linear	**82%**	72 %	77%	**82%**
Quadratic	75%	**85%**	82%	82%
Mahalanobis	82%	87%	**95%**	92 %

shown in Table 1. The standard deconvolution method performs better than the FrFT method (for both Wigner and Choi Williams distributions) for the linear discriminant function as illustrated in Tables 6, 7 and 8. The highest accuracy achieved is 70%, on average 4% higher than that obtained with the FrFT method (Table 7). When using the quadratic discriminant function, the FrFT provides the best accuracy for both cases (Wigner and Choi-Williams) as presented in Tables 6,7 and 8. The FrFT method shows the best performance when the Mahalanobis discriminant function is employed for classification based on the Wigner and the Choi-Williams distributions (Tables 6,7 and 8). The highest accuracy of 81% is obtained for data set 6, when the FrFT, the Wigner distribution and Mahalanobis discriminant functions are used.

The author recommendation for sediment classification when using two singular values is a combination of the FrFT/Wigner/ Mahalanobis, when central beams are used.

Table 6. Classification results for data set 5 (sediment classification).

Discriminant Function	Accuracy			
	Standard deconvolution method		FrFT method	
	Wigner	Choi-Williams	Wigner	Choi-Williams
Linear	**70%**	69%	68%	66%
Quadratic	68%	73%	72%	**75%**
Mahalanobis	76%	74%	**79%**	**79%**

The authors recommend the following combination in order to obtain a high accuracy sediment classification (of about 100%): FrFT/ Wigner/Mahalanobis discriminant, using nadir beams only and two singular values as features. However, the same combination can also be used for central beams and a classification accuracy of around 80% can be achieved.

4.2. Target Classification

The proposed technique is based on a pattern recognition approach and includes a representation of the target impulse response in the time-frequency domain. The singular value decomposition of the Wigner distribution as well as of the Choi-Williams distribution of the impulse response is next applied. This way, the discriminant features for classification are achieved due to the fact that the singular value spectrum encodes the relevant

Table 7. Classification results for data set 6 (sediment classification).

Discriminant Function	Accuracy			
	Standard deconvolution method		FrFT method	
	Wigner	Choi-Williams	Wigner	Choi-Williams
Linear	**70 %**	**70%**	68%	66%
Quadratic	68%	73%	74%	**76%**
Mahalanobis	75%	76%	**81%**	79%

Table 8. Classification results for data set 7 (sediment classification).

Discriminant Function	Accuracy			
	Standard deconvolution method		FrFT method	
	Wigner	Choi-Williams	Wigner	Choi-Williams
Linear	**68%**	**68%**	66%	64%
Quadratic	66%	71%	71%	**73%**
Mahalanobis	74%	75%	**78%**	76%

features of the signal. These features are mapped in a reduced ($3D$) dimensional space. Three types of discriminant functions, namely linear, quadratic and Mahalanobis, are used. Various experiments are employed for investigating the performance of the proposed target classification method. The shape of the targets is assumed to be cylindrical. In our simulation we used seven target radii: $ra_1 = 1.25\ cm$, $ra_2 = 1.5\ cm$, $ra_3 = 1.8\ cm$, $ra_4 = 2\ cm$, $ra_5 = 2.3\ cm$, $ra_6 = 2.7\ cm$ and $ra_7 = 3\ cm$ which are the seven classes, class 1 through class 7. The following parameters were initially set: the sound velocity in water $c_w = 1500\ m/s$, the depth of the water $10\ m$, sound velocity in the sediment $c_s = 1475\ m/s$, the burial depth in the sediment was $25\ cm$, the beam width $BW = 2^o$ and nineteen steps each of $\Delta = 0.02\ m$ along track. The first scenario simulated considers the free field while the next one simulates a muddy bottom. In the free field case we perform five experiments. In the first experiment we consider a cylinder for which the compressional velocity is $c_c = 3100\ m/s$ and then for the second experiment $c_c = 2800\ m/s$. The target is assumed to be at a depth of $25\ cm$ in water. The simulation is performed in nineteen steps for seven classes. In order to obtain a supervised classification we use a training data set of seventy vectors that correspond to ten odd steps for each of the seven classes. For the testing data set we use sixty-three vectors from the other even nine steps. Each $3D$ feature vector is composed of the 3 largest singular values. The performances of the various classifiers for the first four experiments are presented in Table 9.

Table 9. Classification accuracy for experiments 1 through 4 (target classification).

	Accuracy Linear, [%]		Accuracy Quadratic, [%]		Accuracy Mahalanobis, [%]	
	Wigner	Choi-Williams	Wigner	Choi-Williams	Wigner	Choi-Williams
Exp 1	71.4	82.25	100	100	100	100
Exp 2	74.6	57.1	100	100	100	100
Exp 3a	84.76	84.76	100	100	100	100
Exp 3b	82	80	100	100	100	100
Exp 3c	83	80	100	100	100	100
Exp 4a	82.62	87.62	100	100	100	100
Exp 4b	81.9	87.62	100	100	100	100
Exp 4c	81.9	85.71	97.14	100	97.14	100

The quadratic and Mahalanobis based classifiers show similar high accuracies comparing to the linear based classifier for both Wigner and Choi-Williams distributions. In the third experiment the classifiers were trained with 105 vectors of data from the free field at a burial depth of 25 cm and then tested with an equal size set of data corresponding for three burial depth conditions: 15 cm, 35 cm and 50 cm. The experimental results for the three burial depths are presented in Table 9, Exp $3a$, $3b$ and $3c$. In the fourth experiment the variation of the environmental conditions such as salinity, water temperature is reflected in the variation of the sound velocity in water $c_w = 1520\ m/s$, 1535 m/s and 1550 m/s. The sound velocity in the water for the training data set was 1500 m/s. The sizes of training and testing data sets are equal to 105 vectors. The experimental results are shown in Table 9 , Exp $4a$, $4b$ and $4c$. The quadratic and Mahalanobis classifiers tested in free field presented a very good robustness comparing to the linear classifier to the changes in the environmental conditions and burial depth. The sensitivity of the algorithm with the target material was tested in experiment 5. In this experiment, for the free field data the size of the training and testing data was 133 vectors. The target sound velocity for the training data set was $c_c = 2800\ m/s$. We use the same depth and three different types of the materials (corresponding to the sound velocities $c_c = 2775\ m/s$, 2750 m/s, and 2725 m/s) for the underwater target in order to test the sensitivity to the target material. The experimental results are presented in Figure 2, where the quadratic based classifier achieved the best accuracy for both Wigner and Choi-Williams distributions comparing to the competing classification techniques. However, the quadratic classifier outperfoms by about 1 % the Mahalanobis classifier. An evaluation of the proposed classification technique for targets buried in sediment using free field target response data for training and mud target response data for testing are considered in the experiments 6 and 7, where the buried cylinder (corresponding to $c_c = 2800\ m/s$) is positioned at two different depths: 15 cm and 25 cm, respectively. The classification results are illustrated in Figure 3 . Both the quadratic and the Mahalanobis based classifiers show considerably higher accuracy than the linear classifier, for both the Wigner and Choi-Williams distributions. The classification accuracy is higher for the Choi-Williams distribution versus the Wigner distribution, and degrades as the burial depth increases.

The proposed classification method presented in this paper is based on feature extraction from a couple of time-frequency distributions (Wigner and Choi-Williams) of the target impulse response. The discriminant features for classification are the 3 most significant singular values of the time-frequency distribution. Three classification approaches were employed each with a different discriminant function.

The quadratic and Mahalanobis based classifiers show, on average, similar accuracy but superior to the linear classifier under various scenarios. High accuracy of the proposed method is obtained even when the environmental conditions and the depth of the buried target are varied. An important characteristic of this method is that good classification accuracy (around 75 %) of an unknown target (of various materials and buried at various depths) is achieved having only the response of a known target in the free field. A higher classification accuracy is expected for larger differences in target sizes.

5. CONCLUSIONS

This paper is focused on developing an algorithm for seafloor bottom classification as well as for buried target classification using acoustic backscattered signals. The novel approach for feature extraction is based on time-frequency techniques that give a representation of the signal that lead to a good discrimination of the patterns. The technique introduced in this work employs the Fractional Fourier Transform (FrFT) in order to compute the impulse response. The FrFT is better suited for chirp sonar applications because it uses linear chirps as basis functions; it has a great potential in sonar signal processing. The work also presents the classical method for determining the bottom impulse response based on frequency domain deconvolution. The two methods are tested and compared on real data collected by the Volume Search Sonar (VSS). The final classification into sediment classes is based on singular value decomposition of the time-frequency distribution applied to the impulse response obtained using the FrFT. The set of singular values represents the desired feature vectors that describe the properties of the signal, and then a supervised classification is performed.

The authors' recommendation for *sediment classification* is to use the combination FrFT/Wigner distribution/Mahalanobis discriminant function using two singular values as features. When only nadir beams are used the classification accuracy is, again, higher than when central beams are used.

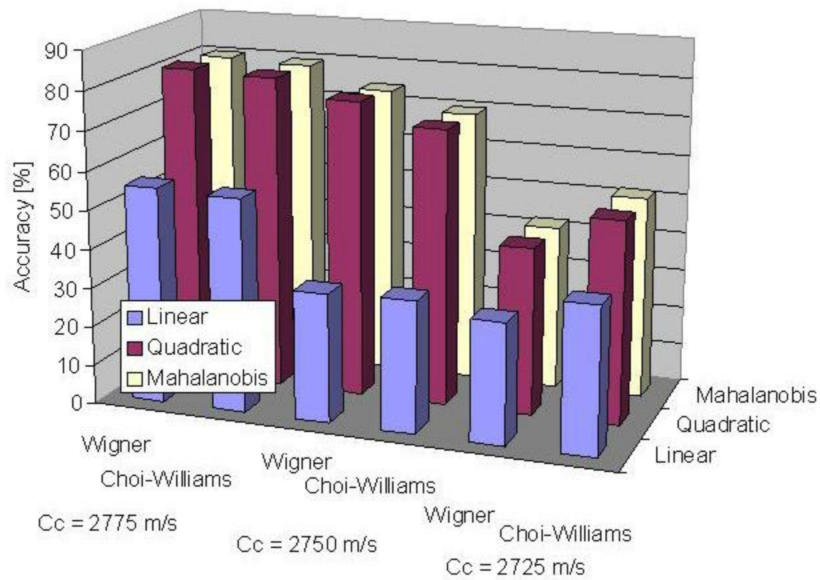

Figure 2. Classification accuracy for experiment 5 (target classification).

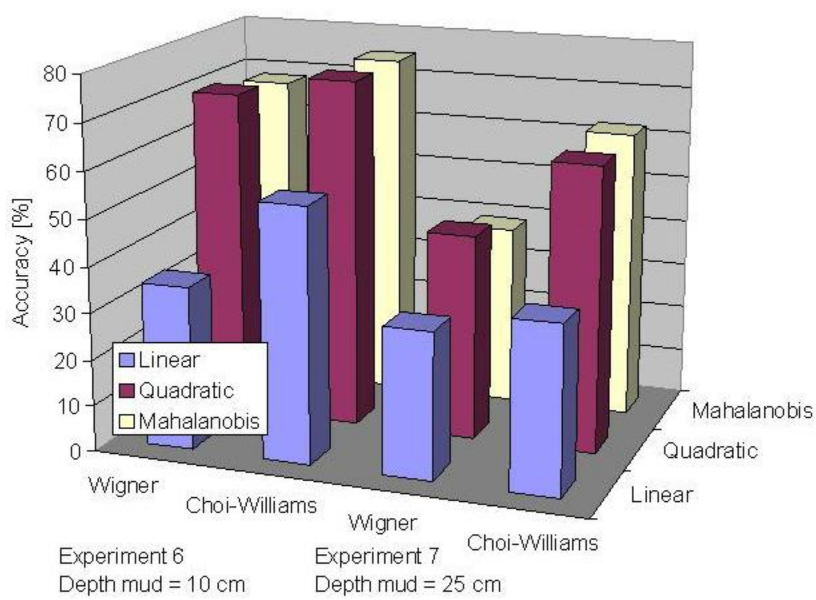

Figure 3. Classification accuracy for experiments 6 and 7 (target classification).

The performance of the proposed classification technique is evaluated on synthetic data sets, simulated for buried targets detected by parametric sonar. Seven cylindrical targets with various diameters are considered in several different testing scenarios. The method used for buried target classification is similar to that used for sediment classification, but in this case the target impulse response is known (simulated). High accuracy of the proposed method is obtained even when the environmental conditions and the depth of the buried target are varied. An important characteristic of this method is that good classification accuracy of an unknown target (of various materials and buried at various depths) is achieved having only the simulated response of a known target in the free field. Higher classification accuracy is expected for targets with large difference in sizes (radius).

A recommended procedure for *target classification* is based on a combination of the Choi-Williams distribution with either Mahalanobis or quadratic discriminant functions using the three highest singular values as features, when the target impulse response is given.

In this work the authors develop a feature extraction method based on the FrFT and time-frequency representations that improve the performance of the acoustic seabed and buried target classification. The FrFT method enhances the seafloor impulse response, and hence higher classification accuracy is achieved when used in combination with Mahalanobis classifier. In addition, the novel proposed algorithm shows classification robustness under various scenarios.

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