
A new concept of ocean acoustic tomography

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SHORT ABSTRACT: *Ocean Acoustic Tomography (OAT) uses powerful active emissions of repetitive signals causing problems when acoustic discretion is required as in military operations. In this paper, we propose to develop a new concept of OAT, called Discreet Acoustic Tomography (DAT), which is based on a stealthy acoustic signals emission. An appropriate global procedure to synthesize a signal waveform in accordance with the compromise between interception probability and accuracy in channel parameters estimation, is proposed. Finally, this procedure was applied to a realistic scenario of which objective consists in hiding a synthetic signal in ship noise with the constraint to have an accurate estimation of the channel parameters. Results obtained illustrate the interest and the potential of the proposed method.*

Keywords: *discreet acoustic tomography, estimation, detection, optimization, performance analysis.*

RÉSUMÉ COURT: *La tomographie acoustique océanique (TAO) utilise des émissions répétitives de signaux acoustiques de forte puissance, pouvant causer des problèmes de discrétion notamment dans le cadre d'opérations militaires. Nous proposons, dans cette communication, de développer un nouveau concept de TAO, baptisé tomographie acoustique discrète (TAD), dont l'originalité consiste à émettre des signaux sonores furtifs. Une procédure globale de traitement a été élaborée afin de synthétiser une forme d'onde permettant de répondre au mieux au compromis entre faible probabilité d'interception et estimation précise des paramètres acoustiques du canal. Enfin, cette procédure a été appliquée à un scénario réaliste dont l'objectif consiste à camoufler le signal synthétique dans un bruit rayonné par le trafic maritime tout en permettant une estimation précise des paramètres d'intérêt du milieu. Les résultats obtenus montrent l'intérêt et le potentiel de la méthode proposée.*

Mots-clés: *tomographie acoustique discrète, estimation, détection, optimisation, analyse de performance.*

1 INTRODUCTION

Ocean acoustic tomography (OAT) is a powerful inversion tool that allows a rapid determination of *in situ* geoacoustic properties of an underwater “deep sea” or “shallow water” acoustic channel [1]. Accurate estimates of acoustic properties involve powerful active emissions of repetitive wideband signals. But, when acoustic discretion is required as in military operations or when mammals species respect is concerned, high power emission should be avoided. These constraints restrict the use of classical OAT systems. By taking advantages of acoustic sources of noise, present in the environment, a new concept of Discreet Acoustic Tomography (DAT) may be developed to tackle disadvantages of classic active tomography. We qualify the tomography process as discreet when an active emission is used with a waveform chosen to be hidden by the ambient noise and consequently,

to have a low probability of interception. This concept requires to emit a copy of a noise component [2] or a well-chosen parametric and synthetic signal in agreement with the observed noise. This last solution is studied in this paper. In this case, the signal to noise ratio (SNR) is reduced compared to usual active tomography systems. However, two constraints must be satisfied: the former is related to the characteristics of transmitted signals that should ensure good performances for impulse channel response estimates by a first cooperative receiver [3] and the latter deals with the choice of waveform assuring low probability of detection by a second non cooperative interceptor.

We propose here an innovative strategy for signals synthesis which on the one hand maximizes the estimation accuracy and on the other hand, minimizes the probability of interception. The particular case of noise radiated by the sea traffic is studied as acoustic noise of opportunity used to hide active emissions of signals.

The present paper is organized as follows, into 8 sections. Firstly, we present in Section 2, the global strategy proposed for this new concept of tomography and then, in Section 3, we draw a list of assumptions employed in our study. Estimation performances of underwater channel parameters and discretion performances of active emissions are then studied in Section 4 and in Section 5 respectively. A synthesis procedure of a stealthy acoustic signal is then proposed in Section 6, followed by an application to a simple case, in Section 7. Finally, conclusions and perspectives are presented in the last section.

2 GLOBAL PROCEDURE APPLIED ON DISCREET ACOUSTIC TOMOGRAPHY

A fundamental stage used in usual active OAT consists generally in estimating Impulse Response (IR) of the water column in order to obtain its geoacoustic parameters. In our case, the estimation stage is carried out by a simple usual estimation method. Our objective doesn't consist in contributing towards a novel optimal estimator of an underwater channel IR, already widely studied [4], but to use a simple usual method well known in the estimation domain and to develop an original effective procedure around the concept of DAT. The Cramer Rao (CR) bounds are used as the reference lower bounds useful to determine the estimation performances as we will see in the Section 4. Moreover, in our context, the signal has to be hidden in ambient noise, making the problem of signal synthesis more complex: we need to evaluate the probability of interception of the emitted signal in order to make it as small as possible. In DAT processing, acoustic discretion constraint can be represented by an additional detection stage used by an external interceptor. The choice of detector and its parameters is very important and has to be well appropriate to the signal waveform, the noise characteristics and the detection means supposed to be used by the interceptor [5]. The objectives of the DAT system consist in choosing a relevant parametric model and its parameter vector in accordance with the compromise between estimation accuracy and detection requirements. The class of the parametric model is chosen in relation to the noise characteristics. In regard to the synthesis stage, it consists in estimating optimal signal parameters according to the compromise thanks to an optimization algorithm. In this way, the signal synthesis is realized with the following optimum criterion: finding the vector value of signal parameters which minimizes CR bounds of IR parameters under the constraint that the probability of detection is lower than an imposed limit (for a low probability of false alarm). This synthesis procedure provides optimal values of signal parameters, according to the DAT compromise. **Fig. 1** sums up the main stages of DAT system described below.

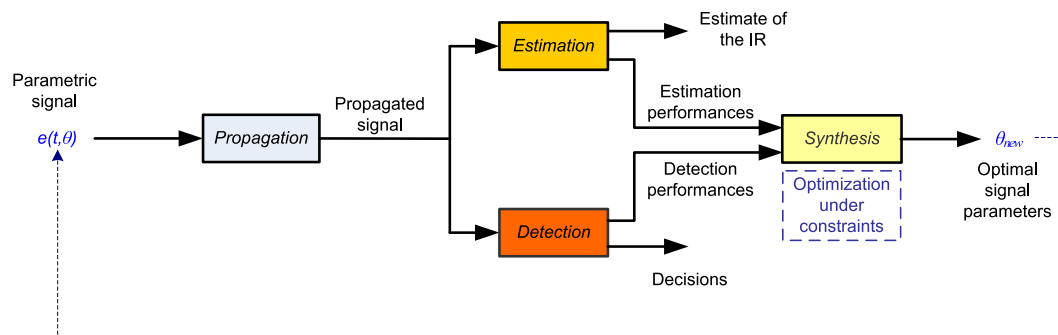


Fig. 1: Signal processing procedure applied on DAT system.

3 WORKING HYPOTHESES

Assumptions on the propagation

We assume that the propagated signal $s(t, \mathbf{p})$ is constituted by a sum of attenuated and delayed versions of original emitted signal $e(t)$. Consequently, the underwater acoustic propagation channel may be represented by a linear filter whose finite IR $h(t, \mathbf{p})$ is sparse and equal to a sum of P delayed and attenuated impulses,

$$h(t, \mathbf{p}) = \sum_{p=1}^P \alpha_p \delta(t - \tau_p), \quad (1)$$

where $\delta(\cdot)$ is the delta function and for the p^{th} ray, α_p and τ_p represent, the attenuation and the time delay. $\mathbf{p} = [\boldsymbol{\alpha} \boldsymbol{\tau}]^T$ is a vector of the unknown IR parameters constituted by the vector of attenuations $\boldsymbol{\alpha} = [\alpha_1 \cdots \alpha_P]^T$ and the vector of time delays $\boldsymbol{\tau} = [\tau_1 \cdots \tau_P]^T$. The parameter vector \mathbf{p} to be estimated, contains all the information about propagation in the channel and is used in an inversion stage to recover physical properties of the channel. Thus, the received signal $m(t, \mathbf{p})$ may be modeled as a filter output, by a convolution (represented by the symbol $*$) between the channel IR describing the multipath propagation (1) and the emitted signal with additive random noise $\varepsilon(t)$:

$$m(t, \mathbf{p}) = h(t, \mathbf{p}) * e(t) + \varepsilon(t) = \sum_{p=1}^P \alpha_p e(t - \tau_p) + \varepsilon(t) = s(t, \mathbf{p}) + \varepsilon(t). \quad (2)$$

Assumptions on the emitter

Estimation performances depend on the emitted signal waveform. As shown in [3, 6], a condition for obtaining good results for OAT systems is to use signals with a large duration bandwidth product. But in the OAT system, because of the transducer distortions, the emitter can modify significantly the signal shape especially in the case of large band signals. In this paper, we consider only a linear spectral distortion. A simple emitter can be simulated by a frequency resonator (or as a sum of frequency resonators) with the following transfer function,

$$G(\nu) = \frac{a}{a + i2\pi(\nu + \nu_r)} + \frac{a}{a + i2\pi(\nu - \nu_r)}, \quad (3)$$

where ν_r is the resonance frequency of the transducer and a is a constant. This assumption is satisfactory in a first approximation, as we can see on **Fig. 2**, where the spectral response of a real transducer [7] and a simulation of the frequency resonator are depicted.

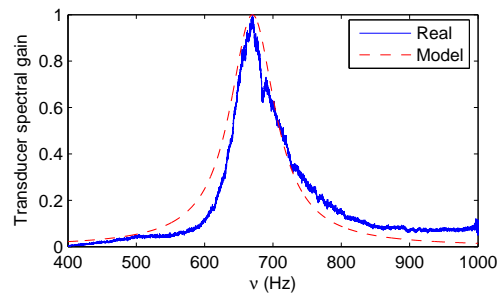


Fig. 2: Comparison between the spectral gain of the real transducer and the frequency resonator model (with $\nu_r=667$ Hz et $a=253.5$ estimated by the least square fitting method).

Therefore, the signal is distorted by the emitter. We assume in this paper that the signal which is emitted in the underwater channel by the transducer is a filtered version of the original signal thanks to the transfer function given in (3).

Assumptions on the radiated noise of ships

Among the different acoustic opportunity sources, ships constitute useful outstanding acoustic sources of noise. The power of noise radiated is relatively important and their machinery generates

vibrations that appear as underwater sound at a distant hydrophone after transmission through the sea. So, it may be possible to use some properties of the noise radiated by the sea traffic in order to hide signals emission in this kind of noise.

According to [8, chapter 10], the noise radiated by ship traffic is stationary and has a particular spectrum composed by two basically different types and may be characterized as having a continuous spectrum containing superposed sinusoidal components. The ship noise spectrum has important narrow spectral bands and so, the AutoRegressive (AR) process is appropriate to model this kind of colored noise. We consider the special case in which the noise component is a centered Q^{th} order AR process defined by,

$$\varepsilon[n] = - \sum_{k=1}^Q a_k \varepsilon[n-k] + u[n] \quad (4)$$

where the coefficients a_k are the AR filter parameters and $u[n]$ is an independent Gaussian white noise process each with a zero mean and a variance equal to σ^2 . The AR power spectral density is a rational function of $e^{-i2\pi\nu}$ [9],

$$P_{AR}(\nu) = \frac{\sigma^2}{\left| 1 + \sum_{k=1}^Q a_k e^{-i2\pi\nu \frac{k}{F_e}} \right|^2},$$

where F_e is the sampling frequency.

4 ESTIMATION STAGE

As shown in **Fig. 1**, a first processing stage in the DAT global procedure consists in estimating geoacoustic parameters of a water column. In this way, we have to estimate the vector parameters \mathbf{p} of the channel IR $h(t, \mathbf{p})$ especially thanks to the knowledge of the received signal $m(t, \mathbf{p})$ modeled by (2) and the emitted signal $e(t)$.

Classical parameter estimation is performed using method based on the principles of Maximum Likelihood (ML) estimation [10] because the ML estimator has the relevant useful property to be asymptotically efficient (for large data records) [11]. The CR bound, based on Fisher information, represents the lower bound on the variance of any unbiased estimator and, in this manner, aids to evaluate estimation performances.

4.1 White noise assumption

The CR bounds of the channel IR have already been studied in the case of white Gaussian additive noise and we can find some results in [12]. For the estimation of the parameter vector \mathbf{p} , the CR bounds are found as the diagonal elements of the inverse Fisher information matrix $\mathbf{I}^{-1}(\mathbf{p})$. In our case, the Fisher information matrix can be written as,

$$\mathbf{I}(\mathbf{p}) = \frac{1}{\gamma_\varepsilon} \text{Re} \left[\int_{-\infty}^{+\infty} \frac{\partial S^*(\nu, \mathbf{p})}{\partial \mathbf{p}} \frac{\partial S(\nu, \mathbf{p})}{\partial \mathbf{p}^T} d\nu \right], \quad (5)$$

where γ_ε is the power spectral density (PSD) of the white noise, $S(\nu, \mathbf{p})$ the Fourier transform of the propagated signal $s(t, \mathbf{p})$ define by (2) and $\text{Re}[\cdot]$ the real part operator. Now, if we expand (5) according to (2), we can obtain the following expressions of Fisher information matrix elements for the different couples of parameters:

$$\begin{aligned} I_{\alpha_i \alpha_j} &= \frac{1}{\gamma_\varepsilon} \text{Re} \left[\int_{-\infty}^{+\infty} |E(\nu)|^2 e^{i2\pi\nu(\tau_i - \tau_j)} d\nu \right] = \frac{\Gamma_e(\tau_i - \tau_j)}{\gamma_\varepsilon}, \\ I_{\tau_i \tau_j} &= \frac{1}{\gamma_\varepsilon} (2\pi)^2 \alpha_i \alpha_j \int_{-\infty}^{+\infty} \nu^2 |E(\nu)|^2 e^{i2\pi\nu(\tau_i - \tau_j)} d\nu = -\frac{1}{\gamma_\varepsilon} \alpha_i \alpha_j \frac{\partial^2 \Gamma_e}{\partial \tau^2}(\tau_i - \tau_j), \quad (6) \\ I_{\alpha_i \tau_j} &= \frac{1}{\gamma_\varepsilon} \text{Re} \left[\alpha_j \int_{-\infty}^{+\infty} (-i2\pi\nu) |E(\nu)|^2 e^{i2\pi\nu(\tau_i - \tau_j)} d\nu \right] = -\frac{1}{\gamma_\varepsilon} \alpha_j \frac{\partial \Gamma_e}{\partial \tau}(\tau_i - \tau_j), \end{aligned}$$

where $E(\nu)$ is the Fourier transform of the emitted signal $e(t)$. The elements of the Fisher information matrix are expressed according to the autocorrelation function of the emitted signal $\Gamma_e(\tau)$

and its derivatives. As we can see in (6), the estimation performances depend highly on the signal waveform. More the autocorrelation function will be concentrated (which is the case for large band signal), more the interferences terms (in other words if $i \neq j$) will be insignificant, and then, more the estimations will be more precise.

Let study the simple case of a bandpass signal $c(t)$ extensively used in usual OAT systems which is modulated in amplitude with the carrier frequency ν_0 higher than the spectral bandwidth B_c of the signal. Then the emitted modulated signal $e(t)$ can be written as,

$$e(t) = c(t) \sin(2\pi\nu_0 t).$$

Now, if we consider the special case where the IR is constituted by a single echo, it can be proved, thanks to the relations below, that the inverse Fisher information matrix of the parameters α and τ can be expressed as,

$$\mathbf{I}^{-1} \left(\begin{bmatrix} \alpha \\ \tau \end{bmatrix} \right) = \frac{\gamma_\varepsilon}{E_c/2} \cdot \begin{bmatrix} 1 & 0 \\ 0 & \frac{1}{(2\pi\alpha)^2(\nu_0^2 + B_c^2)} \end{bmatrix}, \quad (7)$$

where E_c and B_c are the energy and the effective band of the signal $c(t)$, respectively and are defined by,

$$E_c = \int_{-\infty}^{+\infty} |C(\nu)|^2 d\nu, \quad B_c^2 = \frac{\int_{-\infty}^{+\infty} \nu^2 |C(\nu)|^2 d\nu}{E_c}.$$

where $C(\nu)$ is the Fourier transform of $s(t)$. Thanks to (7), we can see that the optimal estimation performances on the attenuation parameter α depends only on the signal to noise ratio (SNR), so on the signal energy emitted according to the ambient noise power. The estimation precision of the time delay parameter τ depends on the SNR too, but especially on the signal waveform thanks to the term $(\nu_0^2 + B_c^2)$. More the carrier frequency and the signal effective band B_c are large, better will be the precision of estimation on the parameter τ . This is why, a condition for obtaining good results for OAT systems is to use signals with a large duration bandwidth product like wide-band white noise such as maximum length pseudo noise sequence and PSK modulation or wide-band chirp.

4.2 Colored noise assumption

Moreover, in an actual context, the noise is non white and the colored noise has a non diagonal covariance matrix what modifies estimation performances and so the CR bounds. The Fisher information matrix has to incorporate characteristics of noise. We assume that the colored noise is modeled by an AR process defined by (4). According to [13] and with the assumptions below, the Fisher information matrix of the parameter vector \mathbf{p} , in the presence of AR noise, can be written as,

$$\mathbf{I}(\mathbf{p}) = \frac{1}{\sigma^2 F_e} \operatorname{Re} \left[\int_{-\infty}^{+\infty} \left| 1 + \sum_{k=1}^Q a_k e^{-i2\pi\nu \frac{k}{F_e}} \right|^2 \frac{\partial H(\nu, \mathbf{p})}{\partial \mathbf{p}} \frac{\partial H^*(\nu, \mathbf{p})}{\partial \mathbf{p}^T} |E(\nu)|^2 d\nu \right], \quad (8)$$

where $H(\nu, \mathbf{p})$ is the Fourier transform of the channel IR defined by (1), σ^2 is the variance of noise and the coefficients a_k are the AR parameters of noise.

Note that the relations (5) and (8) or (6) and (9) are equivalent in the case of white noise, in other words when $\gamma_\varepsilon(\nu) = \sigma^2 F_e$ and if all the coefficients a_k are equal to 0. Furthermore, the Fisher information matrix elements can be reformulated in the same way as in (6) under the following expression:

$$I_{\alpha_i \alpha_j} = \frac{1}{\gamma_\varepsilon} \left(1 + \sum_{k=1}^Q a_k^2 \right) \Gamma_e(\tau_i - \tau_j) + \frac{2}{\gamma_\varepsilon} \sum_{k=1}^Q a_k \Gamma_e \left(\tau_i - \tau_j - \frac{k}{F_e} \right) + \frac{1}{\gamma_\varepsilon} \sum_{k=1}^Q \sum_{\substack{m=1 \\ m \neq k}}^Q a_k a_m \Gamma_e \left(\tau_i - \tau_j - \frac{k-m}{F_e} \right), \quad (9a)$$

$$I_{\tau_i \tau_j} = -\frac{1}{\gamma_\varepsilon} \alpha_i \alpha_j \left(1 + \sum_{k=1}^Q a_k^2 \right) \frac{\partial^2 \Gamma_e}{\partial \tau^2} (\tau_i - \tau_j) - \frac{2}{\gamma_\varepsilon} \alpha_i \alpha_j \sum_{k=1}^Q a_k \frac{\partial^2 \Gamma_e}{\partial \tau^2} \left(\tau_i - \tau_j - \frac{k}{F_e} \right) - \frac{1}{\gamma_\varepsilon} \alpha_i \alpha_j \sum_{k=1}^Q \sum_{\substack{m=1 \\ m \neq k}}^Q a_k a_m \frac{\partial^2 \Gamma_e}{\partial \tau^2} \left(\tau_i - \tau_j - \frac{k-m}{F_e} \right), \quad (9b)$$

$$I_{\alpha_i \tau_j} = -\frac{1}{\gamma_\varepsilon} \alpha_j \left(1 + \sum_{k=1}^Q a_k^2 \right) \frac{\partial \Gamma_e}{\partial \tau} (\tau_i - \tau_j) - \frac{2}{\gamma_\varepsilon} \alpha_j \sum_{k=1}^Q a_k \frac{\partial \Gamma_e}{\partial \tau} \left(\tau_i - \tau_j - \frac{k}{F_e} \right) - \frac{1}{\gamma_\varepsilon} \alpha_j \sum_{k=1}^Q \sum_{\substack{m=1 \\ m \neq k}}^Q a_k a_m \frac{\partial \Gamma_e}{\partial \tau} \left(\tau_i - \tau_j - \frac{k-m}{F_e} \right). \quad (9c)$$

The noise coloration introduces weighting terms into the expression of the CR bounds which have the same behavior as for a white noise but with additive interference terms.

5 DETECTION STAGE

The originality of the DAT concept is based on the constraint that the emitted signal has to be hidden in ambient noise. In order to control the stealthiness of the emitted acoustic signal, a detection stage is added in parallel with the estimation stage described below, as we can see in **Fig. 1**. In fact, a solution consists in modeling a non wanted interceptor as a detection stage and evaluates its performances. The goal is to quantify the performances of signal interception by the knowledge of the detection probability.

The detection problem is equivalent to decide whether a signal is present in noise, or if only noise is present. We model the detection problem as one of choosing between H_0 which is termed the noise-only hypothesis, and H_1 which is the signal-present hypothesis, or symbolically,

$$\begin{cases} H_0 : m(t) = \varepsilon(t) \\ H_1 : m(t) = s(t) + \varepsilon(t). \end{cases}$$

When the noise $\varepsilon(t)$ is Gaussian and the signal $s(t)$ has a known form, the appropriate processing includes a matched filter or its correlator equivalent. In absence of much knowledge concerning the signal, it seems appropriate to use an energy detector to determine the presence of a signal in the noise [14]. Moreover, this detector requires not much *a priori* informations and is based on the energy measures of the received signal over a specific time interval. For all of these reasons, we have decided to implement the energy detector as a reference in the detection stage.

The decision algorithm of the energy detector is described in **Fig. 3**. The received signal $m(t)$ is prefiltered by a bandpass filter which limits the noise bandwidth. A square law device gives the instantaneous energy $x^2(t)$ of the bandpass signal $x(t)$. Then, a lowpass filter eliminates the high frequency terms, higher than $B/2$, due to the square law device. Finally, a finite time integrator gives an energy value λ , over the interval $[0; T_i]$, which is compared to a predetermined threshold λ_T : if the energy value is higher than the threshold λ_T , then the signal-present hypothesis H_1 is validated, else it is the noise-only hypothesis H_0 . According to [14], the decision statistic is shown to have a noncentral chi-square distribution. The probability of false alarm P_{fa} , for a given threshold λ_T , is given by,

$$P_{fa} = \Pr(\lambda > \lambda_T | H_0) = \Pr(\chi_{BT_i}^2(0) > \lambda_T), \quad (10)$$

and for the same threshold λ_T , the probability of detection P_d is defined by,

$$P_d = \Pr(\lambda > \lambda_T | H_1) = \Pr(\chi_{BT_i}^2(\lambda) > \lambda_T), \quad (11)$$

where the symbol $\chi_{BT_i}^2(\lambda)$ indicates a noncentral chi-square variable with BT_i degrees of freedom and a noncentral parameter λ . Therefore, for a given probability of false alarm, it is possible to evaluate the detection threshold λ_T thanks to (10) and to deduce the corresponding probability of detection value.

In the case of colored noise, we use a pre-whitening approach [5]. The received signal is passed through a linear time-invariant filter, such that the noise at the output of the filter is white.

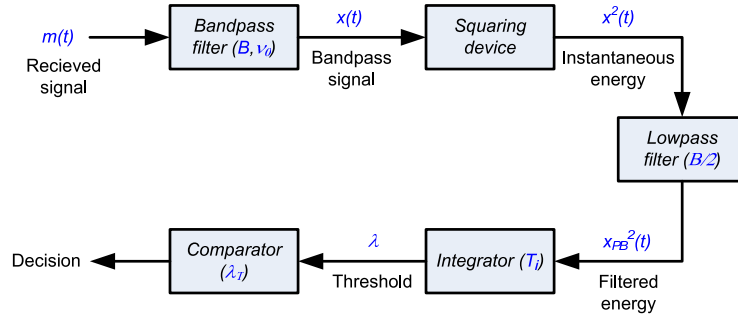


Fig. 3: Decision algorithm of the energy detector.

6 SYNTHESIS PROCEDURE

Thanks to the two sections below, the estimation and detection performances are henceforth available for any signal waveform and AR noise. Now, the objective of the synthesis stage is to propose a model of emitted signal well appropriate to the ambient noise characteristics in order to be hidden in it and to set the model parameters to optimize both the estimation and detection stages. As shown in the Section 2, the ships noise spectrum contains important narrow spectral bands. Therefore, a solution consists in synthesizing a simple parametric model according to the spectral noise characteristics. The synthetic signal is constituted by a superposition of narrowband sinusoidal components and defined by the vector of signal parameters, as,

$$e(t, \boldsymbol{\theta}) = \sum_{i=1}^M A_i \sin(2\pi\nu_i t) \cdot \Pi_{D_e}(t) \quad (12)$$

where the rectangle function $\Pi_{D_e}(t)$ is a function that is 0 outside the time interval $[0; D_e]$ and unity inside it. The amplitude A_i and the frequency ν_i are the two kinds of parameters of each sinusoidal components and defines the parameter vector $\boldsymbol{\theta} = [A_1 \cdots A_M \nu_1 \cdots \nu_M]$. The synthesis problem aims at finding the parameter vector $\boldsymbol{\theta}$ which is an optimal solution in the DAT point of view.

Several criteria based on estimation performances exist [15], but in our case, the entropy criterion seems to be the most appropriate and is defined as the logarithm of the determinant of the parameters covariance matrix which corresponds here to the inverse Fisher information matrix. As shown below in Section 4, the Fisher information matrix depends on the emitted signal waveform and is therefore a function of the parameter vector $\boldsymbol{\theta}$. According to [15], the criterion can be expressed as,

$$J_c(\mathbf{p}, \boldsymbol{\theta}) = -\ln \det \mathbf{I}(\mathbf{p}, \boldsymbol{\theta}). \quad (13)$$

Entropy is defined, in information theory, as a measure of disorder. The value of entropy criterion increases when the knowledge about the parameters decreases or again, when the noise variance and the cross-correlation between two parameters are important. The minimization of entropy has a consequence to reduce disorder. Therefore, the optimization stage can be formulated, in accordance with the assumptions below, by the following expression where the levels are given as an example: "Find the optimal parameter vector $\boldsymbol{\theta}_{new}$ which minimizes the criterion $J_c(\mathbf{p}, \boldsymbol{\theta})$ in function of $\boldsymbol{\theta}$ under the constraints that the detection probability P_d is lower than 10% for a false alarm probability P_{fa} equal to 1%", or symbolically,

$$\text{Find } \boldsymbol{\theta}_{new} = \arg \min_{\boldsymbol{\theta}} J_c(\mathbf{p}, \boldsymbol{\theta}) \quad \text{under the constraints } P_d \leq 10\%, P_{fa} = 1\%.$$

Furthermore, the criterion depends on the channel IR parameters and on the AR coefficients of the noise model. As a consequence, its shape is not convex and therefore contains a lot of local minima and this is why a global optimization is required in our case. A famous and simple global optimization method is the simulated annealing (SA). SA is a generic probabilistic meta-algorithm for the global optimization problem, namely locating a good approximation to the global optimum of a given function in a large search space [16]. This method seems to be well appropriated in our case, because it needs few parameters to regulate and gives satisfactory results in our study.

7 EXPERIMENTAL RESULT

We consider an example of an actual radiated noise of ship coming from the sea trial Passtime 2005 [7]. As we can see on **Fig. 4**, its Power Spectral Density (PSD) (blue solid line) is characterized by a first prominent harmonic component around 385 Hz and a second around 770 Hz. This underwater recording is then modeled with an AR model of order 100 (see the Section 3), thanks to the Levinson-Durbin recursion algorithm [9]. The red dashed line on **Fig. 4** represents the PSD of the corresponding AR model which keeps the main spectral characteristics of the ship noise.

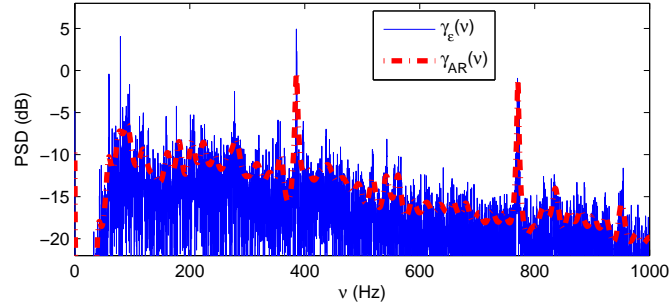


Fig. 4: Power spectral density of a real radiated noise of ship [7] and its 100th order autoregressive model.

Thanks to the relations presented in the subsection 4.2 and the estimated AR coefficients, we are able now to calculate the optimal estimation performances of the channel IR. The next stage consists in optimizing the parameters of the model $e(t, \theta)$ defined by (12). As an example, we consider a simple channel IR characterized by two possible closely spaced times of arrival with the following parameter vector $\mathbf{p} = [\alpha \ \tau]^T$, where $\alpha = [1 \ -0.8]$ and $\tau = [0.200 \ 0.215]$. In this simple case, the optimal solution isn't obvious because of the emitter distortions modeled by (3), the non-white nature of the noise, the closeness of time delays, etc.

Therefore, we consider the particular case, where the model $e(t, \theta)$ is composed by only a single truncated sinusoid, such as, $e(t, \nu_0) = A_0 \sin(2\pi\nu_0 t) \cdot \Pi_{D_e}(t)$. Then, we have decided to estimate the value of the frequency ν_0 which optimizes the estimation accuracy of the time delays. **Fig. 5** depicts the evolution of the criterion $J_c(\nu_0)$ defined in (13) with the Fisher information matrix (9b), over the arbitrary chosen spectral interval [600; 800] Hz. The PSD of the modeled AR noise $\gamma_{AR}(\nu)$ is represented underneath.

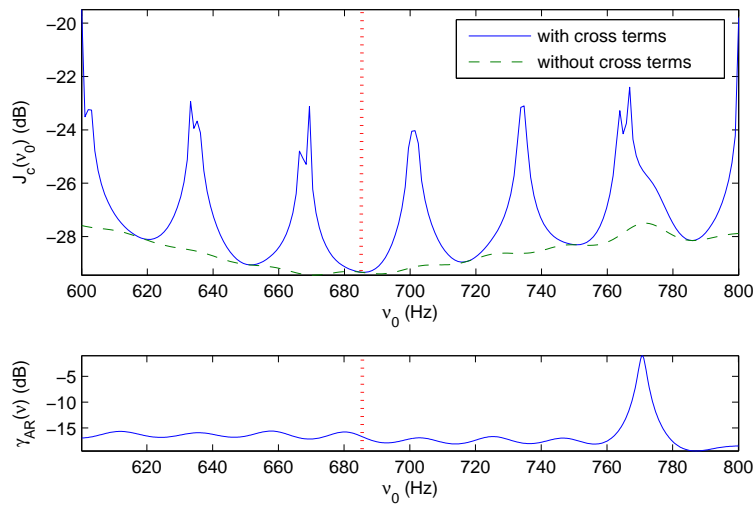


Fig. 5: Evolution of the criterion on the time delays in relation to the signal parameter ν_0 for a single truncated sinusoid.

The green dashed line represents the criterion value without the cross terms corresponding to the non diagonal components of the Fisher information matrix (9b) while the solid line includes this one justifying the presence of peaks. As shown in **Fig. 5**, the criterion shape depends highly on the time difference between the time delays and the shape of the signal autocorrelation $\Gamma_e(\tau)$ as discussed in the Section 4.

When the emitter is assumed to have a plate spectral response, the criterion for a single echo channel, in the presence of white noise, decreases with the augmentation of the frequency parameter value. In this case, the optimal value of ν_0 is the highest admissible frequency. For an AR noise, the criterion has the same behavior as for a white noise but with additive interference terms which can be relatively important. So, the optimal solution can be a little different from the white noise case. Now, if we take in consideration spectral distortions due to the emitter, thanks to (3), the optimal value of ν_0 is often the resonance frequency of the emitter. Nevertheless, when the received signal is constituted by different closely spaced overlapping echoes of the emitted signal, because of resolution of the autocorrelation function, the optimal value can be modified. This is the case on **Fig. 5** where interference terms are very important (several decibels) at the frequency resonance of the simulated emitter (667 Hz) and less important fifteen Hertz around. So, the choice of the parameter ν_0 has a relevant importance on the the accuracy of time delays estimations. The global optimization algorithm provides, thanks to the SA method, a parameter value (depicted in red dotted line), almost equal to 683 Hz and very close to the optimal one.

This simple example illustrates the interest of the synthesis procedure. As we have seen below, the optimal solution isn't obvious and depends on several parameters. For these reasons, the use of a global optimization algorithm is justified.

8 CONCLUSION

We have defined a new concept of OAT, called Discreet Acoustic Tomography, in order to tackle disadvantages of usual active tomography by using the presence of acoustic sources of opportunity. In this way, an innovative strategy for signals synthesis which maximizes the estimation accuracy and minimizes the probability of interception was proposed. This novel procedure is based on three processing stages: an usual estimation stage to estimate underwater acoustic channel parameters, a detection stage to control the discretion of the emitted acoustic signal and a synthesis stage to elaborate a stealth signal. Finally, this procedure was applied on a concrete application of radiated noise of ships.

The optimal estimation performances of the underwater channel IR have been remembered and interpreted for the white Gaussian additive noise case. The influence of noise coloration has also been treated. The CR bounds have been expressed in terms of AR coefficients of noise and the autocorrelation function of the emitted signal (or its derivatives). On the other hand, the acoustic discretion constraint has been modeled by a detection stage. The energy detector is appropriate to decide whether or not the signal is present when the signal waveform to be detected is unknown. If some assumptions on the signal class are made, optimal detectors exist and give better results for a particular class of signals. Furthermore, the DAT system imposes two constraints: the former is related to the characteristics of transmitted signals that should ensure good performances for active tomography signal processing and the latter deals with the properties of the emitted waveform which has to be hidden in the existing background noise. This compromise has been expressed as a minimization procedure under constraint.

The employed propagation model is appropriate for a rapid evaluation (few hours) of the underwater acoustic channel parameters when the geo-acoustic parameters keep constant values. The latter is a good approximation in the case of deep sea underwater channels, but for the smaller one, the model becomes no longer valid because of the non-linear distortions of acoustic rays. The use of a more realistic underwater channel IR model is a perspective to validate the proposed global procedure in most general physical case, nevertheless, with an increasing complexity of algorithms. Moreover, mammalian auditory system has remarkable abilities and capacities to detect and recognize sounds from different sources and is able to accurately work at low signal to noise ratio. A perspective is to elaborate a more complex detector which takes in consideration some psychoacoustic phenomena in order to obtain a auditory perception closed to the mammalian's. On top of that, a multiobjective minimization procedure in the synthesis stage may provide a set of optimal possible solutions [17] and give the possibility to a human operator to decide in agreement with strategic choices at that

moment.

Finally, the proposed strategy has been applied to the specific case of radiated noise of ships but our goal is to adapt this global procedure to an other kind of opportunity acoustic source namely the noise generated from breaking surf [18].

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