P2.1. - Time frequency approach to the study of underwater acoustic channel estimation and source reconstruction

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Abstract

This communication presents a pre-processing scheme possibly included in the global methodology of passive tomography, in an underwater acoustic channel. For a single source, its instantaneous frequency estimate allows for both channel impulse response estimation and source signature deconvolution, in a multipath propagation channel. To achieve these goals, time-frequency tools such as the Wigner-Ville and radial Gaussian kernel distributions, and Wigner-Ville-based signal synthesis are used. Each section includes illustrative numerical tests.

Section 1: introduction

The need for mapping an unknown medium has given rise to the development of several tomographic applications, in the last decades. In 1979, Munk and Wunsch extended the classical tomography concept to ocean mapping, proposing what is called ocean acoustic tomography, that is, use of a measured acoustic transmission, to determine the ocean temperature field [MUN79]. Here, advantage is taken from the fact that the ocean is nearly transparent to acoustic stimuli. By measurements of the stimulus and the medium response, properties like the sound speed profile, medium geometry or salinity may be estimated, constituting what is known by active tomography. These properties can then be used to accomplish other related problems such as source localization, by matched-field processing [BAG88]. Tomographic studies have intensively been developed in deep-water scenarios, with ranges extending from few to hundreds of kilometers [DEM97]. Obviously, many practical advantage can be obtained, if the knowledge of the emitted signal is dispensible, at the receiver, what constitutes the concept of passive tomography.

Here, the idea is to use opportunity sources of acoustic noise, like boat engines, animal sounds or other natural aquatic sounds, as stimuli, without using a known emission.

As the stimulus is considered unknown, a blind inversion study is developed.

In this paper, the following test case will be considered:

- there is a single source;
- the underwater acoustic channel is modeled as a multipath channel, where each path is defined by a travel time and a constant magnitude.

Under these assumptions, the channel impulse response $h(t)$ and the received signal $m(t)$ are modeled by:

$$h(t) = \sum_{i=1}^{N} C_i \delta(t-\tau_i) \qquad\qquad m(t) = \sum_{i=1}^{N} C_i s(t-\tau_i),$$

where N is the number of paths, C_i and τ_i are respectively the amplitude and the travel time of the i^{th} path, δ the Dirac distribution., $s(t)$ the source emitted signal.

The problem addressed in this paper is to demonstrate the abilities of time-frequency tools for the estimation of the impulse response parameters (C_i, τ_i), $i = 1,2,\dots,N$ and the source signature deconvolution, departing from the noisy signal $m(t)$.

This method will give another approach to blind deconvolution, often based in high-order statistics maximization [CAD96].

This paper is organized as follows: Sec. 2 describes the source instantaneous frequency estimation, based on a signal-dependent time-frequency distribution.

The instantaneous frequency function of the source is used in Sec. 3, to estimate the channel response by suboptimal time-frequency matched-filtering and in Sec. 4 to estimate the source signature, by Wigner-Ville-based signal synthesis.

Sec. 5 draws the conclusions and perspectives.

Section 2: Estimation of the Source Instantaneous Frequency Function

From the received time series, considered as a sum of weighted and delayed versions of the source signal, and corrupted with noise, the aim is to estimate the instantaneous frequency function of the source.

If $x(t)$ is an analytic signal, it can be written in the form: $x(t) = A(t)\exp(j\varphi(t))$ with $A(t)$ and $\varphi(t)$ real functions. Its instantaneous frequency function is given by: $f_i(t) = \frac{1}{2\pi}\frac{\partial\varphi(t)}{\partial t}$.

If $x(t)$ is not an analytic signal, instantaneous frequency function is defined by the instantaneous frequency of the sum of $x(t)$ added with the Hilbert transform of $x(t)$.

Unfortunately, this formula is unhelpful, when the signal is composed of a sum of signals and when the interest is the instantaneous frequency function of a specific component.

Quadratic time-frequency representations which provide a good resolution in both time and frequency, seem to be well adapted to this problem.

The solution is analytically found for an infinite duration linear chirp c(t), with modulation rate α, and Wigner-Ville distribution $WV_c(t,f) = \delta(f - \alpha t)$. Looking for local maxima of the Wigner-Ville mapping produce the pair (t_0, αt_0) and an instantaneous frequency function equal to αt.

For finite duration linear or polynomial FM signals, it is demonstrated that looking for a local maximum in the Wigner-Ville mapping creates bias and computing problems because of interference terms which produce 'artificial maxima'.

To estimate the source instantaneous frequency function, a local maxima is sought on an optimal time-frequency mapping which delete the interference terms, without significantly increasing the spread of the auto-terms, in the time-frequency representation. In practice, it is sought the first local maxima greater than a specified threshold, due to the presence of noise. We'll not make use of the WVD, due to the multicomponent nature of the received signal.

These signal-dependent time-frequency transforms are based on the optimal weighting of the ambiguity function by a radially signal-dependent Gaussian kernel (Radial Gaussian Kernel) or based on the optimal weighting of local ambiguity function (Adaptative Optimal Kernel) developed by Baraniuk and Jones [BAR93] [JON95] .

Our approach may be biased but is stable over noise and interferences. It will have to be compared with unbiased estimation using Cross Polynomial Wigner-Ville [RIS94] [RIS96] [WON90] or more recent adaptative time-frequency approach based on high resolution method or Chirplet decomposition [NIC00] [MAN91] .

The algorithm used to estimate the source instantaneous frequency function is the following:

- compute the signal-adapted time-frequency mapping of the received signal, ($RGK_m(t,f)$),
- for each frequency bin f_i , estimate the time of the first local maximum of the function of time $RGK_m(t,f_i)$.

Results are presented in Figure 1, for the sum of two cubic FM signals defined by:

$s(t) = \exp\left(2\pi f_{\min} t + 2\pi \frac{f_{\max} - f_{\min}}{3T^2} t^3\right)$, f_{min}=0.1 Hz, f_{max}=0.4 Hz, T=80s, sample frequency = 1 Hz,

$x(t) = s(t) + s(t-40)$, $m(t) = x(t) + b(t)$, RSB=7 dB, b(t) white Gaussian noise.

Section 3: impulse response blind estimation

The source instantaneous frequency function $\tilde{f}_i(t)$ obtained in Sec. 2 is used to estimate the channel impulse response.

For known source s(t), two optimal detectors of s(t) in noise may be used to estimate the channel impulse: the classical matched-filtering and an equivalent formulation in time-frequency domain proposed by Flandrin [FLA88]

If the signal to be detected is considered as deterministic one and if m(t)=s(t)+b(t) or m(t)=b(t), the optimal detector is based on the use of the time-frequency correlation Q between the cross Wigner-Ville of m(t) and s(t) and the auto Wigner-Ville of s(t). For the case of a random signal s(t), the optimal detector is based on the use of the time-frequency correlation Q between the auto Wigner-Ville of s(t) and m(t):

$$Q = \int_{-\infty}^{\infty} \int_{T} WV_{mm}(t,f) \times WV_{ss}(t,f)\,dt\,df \,.$$

In passive tomography, the source s(t) is unknown, but Sec. 2 give the instantaneous frequency function $\tilde{f}_i(t)$ of s(t), an estimated Wigner-Ville of the source is defined as follows:

$$\overline{WV}_{ss}(t,f) = \delta(f - \tilde{f}_i(t)) \,.$$

A sub-optimal detector is proposed by computing the time-frequency correlation between the auto Wigner-Ville of m(t) and the estimated Wigner-Ville of the source ($\overline{WV}_{ss}(t,f)$).

A curve of energy versus time ($E(t_0)$) is computed by:

$$E(t_0) = \int_{-\infty}^{\infty} \int_{T} WV_{mm}(t,f) \times \overline{WV}_{ss}(t - t_0, f)\,dt\,df.$$

Channel impulse response is estimated by looking for local maxima on $E(t_0)$:

$$\{\tilde{\tau}_i, i=1..N\} = \left\{\tau / \frac{\partial E(\tau)}{\partial \tau} = 0 \, and \, \frac{\partial^2 E(\tau)}{\partial \tau^2} < 0 \right\} and \; \{\tilde{C}_i, i=1..N\} = \left\{\sqrt{E(\tau_i)}, i=1..N\right\}$$

Channel estimation is validated through simulated data for a scenario close to the experiments of INTIMATE 96 [DEM97] in shallow water context. A water column of 135 meter depth with a sound speed profile on a perfectly rigid sub-bottom is modeled. A source is put at 90 meter depth and a single hydrophone is considered at a distance of 5.6 km and 115 meter depth. Theory of rays is used to modeled acoustic propagation and the signal emitted by the source is a linear FM from 300 Hz to 800 Hz with a 62.5ms duration. For such a scenario the model has estimated 45 arrivals.

The results presented Figure 2 prove the performances of 'sub-optimal' time-frequency correlation under realistic conditions. The channel impulse response was estimated by the optimal matched-filter and the blind sub-optimal time-frequency correlation.

Section 4: source signature deconvolution

Sec. 2 gives an estimated instantaneous frequency function on the source ($\tilde{f}_i(t)$), this knowledge may be useful for classification of the emitted signal and may be sufficient for some applications. The problem addressed in Sec. 4 is to improve the methodology by estimating the source signal s(t).

In Sec. 3, a curve $E(t_0)$ of energy was computed by coherent integration.

Research of local maxima allows to estimate the time of arrival of the echos.

For source estimation, the first arrival will be considered.

If $\tilde{\tau}_1$ is the estimation of the first instant of arrival, we are looking for an area around $\tilde{\tau}_1$ defined by:

$$[\tilde{\tau}_1^1, \tilde{\tau}_1^2] = \left\{\tau / E(\tau) > \frac{1}{k} E(\tilde{\tau}_1) \; and \; |\tau - \tilde{\tau}_1| < \varepsilon \right\} \; with \; k > 1 \, and \; \varepsilon \; small$$

This energy support around $\tilde{\tau}_1$ is used to estimate the time-frequency Support of the source s(t) ($\overline{TFS}(t,f)$).

$\overline{TFS}(t,f)$ is a binary mask defined by the time-frequency domain between the two boundaries B_1(t,f) and B_2(t,f):

$$B_1(t,f) = \delta[f - \tilde{f}_i(t - \tilde{\tau}_1^1)] \textit{ and } B_2(t,f) = \delta[f - \tilde{f}_i(t - \tilde{\tau}_2^1)]$$

so

$$\overline{TFS}(t,f) = 1 \Leftrightarrow \tilde{f}_i(t - \tilde{\tau}_2^1) \le f \le \tilde{f}_i(t - \tilde{\tau}_1^1).$$

From $\overline{TFS}(t,f)$ and WV_{mm}(t,f), the product $\overline{WV}_{ss}^0 = \overline{TFS}(t,f) \times WV_{mm}(t,f)$ is an estimate of the Wigner-Ville mapping of the source signal. Unfortunately this estimation in very far from a valid Wigner-Ville mapping, and it does not exist a signal from which $\overline{WV}_{ss}^0$ is a Wigner-Ville distribution.

A regularization procedure is developed to estimate the source based on the work of Wang and Cadzow [WAN90].

For N points of signal y(i) and M frequency digits computed, the Wigner-Ville mapping is an $M \times N$ matrix WV_y defined by:

$$WV_y = F \times Y = F \times [\mathbf{Y}_1\ \mathbf{Y}_2\ \mathbf{Y}_3 \ldots \mathbf{Y}_N]$$

where

$$\mathbf{Y}_i = [p(i), p(i+1), \ldots, p(i+L), 0, \ldots, 0, p(i+L)^*, \ldots, p(i+1)^*]' \qquad p(i+j) = y(i+j)y(i-j)^*$$

and F is the Fourier Transform matrix: $F(k,l) = \exp(-2\pi j \frac{(k-1)(l-1)}{M})$.

The properties that assure the validity of the couple (WV_y, y) are $WV_y = F \times Y$ *and* $rank(Y) = 1$.

From an unvalid $\overline{WV}_{ss}^0$, a valid couple may be build by including the rank r of the true matrix WV_{ss} as an a priori information and applying the following iterations:

- first step $\overline{WV}_{ss}^i = \overline{WV}_{ss}^0$,
- until convergence criteria is verified do,
  - Singular Value Decomposition (SVD) of $\overline{WV}_{ss}^i$,
  - low-pass filtering by SVD threshold at rank r to obtain $\overline{WV}_{ss}^f$,
  - inverse Wigner-Ville to obtain $\tilde{Y}^i = F^{-1}\overline{WV}_{ss}^f$,
  - SVD of $\tilde{Y}_i$,
  - low-pass filtering by SVD threshold at rank 1 to obtain $\tilde{Y}_i^1$,
  - recovery of $\tilde{y}_i(t)$ from $\tilde{Y}_i^1$,
  - $\overline{WV}_{ss}^{i+1} = WV(\tilde{y}_i(t))$,
- end.

The convergence criteria may be a fixed number of iterations, the rank of $\tilde{Y}_i$, a ' small quadratic distance' between $\tilde{y}_i(t)$ and $\tilde{y}_{i+1}(t)$.

The source signature deconvolution step of our method is validated through numerical experiments on simulated data.

We have considered the case of the sum of two delayed cubic FM signal.

$s(t) = \exp(2\pi f_{min} t + 2\pi \frac{f_{max} - f_{min}}{3T^2} t^3)$, f_{min}=0.01 Hz, f_{max}=0.15 Hz, T=80s, sample frequency = 1 Hz,

$x(t) = s(t) + s(t-40)$, $m(t) = x(t) + b(t)$, b(t) white Gaussian noise.

For these simulations, we introduce the rank of WV_{ss} (equal to 40) as an apriori information.

To quantify the performances of the applied algorithm, we define the Signal to Noise Ration (SNR) of the received signal (SNR^m) and the SNR of the estimated source (SNR^s) by:

$$SNR^m = \frac{\sum_{i=1}^{N}[x(i)]^2}{N\sigma^2} \qquad SNR^s = \frac{\sum_{i=1}^{N}[s(i)]^2}{\sum_{i=1}^{N}[\tilde{s}(i) - s(i)]^2}$$

We present on Figure 3, the performance of the algorithm versus measurement noise power.

For each SNR^m value, we have computed 5 simulations with independent noise trial and 15 iterations are applied.
These curves demonstrate the perfomances of source signature deconvolution. One can remark that this section acts as a noise reduction action for SNR^m inferior to 15 dB. Quantifiable differences appear when we used the estimated time-frequency Support which represents the major term of error in the deconvolution step for low SNR^m value. The step of time-frequency Support recovery is sensitive because we are looking for maximum on a noisy curve. We hope to improve this step by including some *a priori* knowledge on the classical time-frequency Support of signal sources in underwater acoustic channel.

Section 5: Conclusions and perspectives

This communication presents a global methodology to perform blind tomography of underwater acoustic channel. Instantaneous frequency function estimation, impulse response channel and source estimation are performed in the case of one single source in a multi-paths propagation context.
To achieve these goals time-frequency tools such as the Wigner-Ville distribution, Radial Gaussian Kernel transform and Wigner-Ville-based signal synthesis have been used.

From a binary time-frequency mapping of instantaneous frequency, our method will be adapted, in the future, to the case where more than one source are present. We will interested in the development of image processors to classify the sources and to research for translated symbols.
An other point of interest is the development of high resolution time-frequency of instantaneous frequency to adapt to the shallow water context.

Section 6: bibliography

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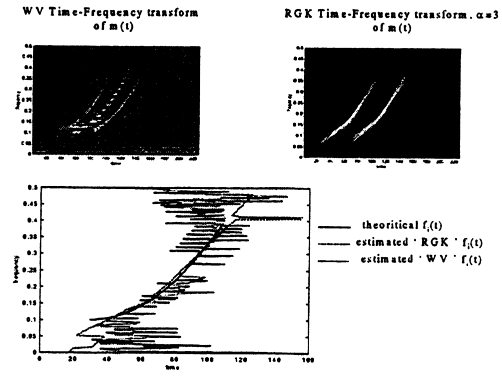

Figure 1: Instantaneous frequency function

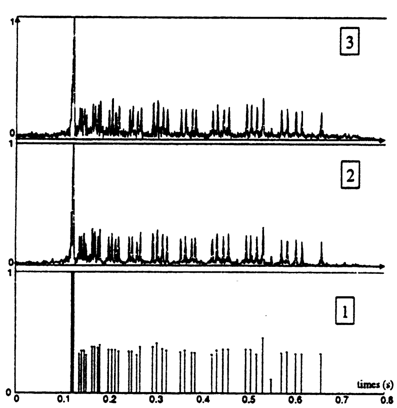

Figure 2 : Impulse response estimation

1 : theoretical impulse response, 2 : impulse response estimation by matched filtering, 3 : impulse response estimation by Time Frequency analysis, SNR=10 dB

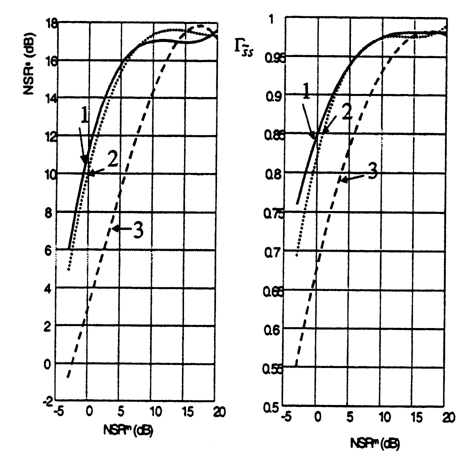

Figure 3 : source estimation algorithm: performance versus noise power

1: true TFS, SVD threshold at rank equal to 35, 2: true TFS, SVD threshold at rank equal to 40, 3: estimated TFS, SVD threshold at rank equal to 35.