

# Blind Estimation of the Ocean Acoustic Channel by Time–Frequency Processing

Nelson E. Martins and Sérgio M. Jesus, *Associate Member, IEEE*

**Abstract**—A blind estimator of the ocean acoustic channel impulse response envelope is presented. The signal model is characterized by a deterministic multipath channel excited by a highly nonstationary deterministic source signal. The time–frequency (TF) representation of the received signal allows for the separation between the channel and the source signal. The proposed estimator proceeds in two steps: First, the unstable initial arrivals allow for the estimation of the source signal instantaneous frequency (IF) by maximization of the radially Gaussian kernel distribution; then, the Wigner–Ville distribution (WV) is sequentially windowed and integrated, where the window is defined by the previously estimated IF. The integral gives the channel impulse response envelope, which turns to be an approximation to the blind conventional matched filter (MF). The blind channel estimator (CE) is applicable upon the following conditions: that the multipath channel contains at least one dominant arrival well separated from the others, and that the IF of the source signal is a one-to-one function. Results obtained on real data from the Internal Tide Measurements with Acoustic Tomography Experiments (INTIMATE'96), where the acoustic channel was driven by a linear frequency modulation signal, show that the channel's envelope detailed structure could be accurately and consistently recovered, with the correlation of the estimates ranging from 0.796 to 0.973, as compared to the MF result.

**Index Terms**—Blind channel estimation, linear frequency modulation (LFM), multipath, time–frequency (TF).

## I. INTRODUCTION

**B**LIND channel estimation is a topic of intense research in the underwater acoustics community [1], [2], as well as in signal-processing-related fields such as wireless communications [4], geophysics [5], etc. Being essentially transparent to sound propagation, the ocean is a favorable medium for transmitting information by acoustic signals, either for biological or human purposes. This information is contained in the signal emitted by the acoustic source, and is sensed by an acoustic receiver, which can be positioned from meters to hundreds of kilometers from the source. The received signal obviously contrasts with the emitted signal due to the severe distortion introduced by the medium boundaries, the space- and time-variable sound-speed, bottom properties, and source and receiver coordinates, among other factors. Both emitted and received signals, and the ocean distortion, can be modeled by time- (or space-)

dependent functions. Assuming the ocean acoustic channel as linear time invariant, the received signal can be modeled as a noisy convolution of the emitted signal with the channel impulse response. At the receiver end, the purpose is usually to interpret the information contained in the source signal, for example, in digital communications [3], or to estimate the physical or geometric (e.g., water depth, source coordinates) parameters responsible for signal distortion, which is the purpose of ocean acoustic tomography [25], [26]. This purpose can be achieved without major difficulty if the source signal is known at the receiver. Otherwise, in ocean monitoring scenarios, where the discretion of the receiver is important, as in biological studies or military applications, the problem of channel estimation transforms itself onto a blind estimation problem, in that the only information available to the receiver is the received signal, which encapsulates the emitted signal, the channel distortion, and the inevitable noise. Consequently, there is an increasing need for the development of blind receivers capable of estimating the ocean physical parameters, or the emitted signal, in the presence of this unknown excitation source signal. Often, this signal is a nonstationary transient that propagates from the source to the receiver after severe channel distortion and noise corruption. Recovering the ocean distortion amounts to solving a blind signal deconvolution problem by modeling the ocean channel as linear and time invariant. Blind deconvolution is itself a research area, with specific principles and methods.

Classical deconvolution is a well-established inversion method, which allows for the estimation of either the channel or the source signal. When the source signal is known, a correlator receiver can be used for channel estimation, which constitutes an application of the classical matched filter (MF). As is well known, the performance of this estimator is dependent on the source signal's bandwidth, which has a direct impact on the estimate quality. For low signal-to-noise ratio (SNR) environments, the correlator can be improved with a prior denoising step. This has been done in [6] by using a chirp signal as training sequence to estimate the impulse response of the channel. The proposed method makes use of the high concentration of the chirp signal when compared to the noise spreading in the joint time–frequency (TF) plane. In essence, a time-variant filter is applied to the received signal, resorting to the Gabor transform, before conventional channel estimation. If the channel has a multipath structure, which is a reliable approximation in the ocean-channel case, then channel estimation can be transformed into a time delay estimation problem [7]–[9]. This can also be addressed in the spectral domain, as proposed by Kirsteins [10]. This method is based on fitting weighted complex exponentials to the spectrum of the received

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The authors are with SiPLAB-FCT, Universidade do Algarve, PT-8000 Faro, Portugal (e-mail: nmartins@ualg.pt; sjesus@ualg.pt).

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signal. In this case, the drawbacks of ill-conditioning and bias, and the requirement of considering contiguous frequency samples, led to the development of other algorithms, which attempt to find least squares unbiased estimates of the time delays [1]. In this last reference, the techniques were extended to the blind deconvolution of a gated sinusoid, where the sinusoid and channel parameters are searched simultaneously. A common problem in signal deconvolution is ill-posedness. In underwater acoustics, this problem was dealt with by observing the source signal through a multichannel array [11], [12]. The method presented in [11] is based on maximum *a posteriori* probability (MAP) likelihood estimation, assuming a stochastic model for the source signal. The approach proposed by Smith and Finette [12] solves an iterative minimization problem using simulated annealing. In this last reference, the authors mention that the proposed method can be extended to the case of the simultaneous estimation of the source signal and the multichannel impulse response.

Blind deconvolution methods that deviate from classical deconvolution generally involve higher order statistics of the source signal or the channel. One important requirement is that the involved signals satisfy ergodicity and stationarity. The techniques are based on the principle that the higher order moments of the input signal are decreased by convolution with a linear and time-invariant channel. The problem is solved by maximization of the higher order moments (equivalently, minimization of the entropy) of the deconvolved quantities. Finding obvious applications, for example, in wireless communications, blind deconvolution has, in this field, exploited also the cyclostationary properties of the received signal. As an example, Gardner [13] has proposed a method for channel identification based on the second-order cyclic autocorrelation function. This method involves the use of a training period, during which, the unobserved channel input is transmitted at a slow rate, making the intersymbol interference negligible. The need for a training period can however fall off (increasing the available bandwidth) for certain channel models, as shown by Tong *et al.* [14], using extensions of Gardner's original method. A comprehensive study on the use of blind deconvolution on communication systems was presented in [4]. Blind deconvolution methods dealing with higher order statistics have been applied also in geophysics [5] to estimate the reflection coefficients of a layered Earth model. The same principles were recently applied, in underwater acoustics, to the deconvolution of signals with a moderate degree of temporal nonstationarity [2]. However, the deconvolution result is influenced by a free parameter—the filter length—and an open question on whether such principles could be applied to signals with a high degree of nonstationarity remains.

This paper presents a blind estimator of the ocean acoustic channel, excited by a highly nonstationary source (probe) signal. Assuming deterministic models for the channel and source signal, the method is divided into two steps. The first step consists of the estimation of the source signal instantaneous frequency (IF). In the second step, the Wigner–Ville distribution (WV) of the received signal is integrated along delayed versions of the source signal IF estimate, giving as output the channel impulse response envelope estimate.

The paper extends the work presented in [15] and [16] and is structured as follows. Section II defines the problem and briefly sketches its solution by TF methods; the TF estimator is presented and characterized in Section III. Experimental results with underwater acoustic data are presented in Section IV, and some conclusions and perspectives are drawn on Section V.

## II. PROBLEM STATEMENT AND TF APPROACH

Consider both an acoustic source and receiver positioned at given locations in the ocean. Assuming that their positions are stationary along the propagation time (here,  $\approx 4.5$  s), and that the environmental conditions do not change significantly along this same period, the acoustic channel linking the source to the receiver can be characterized by a linear and time-invariant impulse response. Note that for different source and/or receiver positions, and/or for environmental temporal variations on time scales that are larger as compared to the observation time (in the considered experimental setup, this time is  $\approx 1.5$  min, see Section IV), as, e.g., tidal-induced water depth variation, the source and received signals will be linked by time-varying impulse responses. Thus, during the observation time, the received signal  $r(t)$  can be modeled by a noisy and channel-distorted version of the deterministic source signal

$$\begin{aligned} r(t) &= x(t) + n(t) \\ &= s(t) * h(t) + n(t) \end{aligned} \quad (1)$$

where  $h(t)$  is the impulse response of the ocean channel,  $n(t)$  is zero-mean stationary additive noise,  $*$  stands for convolution, and  $s(t)$  is the complex representation (analytic signal) of the real source signal

$$s(t) = a_i(t)e^{j\varphi_i(t)} \quad (2)$$

where  $a_i(t)$  and  $\varphi_i(t)$  are the instantaneous amplitude (IA) and phase, respectively. The IF of  $s(t)$  is readily given by

$$f_i(t) = \frac{1}{2\pi} \frac{d\varphi_i(t)}{dt}. \quad (3)$$

One key point in considering an impulse response model for the ocean acoustic channel is its structure, which, when given by a series of delayed impulses, generally constitutes a realistic model. Further, the initial impulses are typically very close in time, and at least one of them has a high amplitude as compared to the remaining well-separated impulses. The initial high-amplitude impulse(s) is (are) due to direct eigenrays or eigenrays with a small number of reflections, while the well-separated impulses are due to several surface and/or sediment reflections.

The problem at hand is, knowing  $r(t)$ , to recover the impulse response envelope  $|h(t)|$ , assuming no knowledge about  $s(t)$ , which constitutes a classical blind channel (envelope) estimation problem. The present TF approach does not allow to estimate the phase of the impulse response, since the procedure is based on TF integration, which gives a measure of signal power. Nevertheless, if this impulse response estimate is to be used, e.g., in travel time acoustic tomography, where only the time

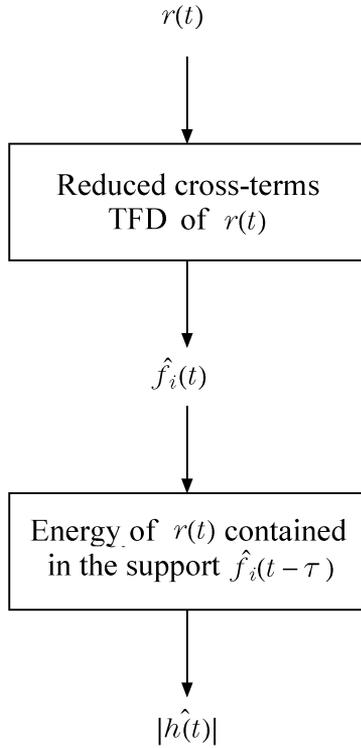


Fig. 1. Blind channel estimation procedure.

delays of the impulse response are important, the envelope estimate is sufficient for postprocessing. Hence, the parameter of interest is designated by

$$\theta(t) = |h(t)|. \quad (4)$$

To solve this problem by a TF approach, it is important to evidence the following key ideas, which emerge as conditions of application.

- 1) The acoustic channel is described by a set of arrivals, with at least one having a high amplitude relatively to the other arrivals.
- 2) The acoustic source emits a deterministic and nonstationary signal, whose IF is an injective (one-to-one) mathematical function.

The channel estimation procedure is schematized in Fig. 1. As illustrated in this figure, the first step relies on the representation of the received signal by a signal-dependent time–frequency distribution (TFD). The maximization of this distribution gives the source signal IF estimate. The second step consists of coherently measuring the WV energy of the received signal on TF supports defined by the source signal IF estimate. The obtained estimator is a suboptimal blind channel estimator (CE), as compared to the MF estimator.

### III. CHANNEL ESTIMATION

Taking into account that nonstationary signals are common in practical applications, TF processing appears in such cases as a

natural tool. TF representations indeed provide a means for detailed analysis of the local TF structure of the received signal. As a consequence, if the channel impulse response and the source signal have “distinct” TF patterns, they can be separated and recovered in the TF domain. In this work, the Wigner–Ville and the radially Gaussian kernel (RGK) [17] TFDs are used.

#### A. Correlator CE

Let us take as a reference CE the correlator receiver. This estimator makes use of the principle behind the MF, and it can only be used when both received and source signals are available. The correlator receiver output is given by

$$\hat{\theta}_{\text{MF}}(t) = \left| \int_{-\infty}^{\infty} r(\tau) s^*(\tau - t) d\tau \right| \quad (5)$$

and is used as a term of comparison to evaluate the performance of the TF blind CE, concerning the real data results presented in Section IV.

#### B. TF Blind CE

This section describes the TF blind CE. A nonblind directly related estimator is first presented, and its similarity to the MF is discussed. Then it is seen that the multipath nature of the channel allows for the derivation of an estimator of the IF of  $s(t)$  and the consecutive definition of the blind CE.

1) *Nonblind Estimator*: Let us state the definition of a TF nonblind CE by first considering the formulation of the MF in the TF domain. This can be accomplished by means of the classical Moyal formula, which relates the overlap of two signals in the time domain with the overlap of their respective bilinear unitary TFDs [18], [19]

$$\begin{aligned} & \iint_{-\infty}^{\infty} C_{x_1 x_2}(\tau, f) C_{x_3 x_4}^*(\tau, f) d\tau df \\ &= \left[ \int_{-\infty}^{\infty} x_1(\tau) x_3^*(\tau) d\tau \right] \left[ \int_{-\infty}^{\infty} x_2(\tau) x_4^*(\tau) d\tau \right]^* \end{aligned} \quad (6)$$

where  $C_{yz}(\tau, f)$  designates any unitary cross distribution of the generic signals  $y(\tau)$  and  $z(\tau)$ . For the particular cases of  $x_1(\tau) = x_2(\tau) = r(\tau)$  and  $x_3(\tau) = x_4(\tau) = s(\tau - t)$ , and when the unitary distribution  $C_{yz}(\tau, f)$  is the  $\text{WV}_{yz}(\tau, f)$ , (6) transforms into

$$\iint_{-\infty}^{\infty} \text{WV}_{rr}(\tau, f) \text{WV}_{ss}^*(\tau - t, f) d\tau df = \left| \int_{-\infty}^{\infty} r(\tau) s^*(\tau - t) d\tau \right|^2 \quad (7)$$

where the second term is simply a squared version of the MF channel estimate (5). This expresses the equivalence between the MF and a correlation in the TF domain with respect to the temporal variable. This equivalence has already been used in the context of detection in [20]. Thus, if the source signal was known at the receiver, an MF estimator could be implemented

in the time domain, by (5), or equivalently in the TF domain, by the TF-based CE

$$\hat{\theta}_{\text{MF}}(t) \equiv \sqrt{\iint_{-\infty}^{\infty} \text{WV}_{rr}(\tau, f) \text{WV}_{ss}^*(\tau - t, f) d\tau df}. \quad (8)$$

In the case that the IA of the source signal does not change significantly with time, the spread in frequency of  $\text{WV}_{ss}(\tau, f)$  can be approximated by [21]

$$\sigma_{f|\tau}^2 = \frac{1}{2} \left[ \left( \frac{a'_i(\tau)}{a_i(\tau)} \right)^2 \right] \quad (9)$$

where  $a'_i(\tau)$  designates the derivative of  $a_i(\tau)$ . The value of  $\sigma_{f|\tau}^2$  will be small, for a slowly varying function  $a_i(\tau)$ , meaning that the WV is highly concentrated along the IF. This will be the case when considering the experimental data in Section IV. Upon this assumption, one can obtain an approximation to (8), by approximating  $\text{WV}_{ss}(\tau, f)$  as

$$\text{WV}_{ss}(\tau, f) \approx \delta[f - f_i(\tau)]. \quad (10)$$

Upon insertion of (10) into (8), a simply structured TF nonblind CE is obtained

$$\hat{\theta}_{\text{TFNB}}(t) = \sqrt{\int_{-\infty}^{\infty} \text{WV}_{rr}[\tau, f_i(\tau - t)] d\tau}. \quad (11)$$

Note that this estimator is suboptimal with respect to the MF, in terms of output SNR, due to the approximation (10). Let us define the conditions upon which (11) can be applied as a CE. Taking into account (1) and the fact that the WV satisfies the convolution property, (11) can be developed as

$$\hat{\theta}_{\text{TFNB}}(t) = \sqrt{\mathcal{S}(t) + \mathcal{N}(t) + \mathcal{SN}(t)} \quad (12)$$

where  $\mathcal{S}(t)$  refers to the signal component

$$\mathcal{S}(t) = \iint_{-\infty}^{\infty} \text{WV}_{hh}(u, f) \Psi(u, f, t) df du \quad (13)$$

with

$$\Psi(u, f, t) = \int_{-\infty}^{\infty} \delta[f - f_i(\tau - t)] \text{WV}_{ss}(\tau - u, f) d\tau \quad (14)$$

and  $\mathcal{N}(t)$  and  $\mathcal{SN}(t)$  refer to the noise and crossed signal–noise components

$$\begin{aligned} \mathcal{N}(t) &= \iint_{-\infty}^{\infty} \delta[f - f_i(\tau - t)] \text{WV}_{nn}(\tau, f) d\tau df \\ &= \int_{-\infty}^{\infty} \text{WV}_{nn}[\tau, f_i(\tau - t)] d\tau \end{aligned} \quad (15)$$

and

$$\begin{aligned} \mathcal{SN}(t) &= 2 \iint_{-\infty}^{\infty} \delta[f - f_i(\tau - t)] \text{Re} \{ \text{WV}_{xn}(\tau, f) \} d\tau df \\ &= 2 \int_{-\infty}^{\infty} \text{Re} \{ \text{WV}_{xn}[\tau, f_i(\tau - t)] \} d\tau \end{aligned} \quad (16)$$

respectively. Let us analyze only the signal component  $\mathcal{S}(t)$ . Note that if, at every frequency  $f$

$$\int_{-\infty}^{\infty} \delta[f - f_i(t)] \text{WV}_{ss}(t - \tau, f) dt \approx \delta(\tau) \quad (17)$$

then (13) can be approximated by

$$\mathcal{S}(t) \approx \iint_{-\infty}^{\infty} \text{WV}_{hh}(u, f) \delta(u - t) df du \quad (18)$$

which, for nonnoisy data, leads to the approximate channel estimate

$$\hat{\theta}_{\text{TFNB}}(t) \approx |h(t)|. \quad (19)$$

Approximation (17) holds, as long as 1) at every frequency  $f$ , the distribution  $\text{WV}_{ss}(t, f)$  has at maximum one peak, and 2) the distribution  $\text{WV}_{ss}(t, f)$  is infinitely concentrated along  $f_i(t)$ . For condition 1) to hold, it is necessary that  $f_i(t)$  be an injective (one-to-one) mathematical function—a function that maps distinct values of  $t$  to distinct values of  $f_i(t)$ . For condition 2) to hold, it is necessary that the WV of the signal  $s(t)$  be defined by a bidimensional Dirac distribution centered on  $f_i(t)$

$$\text{WV}_{ss}(t, f) = |c|^2 \delta[f - f_i(t)] \quad (20)$$

where  $c$  is a complex scalar. It is well established that the class of deterministic source signals, for which both conditions are satisfied, entails the linear frequency modulation (LFM) signal

$$s(t) = c e^{j2\pi(\frac{\alpha}{2}t^2 + f_0t + \varphi_0)} \quad (21)$$

where  $\alpha$ ,  $f_0$ , and  $\varphi_0$  designate the modulation rate, initial frequency, and initial phase, respectively, and the Dirac distribution

$$s(t) = c\delta(t). \quad (22)$$

Note that the requirements for optimality of the TF CE are very similar to the requirement of an impulsive autocorrelation of the emitted signal for the MF estimator. In the former case, the emitted signal is required to have a concentrated signature in the TF plane, while in the latter, it is required to have a concentrated autocorrelation signature. In practice, none of these conditions can be fully verified, which leads to suboptimal estimators. In Section IV, the results obtained with a finite-duration smooth-amplitude LFM signal in a real underwater environment are shown to provide reliable and consistent channel estimates.

2) *Blind Estimator*: To construct a blind CE, it is reasonable to modify (10) according to an estimate  $\hat{f}_i(t)$  of the IF

$$\text{WV}_{ss}(\tau, f) \approx \delta \left[ f - \hat{f}_i(\tau) \right]. \quad (23)$$

Using this approximation in (8), the final TF blind CE is given by

$$\hat{\theta}_{\text{TFB}}(t) = \sqrt{\int_{-\infty}^{\infty} \text{WV}_{rr} \left[ \tau, \hat{f}_i(\tau - t) \right] d\tau}. \quad (24)$$

Thus, in contrast to the nonblind CE, the blind estimator requires prior estimation of the source signal IF  $f_i(t)$ .

3) *Instantaneous Frequency Estimator*: In several real underwater scenarios, the ocean is reliably modeled by a multipath channel, with impulse response

$$h(t) = \sum_{m=1}^M a_m \delta(t - \tau_m) \quad (25)$$

where  $a_m$  and  $\tau_m$  designate each of the  $M$  channel amplitudes and time delays, respectively.<sup>1</sup> For this case, an estimator of  $f_i(t)$  has been derived, taking advantage of a reduced cross-terms TFD. As is well known, TFDs of this type are usually derived as a tradeoff between linearity and high resolution. First, let us consider an ideal (linear and infinitely concentrated) TFD  $I_s(t, f)$  of  $s(t)$  (assumed a monocomponent signal), defined as

$$I_s(t, f) = |c| \delta[f - f_i(t)]. \quad (26)$$

The expected value of the ideal distribution of the received signal, assuming that this expected distribution would represent the noise term as a constant  $I_n$ , would be given by

$$E[I_r(t, f)] = \sum_{m=1}^M a_m I_s(t - \tau_m, f) + I_n. \quad (27)$$

Consider now that the channel highest amplitude impulse is well separated and significantly stronger than the closely spaced impulses. In this case, at least one of the replicas of  $s(t)$  is represented in  $E[I_r(t, f)]$  by a large amplitude along the delayed IF of  $s(t)$ . Thus, maximization of  $E[I_r(t, f)]$  with respect to  $t$ , within a given band of interest  $B$ , would select the strongest arrival, giving an unbiased estimate<sup>2</sup> of  $f_i(t)$ . Obviously, within the available nonlinear TFDs, signal analysis is constrained by the particular characteristics of the kernel and finite data lengths. Nonetheless, it seems reasonable to apply the maximization with respect to  $t$ , to a TFD with reduced cross terms of the received signal, which will give an accurate estimate<sup>3</sup> of  $f_i(t)$ , if this distribution is a good approximation

<sup>1</sup>Here, frequency dispersion effects are neglected, because the ratios water depth/maximum wavelength and source-receiver distance/maximum wavelength are of orders 10 and  $10^3$ , respectively.

<sup>2</sup>It is expected that this estimate, seen as a function of frequency, is also a close estimate of the group delay of  $s(t)$ .

<sup>3</sup>The IF estimate is not rigorously a function of  $t$ , due to its definition as the "inverse function" of a noninvertible function.

to  $I_r(t, f)$ , i.e., it attains a significant cross-terms rejection without causing a significant broadening of the signal components. In this work, the distribution used for IF estimation was the signal-dependent RGK distribution of the received signal,  $\text{RGK}_{rr}(t, f)$ . The signal dependence of this distribution allows a reduced cross-terms TF representation of the multipath received signal, even when the IF of  $s(t)$  is a nonlinear function. This is due to the distribution capability of adapting the shape of a radially Gaussian lowpass filter to a broad class of signals [17], hence, attenuating the TF spurious cross terms. The volume of the distribution kernel was set to 1, since this is the volume of every spectrogram kernel. In the ideal case in which the calculated kernel of the RGK would equal the Doppler-reversed ambiguity function of  $s^*(t)$ , the RGK would coincide with the MF spectrogram. This point is discussed below in more detail. Obviously, other distributions could be applied as well due to their cross-terms rejection capabilities, such as the polynomial or modified WV [22], or TFDs with adaptive window width, to mention only a few.

Considering the presence of  $N$  snapshots at reception—which is the case in the real data presented in the next section—each one obeying model (1), the estimation of the IF may take into account the information contained in the set of snapshots to construct a TF representation that is close to  $E[I_r(t, f)]$ . This TF representation is defined as the average RGK over the snapshots

$$\overline{\text{RGK}}_{rr}(t, f) = \sum_{n=1}^N \text{RGK}_{r_n r_n}(t, f) \quad (28)$$

where  $r_n(t)$  designates the  $n$ th snapshot of the received signal. The multisnapshot estimator is defined by means of the maximization of  $\overline{\text{RGK}}_{rr}(t, f)$

$$\left[ t_i, \hat{f}_i(t_i) \right] = \left\{ (t, f) : t = \arg \left\{ \max_t \overline{\text{RGK}}_{rr}(t, f) \right\}, f \in B \right\}. \quad (29)$$

This signal-dependent maximization on the TF plane will be illustrated with experimental data in Section IV (see Figs. 9 and 10, and discussion). It is expected that the average  $\overline{\text{RGK}}_{rr}(t, f)$  preserves the replicas of  $s(t)$ , while the noise contributes as a simple additive term, in the TF plane. This is difficult to assert theoretically, since the RGK is a signal-dependent TFD. However, a simple analysis can be done by considering a TFD whose kernel is perfectly adapted to the multicomponent received signal. Such a distribution, considering the multipath nature of  $r(t)$ , is the matched filter spectrogram (MFS) [17] whose analysis window is thus coincident with  $s^*(t)$ . The kernel of the MFS can be expressed as

$$\Phi_{\text{MFS}}(\nu, \tau) = \int_{-\infty}^{\infty} s^* \left( t + \frac{\tau}{2} \right) s \left( t - \frac{\tau}{2} \right) e^{-j2\pi\nu t} dt. \quad (30)$$

The MFS represents the best attainable representation of  $r(t)$  by the RGK, in terms of the tradeoff signal terms information/cross-terms rejection. Finally, one can interpret the average

RGK as an estimator of (31) shown at the bottom of the page, where

$$\tau_{mn} = \frac{(\tau_m + \tau_n)}{2}. \quad (32)$$

For a monocomponent signal  $s(t)$ , it is expected that for the terms in (31), for which  $\tau_m \neq \tau_n$ , the different delays in the ambiguity functions will render the integrand approximately null. For the  $M$  terms in which  $\tau_m = \tau_n$ , the integrals transform into

$$\iint_{-\infty}^{\infty} |\text{AF}_{ss}(\nu, \tau)|^2 e^{-j2\pi[\nu(t-\tau_m)+f\tau]} d\nu d\tau \quad (33)$$

which corresponds to slightly broadened signal terms in the TF plane. Thus,  $\text{AF}_{ss}^*(\nu, \tau)$  is to be viewed as a lowpass filter, which will retain only the eigenterms of  $\text{AF}_{xx}(\nu, \tau)$ , leading to an approximate linear TFD  $E[\text{MSF}_{rr}(t, f)]$ . Ideally, the maximization of the expected MFS [requiring the knowledge of  $s(t)$ ] would be meaningful as an IF estimator; in practice, the expected MFS is approximated by the average RGK.

A final concern about IF estimation relates to non-LFM source signals. In this case, each of the source signal replicas (in the received signal) contains its own cross terms in the TF plane, which will be added to the implicit cross terms due to the multipath channel. It is difficult to predict the relative amplitude between the signal terms and the cross terms, and the maximization of the signal-dependent TFD can be trapped into the cross terms at given frequencies instead of the signal term. To avoid this problem, it may be necessary to decrease the volume of the RGK distribution kernel to filter out all the high-amplitude cross terms and guarantee that the global maximization will pick only the signal term(s) due to the initial strong channel arrival(s).

Note that the required minimum time separation ( $\approx 20$  ms, in the considered data) between the strong channel impulse(s) and the remaining impulses is much smaller than the source signal duration (2 s, see Fig. 3), since the considered impulse response structure corresponds to a shallow-water scenario. This implies that each arrival overlaps several other arrivals, in the received signal, in the time domain. This is opposed to the TF domain, where the interarrival overlap is spread in the two dimensions of the plane. For extremely short-duration source signals, or in

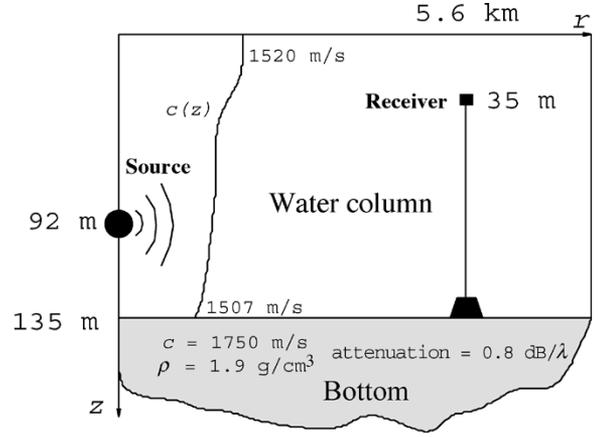


Fig. 2. INTIMATE'96 real data environment scenario.

deep water scenarios, if there was a completely isolated arrival in the received signal, the channel impulse response could be estimated, for example, by simply cross correlating that arrival with the remaining portion of the received signal.

#### IV. EXPERIMENTAL RESULTS

The experimental results presented in this section concern data from the acoustic tomography experiment Internal Tide Measurements with Acoustic Tomography Experiments (INTIMATE'96), whose details have appeared in [23]. The experiment was conducted in the continental platform near the town of Nazaré, off the west coast of Portugal, during June 1996. For the data considered here, the acoustic source and receiving hydrophone were respectively located at 92 and 35 m depth, 5.6 km apart in an approximately 135-m-deep range-independent shallow-water area, as shown in Fig. 2. The SNR estimate at the receiver was 10 dB within the frequency band of interest. The sound source was emitting a 300–800 Hz, 2-s duration LFM sweep  $l(t)$ , repeated every 8 s. At the receiver,  $N = 10$  consecutive sweeps were processed to form one single channel estimate under stationarity assumptions. This process was repeated every 5 min, during 19 h of transmissions, with the objective of analyzing the time variations of the acoustic channel due to tidal waves. The frequency response of the electroacoustic transducer used as sound source presented a main resonance at 650 Hz and a secondary resonance at 350 Hz. The convolution of

$$\begin{aligned} E[\text{MSF}_{rr}(t, f)] &= \frac{1}{2\pi} \left[ \iint_{-\infty}^{\infty} \text{AF}_{xx}(\nu, \tau) \text{AF}_{ss}(-\nu, -\tau) e^{-j2\pi(\nu t + f\tau)} d\nu d\tau + \sigma_n^2 \right] \\ &= \frac{1}{2\pi} \left[ \sum_{m=1}^M \sum_{n=1}^M a_m a_n \iint_{-\infty}^{\infty} \text{AF}_{ss}(\nu, \tau + \tau_m - \tau_n) \text{AF}_{ss}^*(\nu, \tau) e^{-j2\pi[\nu(t-\tau_{mn}) + f\tau]} d\nu d\tau + \sigma_n^2 \right] \end{aligned} \quad (31)$$

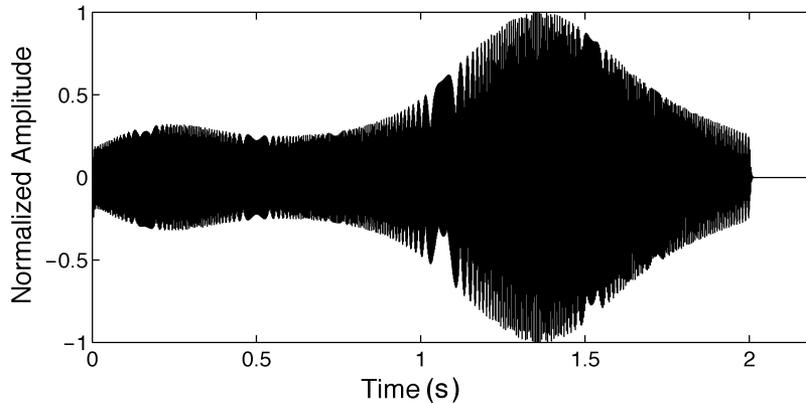


Fig. 3. Computer-generated transducer response to the 300–800 Hz 2-s duration LFM sweep [real part of  $s(t)$ ] used during the INTIMATE'96 sea trial.

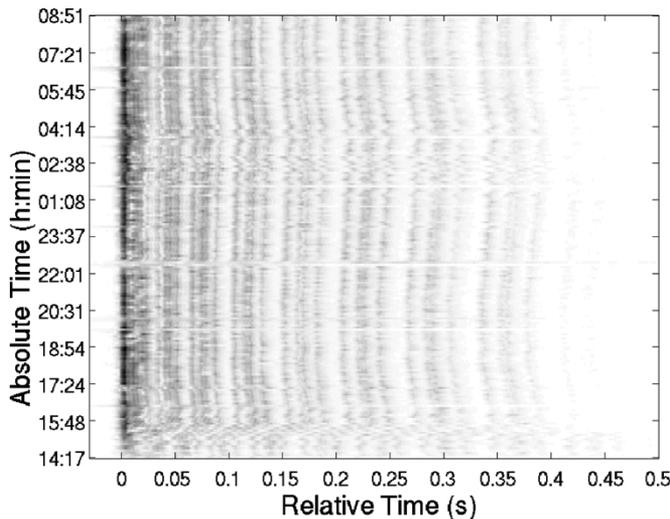


Fig. 4. INTIMATE'96 data set: (Nonblind) channel estimates obtained with the MF [(5) arranged as in (35), with  $N = 10$ ].

one LFM sweep  $l(t)$  with the transducer response is shown in Fig. 3. Straightforward lengthy calculations show that this convolution may be approximately expressed as a product, leading to

$$s(t) \approx l(t)v(t) \quad (34)$$

where  $v(t)$  is a factor due to the transducer response that effectively modulates the source signal in amplitude. As a matter of fact, Fig. 3 clearly shows the influence of the transducer resonances on the amplitude of the emitted signal. Note that the actual signal amplitude, as modified by the transducer, is not taken into account when performing blind channel estimation, and is another contribution (together with the noninfinite concentration of the TFD) to the deviation from the optimal case. Moreover, signal amplitude discrepancy should be taken into account when comparing the (nonblind) MF channel estimate (which “knows” the transducer response) to the blind TF estimate, which does not know the transducer response.

#### A. Channel Estimation Results

Taking into account that for an observation time of the order of minutes, the acoustic multipath channel can be assumed nonstationary in the amplitudes and stationary in the time delays

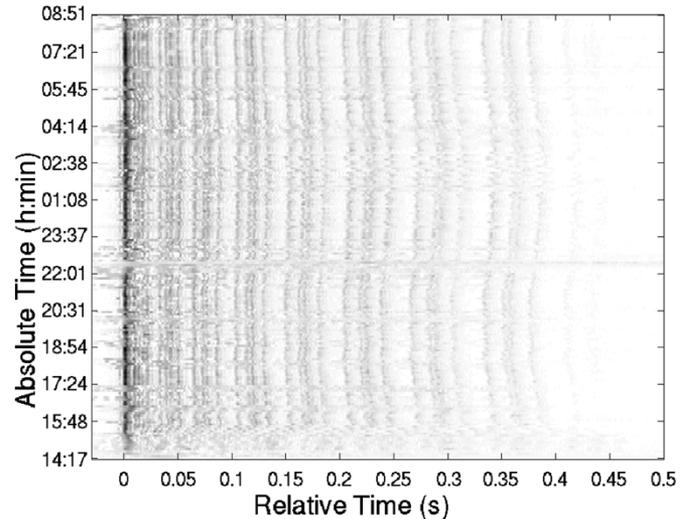


Fig. 5. INTIMATE'96 data set: Blind channel estimates obtained by TF processing [(24) arranged as in (35), with  $N = 10$ ].

[24], and that an accurate estimate of the time delays is sufficient for postprocessing, e.g., in ocean acoustic tomography [26], the presented results privilege time delay estimation. Thus, due to the similarity between the nonblind TF and MF channel estimators, and proceeding as in [24], for the derivation of the MF, in the presence of a set of snapshots at the reception, the effectively used channel estimators were given by

$$\hat{\theta}_{\text{CE}}(t) = \frac{1}{N} \sum_{n=1}^N \hat{\theta}_{\text{CE},n}(t) \quad (35)$$

where CE is to be replaced by MF or TFB, to obtain averaged versions of the estimators (5) and (24), respectively. This is expected to reduce the bias and variance of the final estimators, by comparison to the single snapshot estimators  $\hat{\theta}_{\text{CE},n}(t)$ . The IF estimate to be inserted in (24) was obtained by maximization of the average RGK within the band  $B = [300, 800]$  Hz, coincident with the LFM's band. Note that it is not necessary to have *a priori* knowledge of the emitted signal's band, provided that  $B$  is chosen large enough, since the energy of the received signal will lie essentially within the emitted signal's band, in the TF plane.

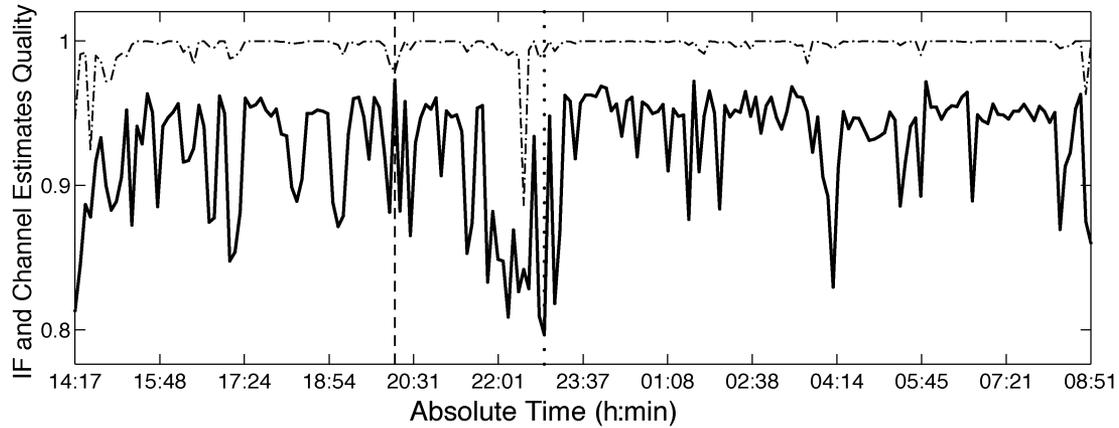


Fig. 6. Measure of quality for the IF estimate, using (36) (dash dots), and for the blind TF channel estimate, as the correlation between the blind TF and the MF estimates (solid), over the whole INTIMATE'96 data set. The vertical dashed and dotted lines indicate 20:08:00Z and 22:52:00Z as the times corresponding to the best and worst blind channel estimates, respectively.

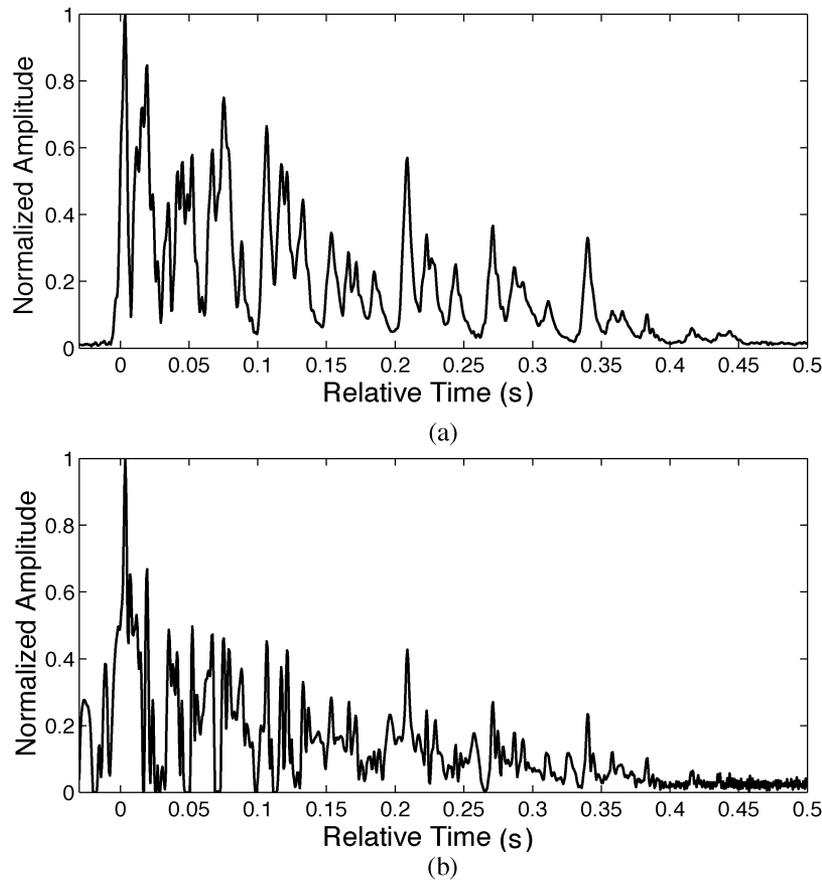


Fig. 7. INTIMATE'96: Channel estimates given by the (a) (nonblind) MF and (b) blind TF channel estimators, corresponding to the worst blind channel estimate, at time 22:52:00Z of Fig. 6. The blind estimate quality [correlation coefficient between (a) and (b)] is 0.796.

The results obtained along the 19-h duration data set are shown in Figs. 4 and 5 for the MF and TF estimators, respectively. It can be seen that the blind channel estimates are, in general, similar to the homologous (nonblind) MF estimates. Of most concern here is the ability to: 1) discriminate closely spaced arrivals; and 2) follow the arrivals waving through time. It can be noted that these concerns are both met: After the initial nonseparated arrivals ( $t \leq 25$  ms), four distinct arrivals can be

seen on each of the following seven packets of arrivals; the long period waving due to tidal influence can clearly be seen on the later arrivals, shown in both figures.

#### B. Performance Analysis

It is now important to quantify the accuracy of the blind TF CE, taking, for example, the (nonblind) MF estimator, as reference. For each TF channel estimate, the quality measure is

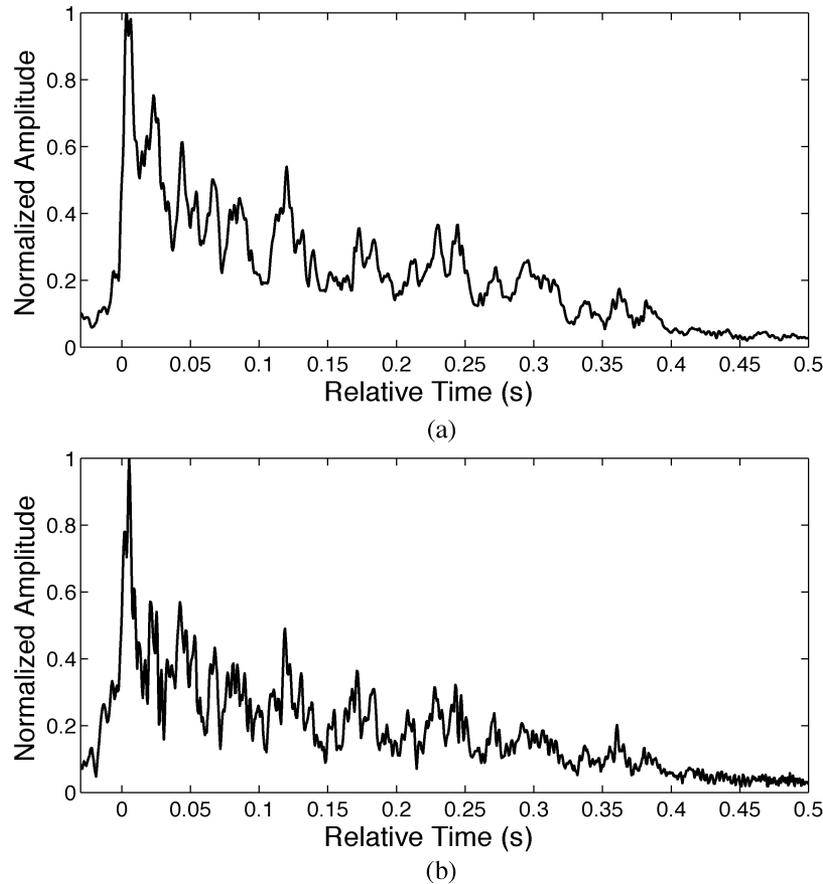


Fig. 8. INTIMATE'96: Channel estimates given by the (a) (nonblind) MF and (b) blind TF channel estimators, corresponding to the best blind channel estimate, at time 20:08:00Z of Fig. 6. The blind estimate quality [correlation coefficient between (a) and (b)] is 0.973.

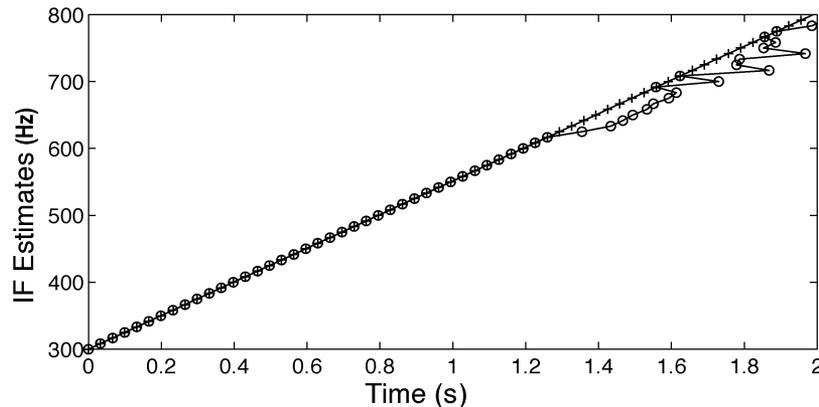


Fig. 9. INTIMATE'96: IF estimates (29) for the worst (o) and best (+) cases as shown in Figs. 7 and 8, respectively. The underlying straight line represents the true IF.

defined as the maximum of the normalized correlation between the TF and MF channel estimates. In the same way, the quality  $\chi$  of the IF estimate (29) is defined as

$$\chi = 1 - \frac{\sqrt{\int_B [t_{iN}(f) - \hat{t}_{iN}(f)]^2 df}}{2} \quad (36)$$

where  $t_{iN}(f)$  and  $\hat{t}_{iN}(f)$  are normalized versions of the instants corresponding to the true IF and its estimate, respectively. Both channel and IF estimate quality measures are shown in

Fig. 6 for the whole 19-h data set. It can be seen in this figure that, in general, the IF and the channel estimates are directly related, i.e., the channel estimate quality is highly sensitive to the IF estimate quality, as can be seen in, e.g., the estimates obtained at times 17:07:00Z and 04:09:00Z. This fact can be explained by the high concentration of  $s(t)$  in the TF plane, which leads to meaningless values for the integral (24), when the IF is not accurately estimated. To closely characterize the proposed IF and blind TF estimators, it is important to look at the worst and best cases over the whole data set.

The reference channel given by the MF, corresponding to the worst blind channel estimate, is shown in Fig. 7(a), while the corresponding blind estimate, with quality 0.796, is depicted in Fig. 7(b). In this case, the acoustic channel consists of a set of leading closely spaced arrivals with large amplitude, followed by a peaky pattern with smaller amplitude and well separated in time. It can be seen that the MF and TF estimates differ mainly on the amplitude envelope but not on the arrival times. However, the total number of arrivals seems to be higher in the TF estimator than in the MF estimator.

According to the measure of quality plot shown in Fig. 6, the best blind TF channel estimate is obtained at time 20:08:00Z, and the corresponding MF and TF estimates are shown in Fig. 8(a) and (b), respectively. The most important difference when comparing Fig. 8(a) to the MF estimate in the worst case of Fig. 7(a) is the rapid progressive amplitude attenuation, leading to a greater amplitude ratio between the initial and the remaining arrivals. The best blind TF estimate, depicted in Fig. 8(b), shows that both the envelope and arrival positions are well estimated and the MF and TF estimates are indeed very similar. As in the worst case, the number of arrivals is overestimated on the TF estimator by comparison to the MF estimator.

Fig. 9 shows the IF estimates for the worst and best cases as discussed above. Clearly, the worst case IF estimate shows a piecewise line where the IF oscillates well away from the true straight line IF, and the best channel estimate corresponds to an accurate IF estimate close to the true straight line. These IF estimates were obtained by maximization of the average RGKs shown in Fig. 10, where one can see that, unlike for the best case in (b), the worst case in (a) corresponds to initial high-amplitude overlapped replicas of  $s(t)$  in the average RGK.

Considering the available data, one can deduce that the quality of the channel estimate is largely dependent on the quality of the IF estimate. A set of close unresolved strong arrivals with similar amplitude, as is the case corresponding to the worst estimate, corresponds to energy spreading in the TF plane, which, added to the lowpass filtering effect on the WV, in the computation of the RGK, gives a biased estimate  $\hat{f}_i(t)$ . This difficulty is not observed for the case corresponding to the best estimate. An additional concern is about the apparent higher resolution of the TF estimator, leading to a larger number of small peaks along the arrival pattern, by comparison to the MF estimator. This can be explained by the use of the IA information of the emitted signal in the MF, while that information is not used in the blind TF. Using the IA means using a reduced bandwidth of the transducer frequency response when compared to the blind TF, where all frequencies are assumed to equally belong to the emitted signal spectrum: Reduced bandwidth implies larger correlation functions and therefore a lower resolution.

## V. CONCLUSION

In this paper, a blind suboptimal TF channel envelope estimator was proposed. This estimator was tested on a 19-h duration real data set from the INTIMATE'96 sea trial, where a severe multipath underwater channel was driven by a deterministic linear frequency modulated signal. Three main topics

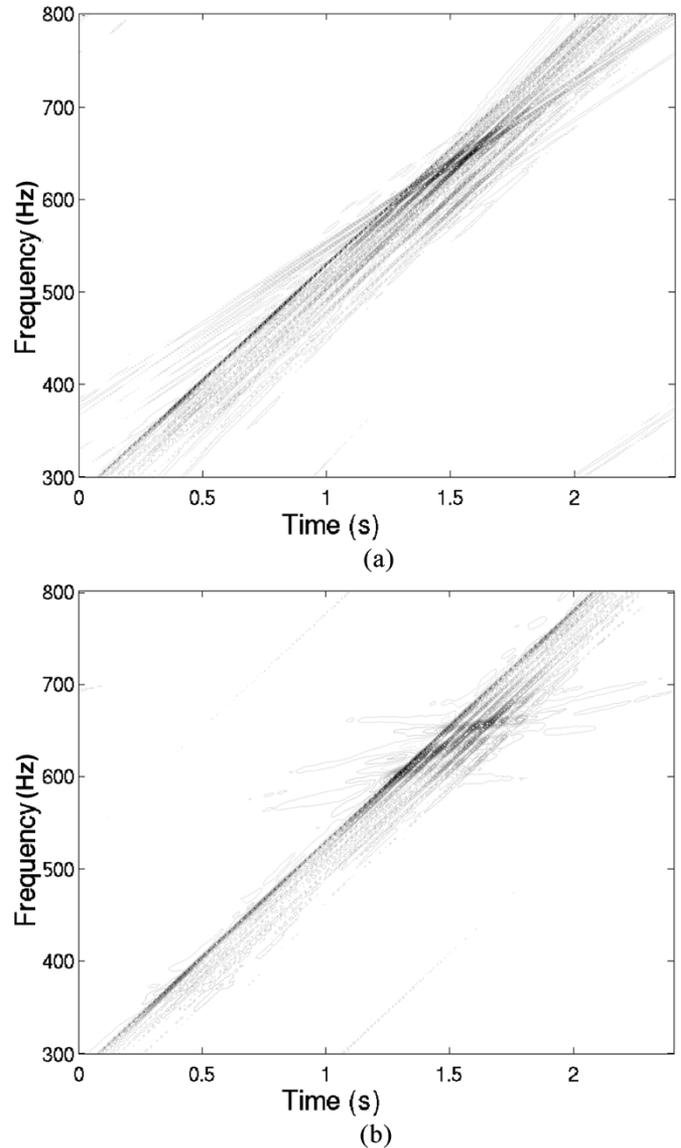


Fig. 10. INTIMATE'96: contour plots of the average RGK distributions from which the IF estimates for the (a) worst and (b) best cases as shown in Figs. 7 and 8, respectively, were obtained.

emerge as conclusions. The first concerns the restrictions imposed by the blind channel envelope estimator. This estimator requires the multipath channel structure to consist of at least one leading strong arrival well separated from the highly attenuated remaining arrivals. In addition, the emitted signal is required to have a concentrated TF signature and an injective (one-to-one) IF function. The second topic concerns the influence of the IF estimate on the channel envelope estimate. The quality of the TF channel envelope estimate is largely sensitive to the source signal IF estimate. Indeed, a small inaccuracy in the IF estimate causes a large degradation in the channel envelope estimate, due to the high TF concentration of the source signal. The last topic is that the TF blind channel envelope estimator is reliable in that it gives similar results to the MF, in terms of the arrival structure and resolution. In addition, though the blind estimator does not achieve an optimal output SNR, its higher resolution can be

viewed as an advantage when emphasis is given to the estimation of the channel time delays.

As future trends, the TF channel envelope estimator will possibly be extended to a broader class of source signals for which the IF estimator could be reformulated by using the product high-order ambiguity function. The integration in the TF domain could be operated on a highly concentrated TFD, e.g., the polynomial or modified WV.

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**Nelson E. Martins** received the B.Eng. degree in systems and computing engineering, in 1998 and the M.Sc. degree in systems and computing engineering, in 2001, from the University of Algarve, Faro, Portugal, where currently, he is working towards the Ph.D. degree in underwater acoustics signal processing, applied to the forecast of the acoustic signal received on an hydrophone array.

His main interests include estimation theory, TFDs, ocean circulation models, and acoustic inversion algorithms.



**Sérgio M. Jesus** (A'93) received the "Doctorat Es-Sciences" degree in engineering sciences from the Université de Nice, Nice, France, in 1986.

From 1986 to 1992, he was a Staff Scientist at the SACLANT Undersea Research Centre, La Spezia, Italy, in the Ambient Noise and Signal Processing Groups. During that period, he was involved with underwater acoustic field noise directionality and early studies on target detection using matched field processing. In 1992, he joined the Electrical Engineering and Computer Department at the University of Algarve, Faro, Portugal, where he is currently an Associate Professor. His interests are underwater acoustics signal processing, model-based inversion, ocean and seafloor tomography, and underwater communications.

Dr. Jesus is a Member of The European Association for Signal and Image Processing (EURASIP) and the Acoustical Society of America.