A SIGNAL SYNTHESIS PROCEDURE DESIGNED FOR DISCREET OCEAN ACOUSTIC TOMOGRAPHY

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ABSTRACT

To assess seabed geoacoustic properties, Ocean Acoustic Tomography (OAT) uses powerful active emissions of repetitive signals causing problems when acoustic discretion is required as in military operations. A solution to avoid this disadvantage consists in developing a new concept of OAT, called "discreet acoustic tomography", which is based on stealthy acoustic signals emissions. In this paper, we propose an innovative strategy to synthesize, thanks to a global optimization method, signals which on the one hand maximize the estimation accuracy of underwater acoustic channel parameters and on the other hand, minimize the detection probability of active emissions by a nearby unknown interceptor. Finally, this procedure is applied to a realistic shallow water 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 validity and the potential of the proposed method.

Index Terms— Acoustic tomography, parameter estimation, signal detection, optimization, performance analysis

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 [2]. 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 [3] or a synthetic signal chosen to be hidden in the noise. This last solution is studied in this paper. In this case, the signal to noise ratio is reduced compared to usual active tomography systems. However, two constrains must be satisfied: the former is related to the characteristics of transmitted signals that should ensure good performances for the channel Impulse Response (IR) estimates by a first cooperative receiver [4] and the latter deals with the choice of waveform assuring low probability of detection by a second non cooperative interceptor.

*The authors are grateful for sustained funds provided by the French "Service Hydrographique et Océanographique de la Marine, Centre Militaire d'Océanographie" under the research contract CA/2003/06/CMO.

In this paper, some assumptions are made on the propagation, the emitter and the radiated noise of ships. These last one are described below.

We assume that the propagated signal 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 $h(t, \boldsymbol{p})$ is sparse and equal to a sum of P delayed and attenuated impulses,

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

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. $\boldsymbol{p} = [\boldsymbol{\alpha}\, \boldsymbol{\tau}]^T$ 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 $\boldsymbol{p}$ 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.

Estimation performance of $\boldsymbol{p}$ depends on the emitted signal waveform. As shown in [4], 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 a sum of frequency resonators) with the following IR,

$$g(t) = 2a \cos(2\pi\nu_r) \, e^{-at} \; u(t), \tag{2}$$

where $u(t)$ is the Heaviside function and the resonance frequency ν_r and the constant a are the transducer parameters. We assume in this paper that the signal which is emitted in the underwater channel by the emitter is a filtered version of the original signal thanks to the IR given in (2).

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. According to [5], 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. So, the AutoRegressive (AR) process is appropriate to model this kind of colored noise. As shown in [6], the AR power spectral density is a rational function of $e^{-i2\pi\nu}$, given by,

$$\gamma_{AR}(\nu) = \frac{\sigma^2}{\left|1 + \sum_{k=1}^{Q} a_k e^{-i2\pi\nu \frac{k}{F_e}}\right|^2}, \tag{3}$$

where F_e is the sampling frequency and the coefficients a_k are the Q^{th} order AR filter parameters of an independent Gaussian white noise process each with a zero mean and a variance equal to σ^2.

2. GLOBAL PROCEDURE APPLIED ON DISCREET ACOUSTIC TOMOGRAPHY

A fundamental stage used in usual active OAT generally consists in estimating the IR of the underwater channel in order to obtain its geoacoustic parameters. 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 usual estimation stage, as we can see in **Fig. 1**. 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 non 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. This synthesis procedure provides optimal values of signal parameters, according to the DAT compromise (cf. **Fig. 1**).

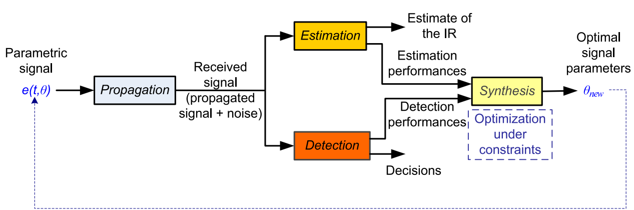

Fig. 1. *Signal processing procedure applied on DAT system.*

2.1. Estimation stage

The first objective is to estimate the vector parameters $\boldsymbol{p}$ of the channel IR $h(t,\boldsymbol{p})$ especially thanks to the knowledge of the received signal and the emitted signal $e(t)$. In our case, the estimation stage is carried out by a simple usual estimation method. Our objective does not consist in contributing towards a novel optimal estimator of an underwater channel IR, already widely studied, 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.

Classical parameter estimation is performed using method based on the principles of maximum likelihood estimation [7] because the maximum likelihood estimator has the relevant useful property to be asymptotically efficient (for large data records) [8]. The Cramer Rao Bound (CRB) represents the lower bound on the variance of any unbiased estimator and, in this manner, aids to evaluate estimation performances. For the estimation of the parameter vector $\boldsymbol{p}$, the CRB are found as the diagonal elements of the inverse Fisher information matrix $\boldsymbol{I}^{-1}(\boldsymbol{p})$. The CRB of the channel IR have already been studied in the case of white Gaussian additive noise and we can find some results in [9].

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 CRB. The Fisher information matrix has to incorporate characteristics of noise. Therefore, we assume that the colored noise is modeled by an AR process. According to [10] and with the assumptions below, the Fisher information matrix of the parameter vector $\boldsymbol{p}$, in the presence of AR noise, can be written as,

$$\boldsymbol{I}(\boldsymbol{p}) = \frac{1}{F_e}\,\mathrm{Re}\left[\int_{-\infty}^{+\infty} \frac{\partial H(\nu,\boldsymbol{p})}{\partial \boldsymbol{p}}\,\frac{\partial H^*(\nu,\boldsymbol{p})}{\partial \boldsymbol{p}^T}\,\frac{|E(\nu)|^2}{\gamma_{AR}(\nu)}\mathrm{d}\nu\right], \quad (4)$$

where $E(\nu)$ is the Fourier transform of the emitted signal $e(t)$, $H(\nu,\boldsymbol{p})$ the Fourier transform of the channel IR defined by (1), σ^2 the variance of noise, the coefficients a_k the AR parameters of noise and $\mathrm{Re}[\,]$ the real part operator.

Now, if we expand (4) according to (1) and (3), we can obtain the following expression of Fisher information matrix elements, for example, for the couple of parameters τ_i and τ_j :

$$\begin{aligned} I_{\tau_i\tau_j}(\boldsymbol{p}) = -\frac{1}{\sigma^2 F_e}\,\alpha_i\alpha_j \Bigg\{ &\left(1+\sum_{k=1}^{Q} a_k^2\right)\frac{\partial^2\Gamma_e}{\partial\tau^2}(\tau_i-\tau_j) \\ &- 2\sum_{k=1}^{Q} a_k\,\frac{\partial^2\Gamma_e}{\partial\tau^2}\left(\tau_i-\tau_j-\frac{k}{F_e}\right) \\ &- \sum_{k=1}^{Q}\sum_{\substack{m=1\\ m\neq k}}^{Q} a_k a_m\,\frac{\partial^2\Gamma_e}{\partial\tau^2}\left(\tau_i-\tau_j-\frac{k-m}{F_e}\right)\Bigg\}. \quad (5)\end{aligned}$$

The elements of the Fisher information matrix are expressed according to the second derivative of the emitted signal autocorrelation function $\Gamma_e(\tau)$ weighted by the corresponding attenuation coefficients. As we can see in (5), the estimation performances depend highly on the signal waveform. More the autocorrelation function will be concentrated (which is the case for wideband signal), more the interferences terms (in other words if $i \neq j$) will be insignificant, and then, more the estimations will be more precise.

2.2. Detection stage

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 (cf. **Fig. 1**).

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. The goal is to quantify the performances of signal interception by the knowledge of the detection probability. When the noise is Gaussian and the signal 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 [11]. 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, defined in [11], as a reference in the detection stage. The detection probability P_d is obtained thanks to the detection threshold value which is deduced itself from a given value of false alarm probability P_{fa}.

Moreover, we do not know where the interceptor is localized. So, to simplify the problem, we assume, in this paper, that each of the cooperative receiver and the non cooperative interceptor receive a signal with the same characteristics.

2.3. Synthesis stage

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 1, 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 made of several narrowband sinusoidal components and defined by the vector of signal parameters $\boldsymbol{\theta}$, as,

$$e(t\,,\boldsymbol{\theta}) = \sum_{i=1}^{M} A_i \sin(2\pi\nu_i t) \cdot \Pi_{D_e}(t) \tag{6}$$

where $\Pi_{D_e}(t)$ 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 [9], but in our case, the entropy criterion seems to be the most appropriate for the estimation performances. 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 the consequence to reduce disorder. This criterion is defined as the logarithm of the determinant of the parameters covariance matrix which corresponds here to the inverse Fisher information matrix. The Fisher information matrix (4) depends on the emitted signal waveform and is therefore a function of the parameter vector $\boldsymbol{\theta}$. According to [9], the criterion without constraint can be expressed as,

$$J(\boldsymbol{p}, \boldsymbol{\theta}) = -\ln\det \boldsymbol{I}(\boldsymbol{p}, \boldsymbol{\theta}). \tag{7}$$

In order to control the acoustic discretion of the emitted signal $e(t\,,\boldsymbol{\theta})$, we have chosen to impose the following constraint: to have a detection probability P_d smaller than a given value χ, (for a given false alarm probability). Also, the simplest solution to take in consideration this constraint, is to modify the criterion $J(\boldsymbol{p}, \boldsymbol{\theta})$ in order to come down the problem without constraint which has the advantage to be compatible with usual methods without constraint and to simplify considerably the optimization problem. A penalty function $C(\boldsymbol{p}, \boldsymbol{\theta})$ is therefore added in the initial criterion expression (7) [10]. The value of $C(\boldsymbol{p}, \boldsymbol{\theta})$ is arbitrary chosen to be smaller than 1 while the parameters verify the constraint and very larger than 1 with an exponential law else. The new criterion with penalty function can be expressed as,

$$J_c(\boldsymbol{p}, \boldsymbol{\theta}) = J(\boldsymbol{p}, \boldsymbol{\theta}) + C(\boldsymbol{p}, \boldsymbol{\theta}) \quad \text{with} \quad C(\boldsymbol{p}, \boldsymbol{\theta}) = e^{\mu(Pd-\chi)}. \tag{8}$$

where P_d is evaluated according to the fixed value of P_{fa}, the noise characteristics and the parameters vectors $\boldsymbol{p}$ and $\boldsymbol{\theta}$. The parameter μ has an influence on the importance of penalty function: more the value of μ will be large, more the penalty will be important.

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 well known and simple global optimization method is the "simulated annealing" which 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 [12]. This method seems to be well appropriated in our case as we will see in the next section, because it needs few parameters to regulate and gives satisfactory results in our study.

3. EXPERIMENTAL RESULTS

In this section, the procedure described below is applied on a realistic scenario. We consider an example of a real radiated noise of ship coming from the sea trial Passtime 2005 [13]. The noise power spectral density is characterized by a first prominent harmonic component around 385 Hz and a second around 770 Hz which are signatures of the ship electric production. This underwater recording is then modeled with an AR model of order 50, thanks to the Levinson-Durbin recursion algorithm [6].

Fig. 2 describes the configuration for the DAT system which is proposed, as an example, in the following study. We consider a shallow water column, with a constant water depth ($h = 100$ m), which is characterized by a constant sound velocity and a sea floor constituted of clayey silt. The signal transmitted by the source arrives at the receiver by a series of rectilinear paths undergoing multiple reflections on the surface and the floor. These different paths correspond to the transmission from image sources by successive symmetries of the source relative to the surface and the bottom. The velocities ($c_1 = 1500$ m/s, $c_2 = 1515$ m/s), the densities ($\rho_1 = 1000$ kg.m^{-3}, $\rho_2 = 1500$ kg.m^{-3}) and the reflection coefficients at normal incidence ($\beta_1 = 8 \cdot 10^{-5}$ dB/λ, $\beta_2 = 0.15$ dB/λ) characterize the water column and the sediments (clayey silt) [14], respectively. The respective depths of the source and the receiver are $z_s = 10$ m, $z_r = 20$ m and the horizontal range is $R = 1500$ m (cf. **Fig. 2**).

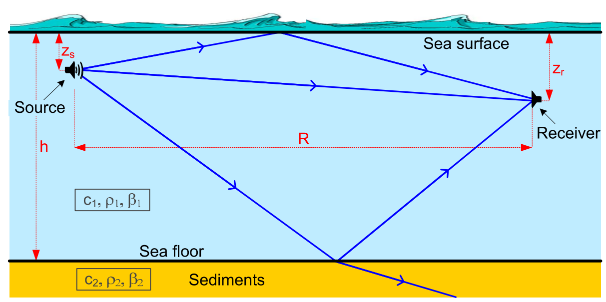

Fig. 2. *A sallow water channel with a constant water depth and sound velocity. The first three acoustic rays propagated between the source and the receiver are represented.*

Thanks to the image source method, we have calculated the propagation times of the first eight prominent rays. The corresponding attenuation coefficients were deduced from the precedent calculus by introducing a complex part in the sound velocity in order to take in consideration the influence of absorption inside the reflecting sediments [14]. Theses parameters define the vector $\boldsymbol{p}$ as described in the Section 1.

The next stage consists in optimizing the parameters of the model $e(t\,,\boldsymbol{\theta})$ defined by (6). In this simple case, the optimal solution is not obvious because of the emitter distortions, the non-white nature of the noise, the closeness of time delays, etc. The emitter is modeled by (2) with $\nu_0 = 667$ Hz and $a = 253.5$ which were estimated from a measure of an actual transducer used in [13] by the least square fitting method. Moreover, in order to make the interpretation of the results easier, we consider in this article, the simple particular case where the model $e(t\,,\boldsymbol{\theta})$ is composed by only a single truncated sinusoid, such as, $e(t\,,\nu_0) = \sin(2\pi\nu_0 t)\cdot\Pi_{D_e}(t)$ (with $D_e = 1$ s). Note that the reasoning presented below can be easily extended to more complex cases where signals are composed of multiple parameters. Thus, we have decided to estimate the value of the frequency ν_0 which optimizes the estimation accuracy of the time delays under the constraint to have $P_d \leq 0.1$ for ($P_{fa} = 0.01$) and a time of integration equal to the signal duration D_e. Simulations was made with $\mu = 50$ which was selected empirically and which gives satisfactory results. The plot on the top of **Fig. 3** depicts, the evolution of the criterion $J_c(\boldsymbol{p},\nu_0)$ (blue solid line line) defined in (7) with the Fisher information matrix (5) corresponding to the times delay parameters, over the arbitrary chosen spectral interval $[600; 800]$ Hz which contains the resonator frequency (667 Hz) and the second harmonic of the ship noise (770 Hz). The criterion $J(\boldsymbol{p},\nu_0)$ without the penalty function $C(\boldsymbol{p},\nu_0)$ is represented by a green dashed line. The probability of detection, for $P_{fa} = 1\%$, is depicted in the middle of **Fig. 3** and the power spectral density of the modeled AR noise $\gamma_{AR}(\nu)$ is represented underneath.

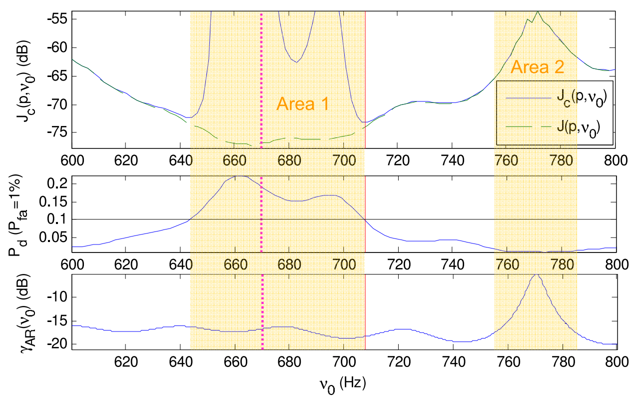

Fig. 3. *Evolution of the criterion on the time delays in relation to the signal parameter ν_0 for a single truncated sinusoid.*

The shape of the criterion $J(\boldsymbol{p},\nu_o)$ depends highly on the spectral characteristics of the noise, as we can see on **Fig. 3**, where the criterion increases around its second prominent harmonic component at 770 Hz (cf. Area 2 in yellow). On the other hand, around the resonator frequency (magenta vertical dotted line), the constraint is not anymore respected ($P_d > 0.1$) and the penalty function $C(\boldsymbol{p},\nu_0)$ becomes very important as shown in **Fig. 3** (cf. Area 1 in yellow). The global optimization algorithm provides, thanks to the simulated annealing method, a parameter value (red vertical solid line), almost equal to 708 Hz which optimizes the estimation performances of the channel time delays with a probability of detection smaller than 10%.

This simple example illustrates the interest of the synthesis procedure with only one parameter. But this procedure was applied with success on the case of synthetic signals with multiple parameters. As we have seen previously, the optimal solution is not obvious and depends on several parameters and, on the other hand, the presence of local minima justifies the use of a global optimization algorithm.

4. CONCLUSION

We have proposed an innovative strategy appropriate to the discreet acoustic tomography, which synthesizes a signal maximizing the estimation accuracy and minimizing the probability of interception by a nearby unknown interceptor. 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 in the DAT point of view.

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 was expressed as a minimization procedure of a criterion having a penalty function. On top of that, a multiobjective minimization procedure in the synthesis stage may provide a set of optimal possible solutions and give the possibility to a human operator to decide in agreement with strategic choices at that moment.

Finally, this procedure was applied on a concrete application of radiated noise of ships. The results obtained illustrate the potential of the proposed method.

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