High Resolution Identification of an Underwater Channel from Unknown Transient Stimuli

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Résumé – Cette communication présente un pré-traitement dédié à la tomographie passive océanique. Pour une source unique, l'estimation de sa fréquence instantanée permet l'estimation de la réponse impulsionnelle du canal en présence de trajets multiples. Grâce à l'utilisation de la transformée de Wigner Ville ou de transformées basées sur un noyau gaussien, des performances équivalentes à celles du filtrage adapté sont obtenues. Deux outils Temps Fréquence Haute Résolution sont alors proposés pour améliorer la solution initiale.

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 channel impulse response in a multipath propagation channel. Thanks to the use of Wigner Ville or Radial Gaussian Kernel distributions, performances such as classical matched filtering are obtained. Then 2 tools for High Resolution are proposed to improve our flow chart.*

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 temperature field, sound speed profile, medium geometry or salinity may be estimated, constituting what is known by active tomography [BAG88] . These properties can then be used to accomplish other related problems such as source localization, by matched-field processing . Tomographic studies have intensively been developed in deep or shallow water scenarios, with ranges extending from few to hundreds of kilometers [DEM97] . Obviously, many practical advantages 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 an active emission given improvements in civil research area by protecting mamal species from powerful nuisance signals and in military context which requires a high level of discretion on the area of operation.

Many tomographic applications proceed in 2 steps, a first step estimates the channel impulse response from emitted and received signals then a second step uses this impulse response to solve an inverse problem to estimate the physical properties of interest.

This communication focuses on the first step in the case of passive tomography. A first part describes the model of data, then a second part proposes a flaw chart composed of the association of an instantaneous frequency estimation stage and a time frequency detector. A third part presents 2 Time Frequency tools allowing High Resolution performances to improve the flow chart of the second part.

2. Model of Data

In this communication, the case of a single source emitted a signal s(t) in a non-dispersive multi-paths underwater acoustic channel is considered. Under these assumptions, the channel impulse response $h(t)$ and the received signal $m(t)$ are modeled by:

$$h(t)=\sum_{i=1}^{N} C_i \ d(t-t_i) \text{ and } m(t)=\sum_{i=1}^{N} C_i \ s(t-t_i)+b(t)$$

where *N* stands for the number of paths, C_i and τ_i for respectively the amplitude and the travel time of the i^{th} path, d for the Dirac distribution, b(t) for stationnary, white, gaussian ($N(0,\sigma^2)$) noise.

3. Time Frequency Flow Chart for Channel Impulse Response Estimation

A theoretical Time Frequency mapping of the received signal m(t) concentrates the power tempo-spectral density around N translated in time area centered around the instantaneous frequency curve of the source s(t). The flow chart we are proposing and which is detailed in this part is based on the main characteristics of this Time Frequency mapping. A first stage is dedicated to the instantaneous frequency of s(t) then a second stage performs a Time Frequency matched filtering of m(t) with s(t).

To estimate the source instantaneous frequency function, a local maximum is sought on an optimal time-frequency mapping which deletes the interference terms, without significantly increasing the spread of the auto-terms (RID: Reduced Interferences Distributions), in the Time Frequency representation. 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, RGK) or based on the optimal weighting of local ambiguity function (Adaptative Optimal Kernel, AOK) developed by Baraniuk and Jones [BAR93] [JON95] . Our approach may be biased but is stable over noise and interferences. 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 $RGK_m(t,f_i)$.

The source instantaneous frequency function $f_i(t)$ obtained in this stage 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 random 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 auto Wigner-Ville of s(t) and m(t):

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

In passive tomography, the source s(t) is unknown, but the instantaneous frequency function $f_i(t)$ of s(t) in given by the first stage, 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 ($\overline{WV}_{ss}(t, f)$). The Channel impulse response is estimated by looking for local maxima on $E(t_0)$ computed by:

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

The channel impulse response estimation is validated through simulated data for a scenario close to the experiments of INTIMATE 96 in shallow water context [DEM97] . 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 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.

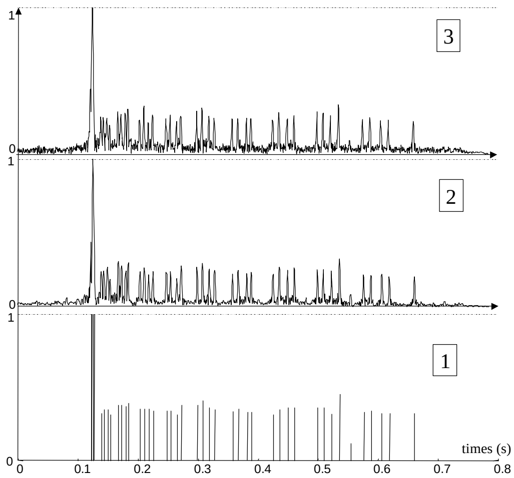

Figure 1 : Impulse response estimation

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

At the end of this part, the capabilities of designing a flow chart dedicated for the channel impulse response estimation needed in passive tomography are demonstrated. Performances closed to the classical matched filtering are obtained by associating a stage for instantaneous frequency estimation and a stage for time frequency match filtering. A more detailed version of this work and a part dedicated to source estimation may be found in [GER01] .

4. Two Time Frequency Tools for High Resolution Treatment

The simulation of Part 3 presents a first group of 4 paths which are not resolved neither by the classical active matched filtering nor by our passive flow chart. Such as in active process where High Resolution scheme may be used, we are now focussing on the development of High Resolution Time Frequency Mapping to replace the RGK transform in the flow chart proposed in Part III. A first mapping associates a optimal time windowing stage with a dechirp and MUSIC stages, whereas a second associates an optimal time windowing stage with the Modified High Resolution Capon method stage developed by Luzin [LUZ98].

4.1 Time Windowing – Dechirp – MUSIC

This tool is dedicated for signals s(t) having a curvilinear distribution of power time spectral density. Each signal of this family can be locally approximated by a Chirp signal and then if the area of validity of this assumption and the chirp parameters (central frequency and bandwidth) are known, MUSIC algorithm can be applied to m(t) in order to estimate each delay τ_i. The criticism point of the algorithm is to determine automatically for each time t_0, the optimal neighborhood where the chirp-like assumption is valid. This is achieved by looking for the length L of a rectangular time window ($w_L(t-t0)$) to apply to m(t) which minimizes the spread of the Fractionnal Fourier Transform of the windowed signal. The algorithm developed follows the flow chart presents Figure 1.

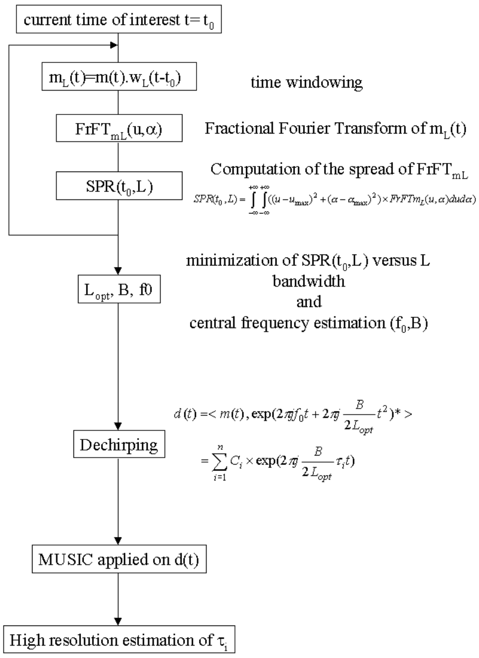

Figure 2 : Time Windowing – Dechirp – MUSIC Flow Chart

This algorithm is applied to the following synthetic signal

$$s(n) = \exp(2\pi j f_{\min} n + 2\pi j \frac{B}{3T^2} n^3) \times w_T(n)$$

$$+ \exp(2\pi j f_{\min}(n-15) + 2\pi j \frac{B}{3T^2}(n-15)^3) \times w_T(t)$$

$$+ 0.1 b_r(n) + 0.1 j b_i(n)$$

with f_{min}=0.1Hz, B=0.3 Hz, T=350 s, fe=1Hz, b_r and b_i two independent gaussian white noise of unity variance.

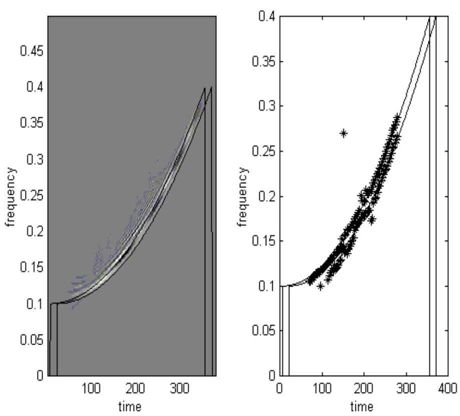

Figure 3 : High Resolution Instantaneous Frequency estimations

left : gray level = Wigner Ville transform of s(n), plain black curves = theoretical instantaneous frequencies

right : plain black curves = theoretical instantaneous frequencies, black stars = estimated instantaneous frequencies

The algorithm proposed in this part succes in resolving two closed arrivals until a signal to noise ratio equal to 10 dB. Unfortunately this algorithm can not be applied to more than two delayed arrivals because it demands a too drastic tradeoff to achieve :

- L must be small to obtain a ‘chirp – like’ signal,
- L must be high to allow MUSIC to separate the multiple arrivals.

4.2 Time Windowing – Modified Capon

Any high-resolution technique needs some *a priory* assumption on received signal. The proposed algorithm is constructed under assumption that received signal consists of several tone pulses with different delays. The main final goal of this algorithm is to show a possible way to achieve high-resolution estimates of instantaneous spectrum. Let’s consider the following diagram (Figure 4). The analysed signal (1) consists of two tone pulses with different delays. The task concludes in estimation of spectral power density of the signal inside the short signal window (WS).

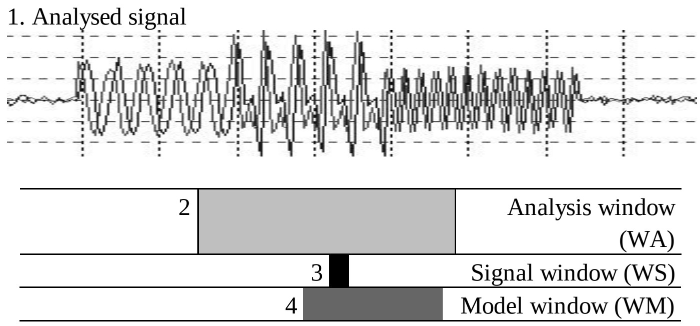

Figure 4 : Time Window Chart

It will be based on two assumptions – the signal is supposed being a mixture of tones and parameters of the model (spectral modes) was estimated basing on data sample into the window (WM) that is covering the nearest neighbourhood of the analysed window.

Thus, the final task can be formulated as following - what is the better time position of model window (WM) for given position of signal window (WS), which corresponds assumed signal model.

Assuming that the covariation matrix of the signal is a sufficient statistics the unique most powerful invariant rule for recognition of stochastic signal is

$$X^+ R_0^{-1} X \geq C \cdot X^+ \left(g_0 R_{0s} + R_0 \right)^{-1} X, \quad C > 1,$$

where R_{0s}, R_0 are covariation matrixes of desired signal and noise respectively, X is the signal sample, and constant C determines predefined value of the false alarm. This rule can not be applied directly to the considered task because of as signal as noise models are determined with accurate to unknown parameters – positions of spectral components and their powers. But it shows that statistics based on comparison of inverse covariation matrixes can be used as a tool to compare signal model [BAK84]

The discussed algorithm is based on modified Capon estimate proposed at [LUZ98], which is based on two sequential procedures – 1) adaptive filtering and 2) estimation and non-coherent suppression of white noise.

Formula below represents solution of the modified Capon estimate for two window configuration, where covariation matrix R corresponds model estimation window WM and where covariation matrix R_γ corresponds signal windo WS, and V is steering vector.

$$\widehat{P}_{inst} = \frac{1}{\vec{V}^{+}\left(R+R_g\right)^{-1}\vec{V}}\left(\begin{array}{l} 1-\dfrac{\vec{V}^{+}\left(R+R_g\right)^{-1}R\left(R+R_g\right)^{-1}\vec{V}}{\vec{V}^{+}\left(R+R_g\right)^{-1}\vec{V}} \\ -\left(l'_{\min} + l''_{\min}\right)\dfrac{\vec{V}^{+}\left(R+R_g\right)^{-2}\vec{V}}{\vec{V}^{+}\left(R+R_g\right)^{-1}\vec{V}} \end{array}\right)$$

$l'_{\min}$, $l''_{\min}$ are minimal self-values for modified Capon algorithm for windows WS and WM respectively.

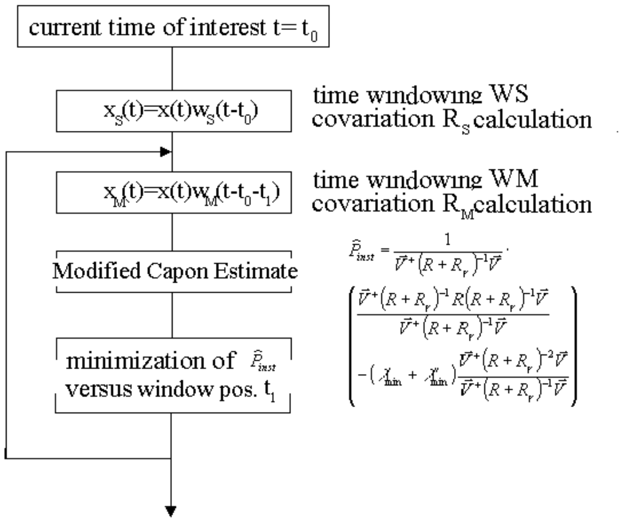

Figure 5 : Modified Capon Algorithm Flow chart

The flow chart of the developed algorithm is presented at Figure 5. At Figure 6 and 7 the simulation results of the proposed algorithm are presented. The signal sample of length 128 is formed by 4 tone pulses with duration 40 samples at frequency positions 40,50,60,70 with delays 30,30,60,60 samples.

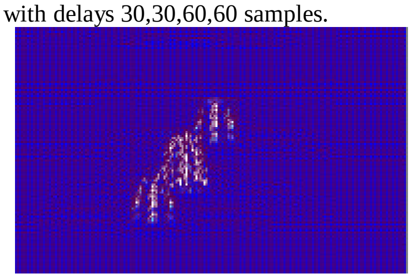

Figure 6 : Wigner-Ville Distribution

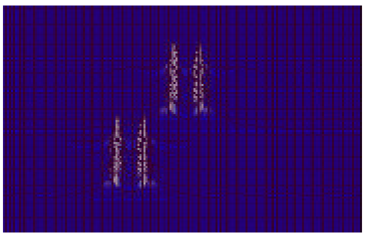

Figure 7 :.Time Windowing – Modified Capon Distribution

Figure 6 shows typical for Wigner-Ville transform cross-term interference, but the distribution based on modified Capon shows cross-term sidelobes supression. It gives a possibility to use such technology for instantaneous spectrum estimation basing on a priory information on structure of the signal.

5. Conclusion

In this communication, we have demonstrated the capabilities of Time Frequency tools to perform the identification of the impulse response channel without using the knowledge of the emitted source signal in the case of a single source and a single hydrophone. A flaw chart using an instantaneous frequency estimation stage added with a Time Frequency detector allows to achieve the same performance as the classical active matched filtering ones. Then, we have proposed two Time Frequency tools to achieve High Resolution performances. The first one allows the separation of only two components whereas the second presents good performances only on a small class of signals. This second method will be improved by inserting some corrections allowing a deviation from the assumed model and then enlarge the class of signals of interest. The case of multi sources will be treated thanks to an improvement of the measurement system (a linear array of hydrophones), then the different arrivals may be separated through the joint measurement of delays and directions of arrival.

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