On the Use of Time-Frequency Methods in the Oceanic Passive Tomography Context

André Quinquis, Cornel Ioana

ENSIETA, 2 rue François Verny,
29806, Brest - FRANCE
quinquis@ensieta.fr, ioanaco@ensieta.fr

Krystel Frezza-Boin, Jean-Claude Le Gac

Centre Militaire d'Océanographie, EPSHOM
29603, Brest - FRANCE
frezzakr@shom.fr, legac@shom.fr

Abstract A modern method for acoustic underwater channel characterization is the passive tomography concept. The technique relies on the use of opportunity sources thus avoiding the use of dedicated active sources. As a consequence, one of the main difficulties of the concept is due to the lack of any information about the emitted signals.

In this paper, we will propose a time-frequency method in the case of linear frequency modulated signals. For an ideal acoustic channel, the received signal is composed of a sum of shifted chirps that have the same chirp rate and start frequency as the emitted signal. Hence, using the fractional Fourier transform (FRFT), it is possible to express the received signal as a sum of sinusoids. Their frequencies are directly related to the time delays of the arrivals. In order to distinguish the closed arrivals, we apply a high resolution spectral estimation method, providing their time delays. Furthermore, we obtain some information related to their amplitudes by comparing the pseudo and the real spectra. These results can further be used in order to estimate the envelope of the impulse response of the acoustic channel.

I. INTRODUCTION

Two fundamental problems arising in many signal processing applications (reverberation cancellation, seismic signal processing, speech recognition, etc) are channel and source signature estimation, often referred as *deconvolution*. One potential application of this technique can be the oceanic passive tomography, where a fundamental problem is the passive characterization of acoustic transients and of the ocean environment.

In this paper, we propose a time-frequency based approach to solve the problem of blind deconvolution in ocean acoustics, obtaining the medium impulse response (IR), representative of its physical properties.

As it was shown in [3], the time-frequency (TF) processing has proved to overcome the typical ill-conditioning of single sensor deterministic deconvolution techniques. Nevertheless, the method proposed in [3] performs well only if some *a priori* information, related to signal duration, is available. This assumption can be a serious limitation for practical applications. Consequently, the method that is presented in section 2 and that is based on the high-resolution spectral analysis in the fractional Fourier domain, performs in a total passive context. In section 3 we study the performances of this method for simulated and realistic signals limited to linear frequency modulations. Section 4 highlights the significance of the results and describes some realistic perspectives.

II. SPECTRAL ESTIMATION IN THE FRACTIONAL FOURIER DOMAIN

A. FRFT definition and its application for chirp rate estimation

The fractional Fourier transform (FRFT) is the generalization of the classical Fourier transform. It provides a measure about the angular distribution of energy in the time-frequency plane. The FRFT depends on a parameter α. As shown in figure 1, the FRFT can be interpreted as the counterclockwise rotation of the signal representation by an arbitrary angle α [1].

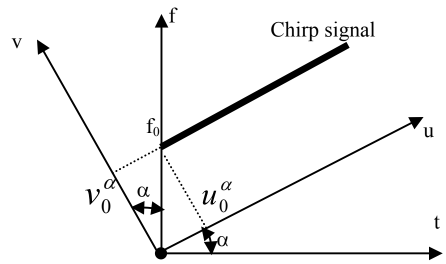

Fig. 1. The fractional Fourier transform definition

The FRFT of a signal s*(t)* is defined as :

$$FRFT_{\alpha}\{s\} \stackrel{\Delta}{=} \sqrt{\frac{1-j\cot\alpha}{2\pi}}\, e^{j\frac{\cot\alpha}{2}x^2} \int_{-\infty}^{\infty} s(\tau)\, e^{j\frac{\cot\alpha}{2}\tau^2}\, e^{-j\csc\alpha\cdot x\tau}\, d\tau, \quad (1)$$

where $p = 2\pi/\alpha$ is the order of the FRFT. The relationship between the time-frequency coordinates (in standard time-frequency plane - α=0) and the fractional ones, may be expressed as follows (see figure 1):

$$\begin{pmatrix} u \\ v \end{pmatrix} = \begin{pmatrix} \cos\alpha & -\sin\alpha \\ \sin\alpha & \cos\alpha \end{pmatrix} \begin{pmatrix} t \\ f \end{pmatrix} \quad (2)$$

Conventionally, the (*u,v*) axes denote the fractional time axis and the fractional frequency axis, respectively.

One important FRFT property is that a chirp signal is represented by a monochromatic component in the fractional domain when the angle α is equal to the chirp rate. Thus a sum of chirp signals whose characteristics are identical in the standard time-frequency plane is also represented as a sum of tones in the fractional domain [1]. Given a chirp $s(t)$, the first step of the procedure consists in estimating the order of FRFT adapted to the chirp in order to transform it in a sinusoid in the fractional domain. One of the simplest method is to find in the ambiguity plane, the optimal radial gaussian kernel (RGK) of the analyzed signal [7]. In polar coordinates, this kernel has the following form :

$$\Phi(r,\psi) = \exp\left(-\frac{r^2}{2\sigma^2(\psi)}\right), \tag{3}$$

where $\sigma(\psi)$ controls the spread of the Gaussian at radial angle ψ . $\sigma(\psi)$ is called the *spread function.* The angle ψ is measured between the radial line through the point (τ, θ) and the τ-axis (figure 2.b):

$$\psi = \arctan \frac{\theta}{\tau} . \tag{4}$$

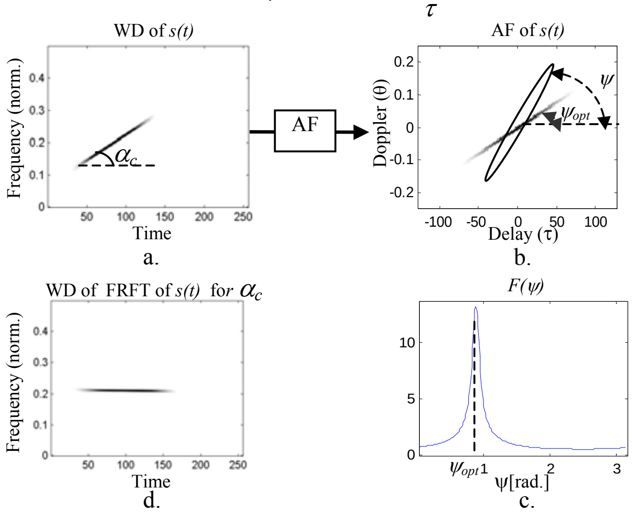

Fig. 2. Chirp rate estimation by RGK-based procedure

When the kernel is well matched to the component of a given signal (figure 2.b), we obtain the optimal angle ψ_{opt}. Therefore, the optimal direction of the kernel (and implicitly, the optimal angle) is computed thanks to the maximization of the matching function F (figure 2.c) defined in the ambiguity plane as [7]:

$$F(\psi) = \int_0^{2\pi} \int_0^{\infty} |A(r,\psi)\Phi(r,\psi)|^2 \, r dr d\psi \tag{5}$$

where $\Phi(r,\psi)$ is given by (3) and $A(r,\psi)$ is the ambiguity function (AF), expressed in polar coordinates [7]. Following [2] the chirp rate α_c is related to ψ_{opt} by:

$$\alpha_c = \frac{\pi}{2} - \psi_{opt} . \tag{6}$$

Thus, the chirp rate estimation can be performed by solving the following optimization problem :

$$\max_{\psi} |F(\psi)| . \tag{7}$$

A simple gradient-based method is used to solve equation (7).

Figure 2.c. shows the $F(\psi)$ curve for $\alpha = 0 - \pi$. On this figure and using (6) we estimate that $\alpha_c = 0.35$ (whereas the real value is 0.3491). The Wigner Distribution (WD) of the corresponding FRFT shows that the chirp is now represented by a sinusoid.

This property allows us the posibility to use a classical spectral estimation method designed for sinusoidal signals.

B. Spectral estimation using the MUSIC method

The simplest linear model of the received signal in a multipath underwater channel is composed of several replica of the emitted signal, which can be written :

$$s_r(t) = \sum_{k=1}^{N_p} A_k s(t - t_k) , \tag{8}$$

where A_k is the amplitude of the k^{th} replica , t_k its arrival time and N_p the number of paths that is taken into account. Making the assumptions that the source is motionless and that the emitted signal is a chirp, the received signal is composed by a set of chirps having the same chirp rate and start frequency (figure 3.a.). Using the procedure described above, we first estimate the chirp rate α_c, and then applying the corresponding FRFT, we obtain a sum of N_p sinusoids (see figure 3.c.).

The time delays may be close (see for example [6] for a shallow water environment). Consequently, it is necessary to use a high resolution spectral estimation method in order to distinguish the received pulses. We choose the MUSIC method [4], which is based on the observation space decomposition on signal and noise subspaces.

Writing $F = \{\nu_1, \nu_2, \ldots, \nu_K\}$ the set of estimated frequencies, sorted in decreasing order, and using relation (2), we can write :

$$\Delta t_i = |(\nu_1 - \nu_i) \sin \alpha_c|, \; i = 1 : K , \tag{9}$$

where Δt_i is the time delay of the i^{th} path relative to the first arrival. The size K of signal subspace is chosen sufficiently large in order to be able to capture all the real arrivals. In practice, even if $K >> N_p$, the spurious components do not influence further results , because their amplitude is negligible (section II.C).

This procedure is illustrated in the following example. We suppose a test signal $s(t)$ composed by 4 chirps temporally separated by 10 samples ($F_s = 4096$ *Hz*). The WD of this signal is depicted in figure 3.a. As it can be observed, we cannot distinguish the four chirps components because of the WD cross terms [2].

On the contrary, using the RGK-based procedure, we can estimate the optimal gaussian kernel, given by the angle ψ_{opt}=*1.22* rad. (figure 3.b.). Computing the corresponding FRFT ($\alpha_c=\pi/2$; $\psi_{opt}=0.35$) of the original signal, we transform the chirp set in a sum of sinusoids (figure 3.c).

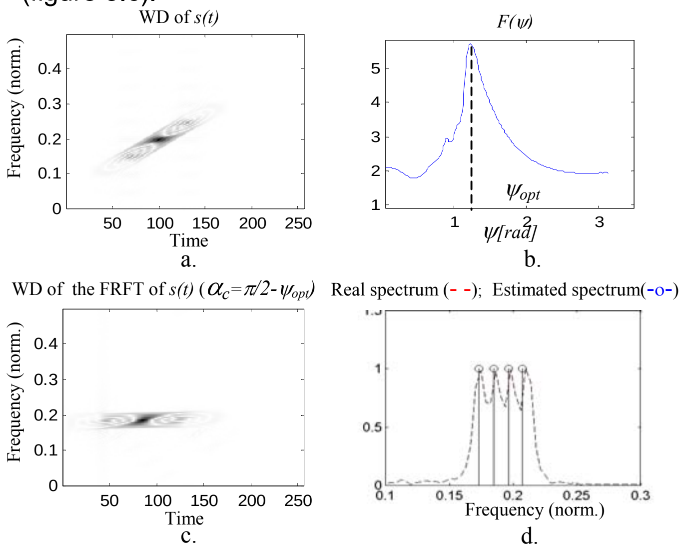

Fig. 3. Time of arrival estimation by spectral estimation in fractional domain

Using MUSIC methods, the four associated frequencies of the FRFT of *s*(*t*) (figure 3.d) are finally estimated. We obtain (in normalized frequency coordinates) the following values : $\upsilon_1 = 0.20704; \upsilon_2 = 0.19631; \upsilon_3 = 0.18499; \upsilon_4 = 0.17292$. The corresponding shift between two consecutive chirps [equation (9)] is 10.029 which is close to the real value.

In this example, the four chirps have the same amplitude. For real applications this is not the case due to the distinct attenuation of each propagation path. Therefore, in order to completely characterize the channel, it is necessary to estimate these amplitudes.

C. Amplitude estimation

The amplitudes can be directly estimated from the FRFT spectrum (analysis with respect of *v* axis) by taking the values corresponding to the estimated frequencies $\{\upsilon_i\}_{i=1:K}$. More specifically, if we denote the spectrum of FRFT of the signal *s(t)* by $S^{\alpha}(\upsilon)$, the amplitude information can be obtained as :

$$A_k \approx C \cdot S^{\alpha}(\upsilon_i) \tag{10}$$

where *C* is a proportionality factor, the *same* for all components [4], due to the unitarity property of the FRFT [1].

As a summary, the proposed procedure for blind estimation of an underwater channel is presented in figure 4.

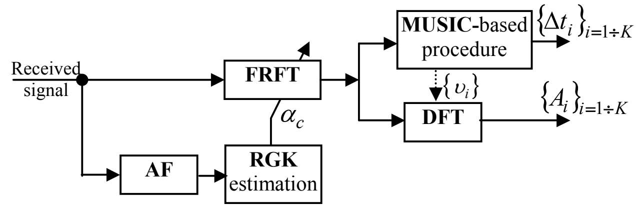

Fig. 4. The proposed parameter estimation procedure of an underwater channel

III. SIMULATION RESULTS

In this section we study our procedure for a realistic scenario. It corresponds to the INTIMATE'96 sea trial which has already led to several active tomographic approaches for ocean tomography [6], source localization [8][9] or geoacoustic inversion purposes [10]. The environment is characterized by a 135 m depth channel and a slightly downward sound speed profile (figure 6.a). The bottom is modeled by a semi-infinite fluid half space of sandy sediments. The acoustic source depth is 91 m; the receiver is located at 5.63km range and 116m depth. The source is motionless.

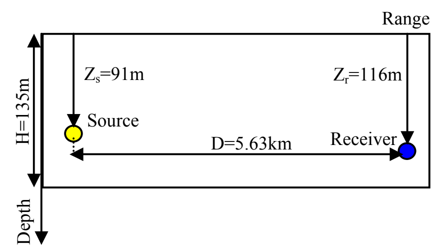

Fig. 5. Scenario of the INTIMATE'96 sea trial

The emitted signal is a chirp spanning the [300, 1000] Hz band. The impulse response of the acoustic channel is computed with the normal modes ORCA model [5]. The received signal (figure 6.d) is composed of a first energetic peak corresponding to low grazing angle unresolved paths mostly refracted in the thermocline with a few bottom bounces. The second part of the signal exhibits a textbook multipath resolved structure, corresponding to multiple bottom and surface reflected arrivals (figure 6.b).

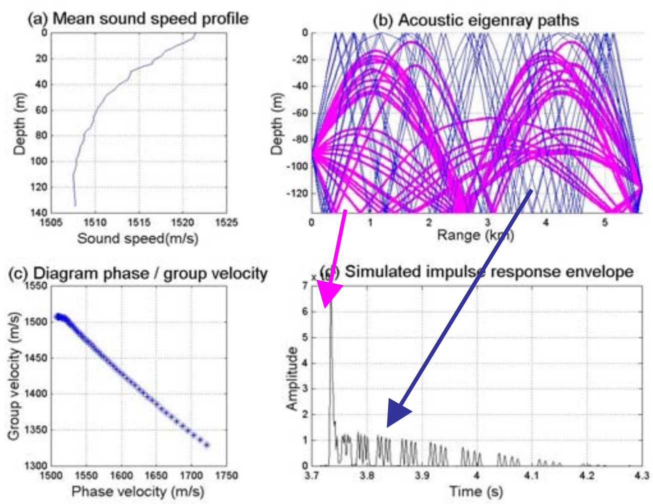

Fig. 6 . Joint analysis of acoustic propagation and impulse response of the acoustic channel - (a) Mean sound speed profile. - (b) Acoustical eigenray paths. - (c) Diagram phase velocity / group velocity. - (d) Simulated envelope of the impulse response with ORCA normal modes model [5]

In order to estimate the performances of the algorithm, we define the normalized amplitude estimation error (Γ_A) and normalized time of arrivals estimation error (Γ_t) :

$$\Gamma_A = \frac{\left\|A - \hat{A}\right\|}{\left\|A\right\|} \text{ and } \Gamma_T = \frac{\left\|T - \hat{T}\right\|}{\left\|T\right\|} \tag{11}$$

where $\hat{A} = \left(\hat{A}_1, ..., \hat{A}_K\right)$ - the vector of K-estimated amplitudes and $\hat{T} = \left(\hat{t}_1, ..., \hat{t}_K\right)$ - the vector of K-estimated time delays. The vectors of the real values of the amplitude and arrivals, A and T, are given by the normal mode model ORCA [5].

As a first performance test, we measure these errors for a received observation (composed by 10 unresolved arrivals [6], corrupted in a complex white gaussian noise), versus signal-to-noise ratio, defined in the useful frequency band [300,1000] Hz. (We used 100 trials for each SNR value).

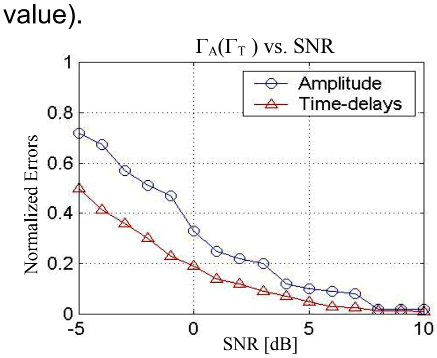

Fig. 7. Source estimation performance in noise

The results are shown in figure 7. It can be observed that, for SNR lower than 0 dB, the normalized errors are relatively small. Therefore, for a null SNR it is technically possible to distinguish the 10 unresolved peaks.

Another test operation is devoted to the comparison of the precision achieved by the proposed method with the one obtained by the classical matched-filtering technique[3]. We suppose that the test signal is a sum of two chirps, variably shifted, in the band [300,1000] Hz, sampled at *Fs=4096 Hz*. The duration, necessary to construct the adapted filter, is about *D=0.0625* sec. With these assessments, the limit of the potential resolution, provided by adaptive filtering, is $\Delta\tau=1/\Delta F=2$ ms (figure 8.a.), which, for a given F_s, corresponds to a $\Delta\tau{\cdot}F_s \cong 9$ samples shift.

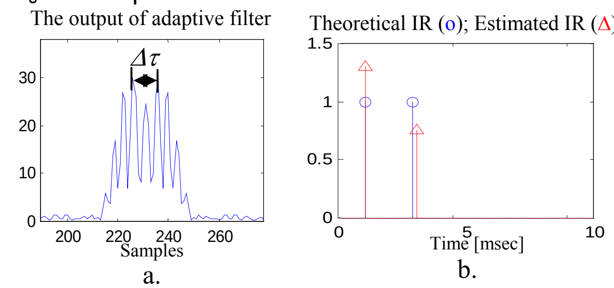

Fig. 8. Adaptive filtering vs. FRFT-based method

The estimated IR for this critical scenario is depicted in figure 8.b.. We observe that we can still distinguish the two peaks, as in the adaptive filtering case, and we remark also that the estimated IR is close to the theoretical one.

The performances of the proposed method, proved through the previous two examples, are reflected, in a real application case [6], by an accurate channel estimation (see figure 9). The test signal is composed only by the first *12* unresolved arrivals. On this figure, we remark that all the arrivals are correctly detected which leads to an accurate deconvolution process. This is explained by the high resolution, provided by MUSIC method, applied in the fractional Fourier domain.

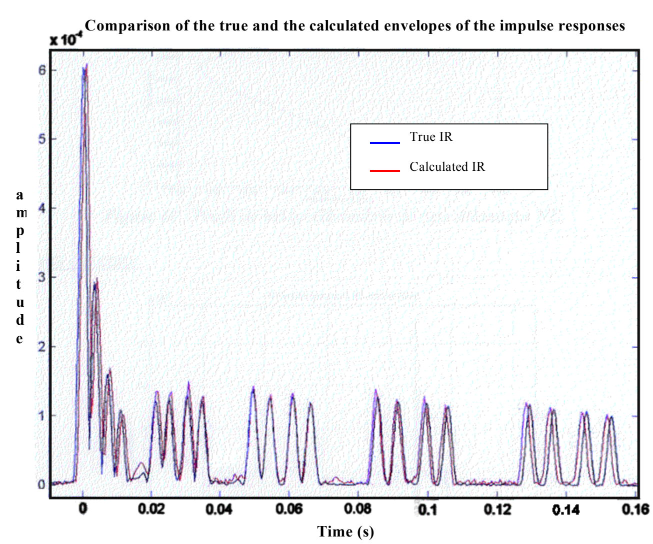

Fig. 9. Channel estimate obtained by classic matched-filtering (blue) and FRFT-based method (red)

IV. CONCLUSION AND PERSPECTIVES

The work presented in this paper has illustrated the feasibility of a single sensor blind deconvolution by TF processing, for a realistic multipath acoustic channel in a *complete* passive context. Hence, we have proposed an approach based on different time-frequency methods, which fully overstep the lack of any *a priori* information to estimate the envelope of its impulse response.

The simulation results showed the effectiveness and the robustness of the channel estimation for SNR potentially lower than 0 dB. Moreover the achieved precision by the proposed method is similar to that of matched filtering. These performances, achieved without any *a priori* knowledge about the emitted signal, prove the capacity of the proposed method to accurately perform in a total passive context.

Further work should deal with the generalization of the method to non-linear frequency modulations and to moving sources. The frequency dispersive characterics of the acoustic channel will also be studied.

REFERENCES

[1] O.Arikan, M. A. Kutay, H. M. Özaktaş and Ö. K. Akdemir, “The Discret Fractional Fourier Transform”*, IEEE Int. Symp. TFTS*, Paris, 1996.

[2] L. Cohen , “Time-frequency Analysis”, *Pretince Hall, PTR*, 1995.

[3] N. Martins, S. Jesus, C. Gervaise, A. Quinquis, "A time-frequency approach to blind deconvolution in multipath underwater channels", *ICASSP2002*, Orlando.

[4] P. Stoica, R. Moses, "Intoduction to spectral analysis", *Pretince Hall*, 1997.

[5] E.K.Westwood, C.T.Tindle, N.R.Chapman, "A normal mode model for acousto-elastic ocean environments", *J.Acoust.Soc.Am*. vol. 100 (6), pp. 3631-3645, Dec.1996

[6] Y.Stéphan, X.Demoulin, T.Folegot, S.Jesus, M.B.Porter, E.Coelho, “Acoustical effects of internal tides on shallow water propagation : an overview of the INTIMATE96 experiment”, in *Experimental Acoustic Inversion Methods for exploration of the shallow water environment,* A.Caiti et al Eds, Kluwer Academic Publishers, pp.107-124, 2000

[7] R.G. Baraniuk and D.L. Jones, "A signal-dependent time-frequency representation: optimal kernel design*", IEEE Trans. Signal Processing,* vol. 41, pp. 1589-1602, April 1993.

[8] M.B.Porter, S.Jesus, Y.Stéphan, X.Demoulin, E.Coelho, “Tidal effects on source inversion”, in *Experimental Acoustic Inversion Methods for exploration of the shallow water environment,* A.Caiti et al Eds, Kluwer Academic Publishers, pp.107-124, 2000

[9] S.Jesus, O.Rodriguez, M.B.Porter, Y.Stéphan, X.Demoulin, E.Coelho, “Single hydrophone source localization”, *IEEE J.Oceanic Eng*., vol. 25 n°3, pp.337-346, July 2000

[10] J-C. Le Gac, M.Asch, Y.Stéphan, X.Demoulin, "Inversion of broadband acoustic data on a single hydrophone by use of an equivalent geoacoustic model", *ECUA2002,* Gdansk, Poland, pp.483-488, 2002