Full Bayesian Approach for Signal Detection with An Application to Boat Detection on Underwater Soundscape Data

Paulo Hubert, Julio M. Stern and Linilson Padovese

Abstract The problem of detecting a signal of known form in a noisy message is a long-studied problem. In this paper, we formulate it as the test of a sharp hypothesis, and propose the Full Bayesian significance test of Pereira and Stern as the tool for the job. We study the FBST in the signal detection problem using simulated data, and also using data from OceanPod, a hydrophone designed and operated by the Dynamics and Instrumentation Laboratory at EP-USP.

Keywords Underwater acoustics · Bayesian inference · Signal detection

1 Introduction

The problem of detecting the presence of a signal in a noisy sample can be stated as an inference problem where we compare two alternative hypothesis, H_0: *data is composed of noise only*, against H_1: *data is signal plus noise*. By *signal*, we understand a function of time, usually discretely sampled; data is, thus, a sequence of points indexed by a time variable.

One common application of signal detection is in telecommunications, where one intends to transmit a message through a noisy channel from a *transmitter* to a *receiver*; when the message is binary, the receiver must decide at each instant if a given (known) signal is present (in which case she assumes a 1 was transmitted) or

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absent (in which case she assumes a 0 was transmitted). In this kind of application, usually, the exact signal form is known both at the transmitter and the receiver, and the problem arises only because the channel is not ideal, i.e. it adds noise to the data that is collected at the receiver.

It is natural, in this situation, to postulate the model [1] $Y = \xi X + R$, where Y is the recorded noisy message, X is the particular signal form we are interested in, and R is noise, where by noise we understand whatever forms of random or non-random patterns besides the one that codifies the signal. The unknown parameter ξ is interpreted as a nonnegative gain factor. In this formulation, the problem of signal detection amounts to testing $H_0 : \xi = 0$ against $H_1 : \xi > 0$.

Testing hypothesis of equality, like the one defined above, is the main goal of the FBST (*Full Bayesian significance test*) [2] framework. In this work, we analyze the problem of signal detection as a sharp hypothesis test problem, and propose the FBST as the tool of choice for the job. We analyze both the simplest case, where the signal form is completely known at the receiver, and a more complicated version of the signal detection problem, namely the situation where the functional form of the signal is known, but not the values of the parameters that completely define it. After analyzing the performance of the FBST with simulated data, we apply it to the problem of detecting the presence of ships in soundscape data.

2 FBST for Signal Detection

2.1 Signal Known at the Receiver

We analyze first the problem of digital signal detection, which can be stated in the following terms: a transmitter sends a signal, modelled as a continuous function of time $x(t), t \in [0, T]$, through a noisy channel. The signal plus noise reaches a receiver, whose task is to analyze the message and decide whether the signal was or was not embedded in the message. The received message can be modelled as $y(t) = \xi x(t) + r(t), t \in [0, T]$, where $r(t)$ is noise, and ξ is a gain factor that represents the intensity of the signal (assumed constant for $t \in [0, T]$).

From a statistical point of view, the problem can be stated as the test of the sharp hypothesis $H_0 : \xi = 0$. Acceptance of the null hypothesis implies that no signal was present in the recording (i.e. a 0 was transmitted), whereas its rejection means that a signal was indeed present (a 1 was transmitted).

In many applications, specially in communications, the exact form of the signal is known both at the transmitter and the receiver. Given this information, the problem is greatly simplified, since our parametric space is only one-dimensional (ξ is the only unknown quantity, if one assumes known noise power).

In this section, we evaluate the performance of the *Full Bayesian significance test* (FBST) in this simpler version of the problem using simulated data. We consider, henceforth. a signal of the following form

$$x(t) = \sum_{h=1}^{m} A_h cos\,(2\pi h\omega t + \phi_h) \tag{1}$$

This form is the one of a sinusoidal wave with fundamental frequency ω and m harmonics. The A_h and ϕ_h represent each harmonic's amplitude and phase, respectively.

The choice for this particular form is motivated by our later application, namely the detection of ships in hydrophone recordings. The literature [3–6] of subaquatic acoustics suggests that the noise radiated by a moving ship is of the form in (1), plus broadband noise. We discuss this model in further detail in a later section.

For now, supposing that $\Theta = \{\omega, A_1, \ldots, A_m, \phi_1, \ldots, \phi_m\}$ is known, the problem of detecting this signal in a noisy recording can be modelled in the following way: the message at the receiver is given by $y(t) = \xi x(t) + r(t)$. We model the noise $r(t)$ as a Gaussian random variable with 0 db mean amplitude, and a variance of σ_r^2. The gain factor ξ is constrained to have values between 0 and 1.

We assume the message to be uniformly sampled at the receiver, at a sampling rate high enough to avoid aliasing problems. Thus our actual data is a set of N points $y[t_i], i = 1, \ldots, N$.

In this situation, and assuming a uniform prior in [0, 1] for ξ, and an improper prior for σ_r^2, the posterior distribution for ξ, given data $y[t_i]$, is

$$p(\xi|y, \Theta) = (2\pi\sigma_r^2)^{-N/2} exp\left[-\sum_{i=1}^{N} \frac{(y[t_i] - \xi x[t_i])^2}{2\sigma_r^2}\right] \tag{2}$$

Under $H_0 : \xi = 0$, the posterior is

$$p_{H_0}(\xi|y, \Theta) = (2\pi\sigma_r^2)^{-N/2} exp\left[-\sum_{i=1}^{N} \frac{y[t_i]^2}{2\sigma_r^2}\right] \tag{3}$$

In the FBST framework, the evidence against H_0 is defined as the integral of the posterior distribution over the surprise set, defined as the set of points, in the full parametric space, whose posterior values are higher than the maximum posterior under H_0. To calculate the evidence, then, we first need to obtain $\hat{p}_{H_0}$, the maximum posterior under H_0, which in this case is simply the value in (3) calculated at the maximum likelihood estimate for σ_r^2.

To calculate the integral of the full posterior, we use a traditional Metropolis-Hasting algorithm, with a uniform [0, 1] candidate distribution for ξ and an inverse gamma candidate for σ_r^2.

2.2 Simulated Data

To evaluate the FBST performance in the signal detection problem, we simulate a message with the following form: the signal has the functional form in (1), with

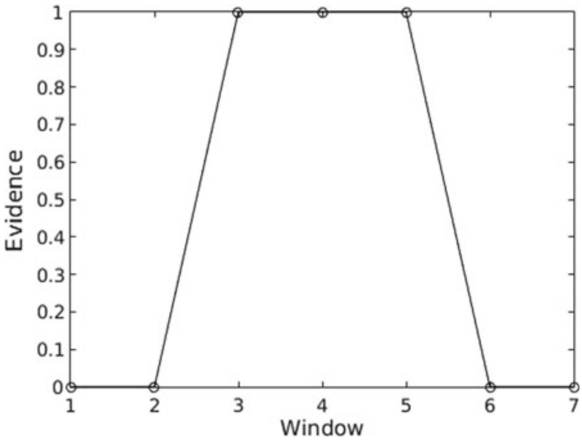

Fig. 1 Evidence values - known signal form

$m = 5$, $\omega = 60$, $A_i = \{0.005, 0.004, 0.003, 0.002, 0.001\}$, $\phi_i = \{-\pi, -\pi/2, 0, \pi/2, \pi\}$. We simulate a 7 s long signal, with $\xi = 0$ during the first and final 2 s, and $\xi = 1$ in the middle 3 s. We assume a sampling rate of 11025 Hz. We will use this same values for both cases (signal form completely known, and signal parameters unknown).

We simulate the message for four different SNR values: 0.9, 1.2, 1.5, 2 (SNR is here defined as the quotient between the deterministic signal's power, and noise power).

The results for the case where the signal form is completely known, and for the different SNR values, are shown in the Fig. 1. The results were the same, regardless of the SNR.

2.3 *Unknown Signal Parameters*

Now, we complicate matters a little bit further and assume that the signal form is known at the receiver, but not the parameters that fully define it. This situation might arise when, for instance, the receiver is not stationary with relation to the transmitter, or if the characteristics of the channel medium change over time.

Our model remains essentially the same as before, except that now the full posterior is 12-dimensional (the parameters are the gain factor, the fundamental frequency, the five amplitudes and five phases). In most real situations, however, there is strong prior information on the signal parameter's. We model this fact by imposing a Gaussian prior on ω, the fundamental frequency. The prior hyperparameters used were $\mu_\omega = 50$, $\sigma_\omega = 10$. Amplitudes and fundamental frequency are constrained to be positive, and phases lie in $[-\pi, \pi]$ by symmetry considerations. For these parameters and also for the signal noise variance, uninformative priors were adopted.

Given the prior distribution on ω, the new posterior has the form

$$p(\xi, \Theta|y) = \quad (200\pi)^{-1} exp\left[-\frac{(\omega-50)^2}{200}\right] \times \tag{4}$$

$$(2\pi\sigma_r^2)^{-N/2} exp\left[-\sum_{i=1}^{N}\frac{(y[t_i]-\xi x[t_i])^2}{2\sigma_r^2}\right] \tag{5}$$

This time the evaluation of the posterior integral is not so straightforward; the parametric space is multidimensional, and there might me many local maxima in the posterior. Actually, the signal model we adopted is guaranteed to possess at least m local maxima, for $\omega = \omega_0, 2\omega_0, \ldots, m\omega_0$, where ω_0 is the true value of the fundamental frequency.

Given these characteristics of the problem, we choose to apply an evolutionary strategy to sample from the posterior, namely the DiffeRential Evolution Adaptive Markov Chain (DREAM) method of ter Braak and Vrugt [7]. This method consists in initializing a number of parallel Markov chains, which evolve dynamically by taking steps in a random direction given by the difference between one (or more) pair of chains. The method preserves ergodicity of the chain by application of the usual Metropolis acceptance ratio. This method is specially well suited for multimodal distributions; details can be found in [7, 8]. We use a version of the algorithm implemented in MATLAB by ourselves.

Again, the optimization step involved in the FBST calculation is immediate, since under H_0 the parametric space is one-dimensional and the maximum posterior is obtained by using the maximum likelihood estimate of σ_r^2. We apply the DREAM algorithm using 7 parallel chains (which as a side effect allows us to monitor the chain's convergence using, for instance, Gelman and Rubin's $\hat{R}$ statistic [9]), and sample 15.000 points after a burning period of 15.000. The results are shown in the Fig. 2.

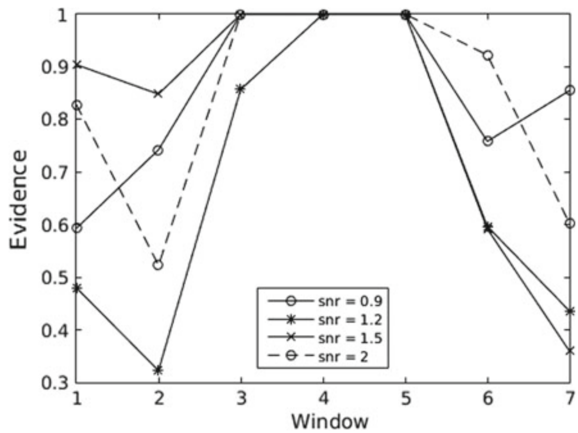

Fig. 2 Evidence values - unknown signal parameters

The method is thus very efficient in pointing out the signal's presence (rejecting a false H_0). However, it gives high values for the evidence against H_0 when it is true. This is caused by the generality of the model we adopted for our signal. We comment further on this fact in the next section.

3 Application to Soundscape Data

Soundscape data are audio recordings made by one or more hydrophones (acoustic recording devices that work underwater). This kind of data is used, among other things, to monitor the traffic of vessels (military or not) and to study the behaviour of marine species.

From the past 10 years, the Acoustics and Environment Laboratory (LACMAM) at EP-USP has been developing technology in the area of subaquatic acoustics. One of these technologies is the OceanPod [10], a hydrophone capable of 3-month continuous recordings, with a frequency band of 5–24 kHz.

One such hydrophone has been installed at a 20 m depth in the region of the *Laje de Santos* park, at the city of Santos in the Brazilian coast. This park is a marine preservation area, with the abundant presence of several marine species. The hydrophone recorded 3-months of sound before its retrieval by the LACMAM's team. The OceanPod mission has being repeated four times already, with a total of 1-year recording time.

In possession of these recordings, the laboratory has been using it with many different goals [11, 12]. One of these goals is to aid the development of a ship detection algorithm: since the park is a state preservation area, it is forbidden to fish in the park's area (actually, it is forbidden to even navigate through the park with fishing equipment inside the boat).

Nevertheless, given the abundance of fish in the park, many fishing boats disobey the park's regulation, specially at late hours of the night. Since the park's borders are at a 40 km distance from the coast, fiscalization is costly. Thus, the park administration, in a combined effort with the laboratory, intend to use the hydrophone's data to improve their fiscalization policies.

The problem of ship detection in sound signals is an old and much studied problem [4–6]. Recent work on the subject proposes the use of classification algorithms such as neural networks to identify the presence of ships. However, this kind of classification algorithm demands a large annotated sample, with which algorithms can be trained. This means that the researcher must either know beforehand the times of ships' passages, or else manually (auditively?) inspect the 3-month signal in order to separate and annotate samples. This is a demanding task, since the passage of boats is not very frequent. Also, listening to 3-month recordings of subaquatic sounds might be a rather dull job.

In order to help the preprocessing of these data, we propose in this paper a non-supervised classification algorithm, that can be run through the samples to select samples where it is at least highly likely that a ship was passing in the hydrophone's vicinity.

This task is similar to the detection problem we presented in the previous sections. However, this setting is a much more complicated one.

First of all, there is the functional form of the desired signal. As noted already, the literature of acoustic ship signature indicates that a ship's noise has mainly two components: a tonal component, given by a sinusoidal signal with a fundamental frequency and several harmonics, and a broadband noise component. The fundamental frequency of the tonal component, as received by the hydrophone, can vary depending on the ship's speed and direction of movement, and several other factors involving the ocean and wind conditions, the specific features of the ship's engine and propeller, etc. For the broadband noise, the situation is even worse, since no well-accepted functional form is known for this component, which is caused by many factors, including (but not limited to) cavitation effects from the propeller.

Even if we can find a suitable parametric model for the ship's noise signal, there's the problem of background noise in the recording. Noise, here, is taken to mean anything but the signal of interest; so it might include fish vocalizations, snapping shrimp and barnacle noise, the sound of waves, rain, etc. Worst of all, many biological sources of noise have precisely the same spectrum form as the tonal component of a ship's noise, namely a sequence of evenly spaced delta functions in the log-frequency domain.

As a first approach, we replicated the model used in the simulated data, where we test the presence of a tonal signal with m harmonics, against random, white noise. This approach failed miserably; the signal recorded by the hydrophone was far from being well described by a Gaussian noise component, and this first algorithm showed a profusion of false positives. It became then evident that a more precise model was needed.

To build this new model, we noticed an important difference in the spectrum taken from two different kinds of ships: Fig. 3 shows a spectrogram of the noise radiated by a large vessel, moving with close-to-constant speed, and at a large distance from the hydrophone. We see the equally spaced spectral lines almost parallel to the x-axis, mainly in the low frequency (20–500 Hz) band. It is known that low-frequency sounds are less attenuated by the ocean than high-frequency ones. Such sounds can then be detected at large distances, as is the case with the example below.

Figure 4, on the other hand, shows the spectrogram of a small vessel approaching the hydrophone with non-zero acceleration. The signal to noise ratio is much greater in this case, and also we see that the spectrum is distorted, showing negatively sloped lines in the spectrogram.

Since the actual goal of the analysis is to detect small, quicker vessels as the ones in Fig. 4, and since most biological acoustic signatures have the same functional form as (1), our next model thus incorporates the fact that *the fundamental frequency in*

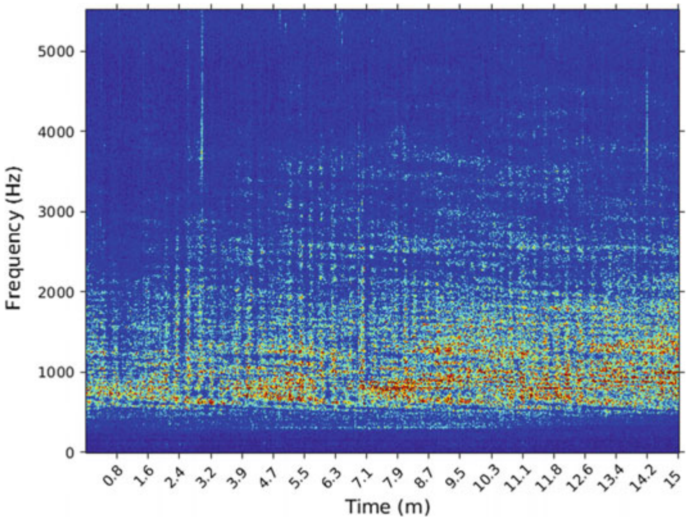

Fig. 3 Spectrogram for large boat

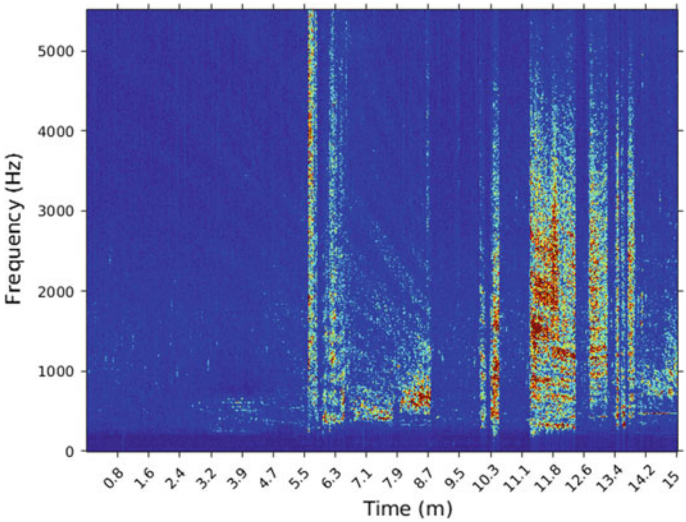

Fig. 4 Spectrogram for small boat

(1) *is time-dependent* for the kinds of events we want to detect, but constant to either large ships moving slowly and far away, or sounds of a biological nature. Our full model for the small vessel then becomes

$$x[t_i] = \sum_{h=1}^{m} A_i cos\ (2\pi h\omega(t_i)t_i + \phi_i) \tag{6}$$

where

$$\omega(t_i) = \omega_0 + \delta t_i \tag{7}$$

We use, thus, a linear function of time for the fundamental frequency of the ship's radiated noise. The full model then becomes

$$y[t_i] = x[t_i] + r[t_i] \tag{8}$$

and our new null hypothesis is $H_0 : \delta = 0$. This model, we expect, will differentiate between *statical sources* and *moving* ones. Incidentally, this might help us to detect more specific events, namely the *approximation* and *departure* of boats, rather than a stationary boat with engine turned on. In terms of aiding fiscalization in the park, this might be of greater interest than detecting any kind of ship-related events whatsoever.

Again, we model prior information available on the ship's fundamental frequency with a Gaussian prior, with $\mu_\omega = 40$, and $\sigma_\omega^2 = 25$. The reason for such a precise prior distribution is twofold: first of all, it helps to prevent the MCMC algorithm from wandering to much in the parametric space, helping it to avoid the inevitable local maxima at integer factors of the true fundamental frequency. Also, there is plenty of the literature in the subaquatic acoustic signature of small ships, and this literature points to fundamental frequencies usually in the range of 20–40 Hz.

Thus the posterior for this problem has the same form as in (4). To calculate the evidence against H_0, we first obtain the maximum posterior under H_0, applying a combination of the DREAM method and an interior-point optimization algorithm. We start 20 parallel chains, run it for a small number of iterations, and then apply the optimization algorithm to the maximum point of each chain. We then simulate again the 20 chains, using as starting values the maximum points, and repeat this procedure until convergence.

After obtaining the maximum posterior under H_0, we run the DREAM algorithm in the full parametric space to estimate the evidence value. We run the chains for 30.000 iterations, discarding the first 15.000.

There remains the choice of m, the number of fundamental harmonics. The number of harmonics in a ship's radiated noise can be as high as 20, if the signal has enough power. In our tests below, we apply the algorithm using $m = 7$ and $m = 10$.

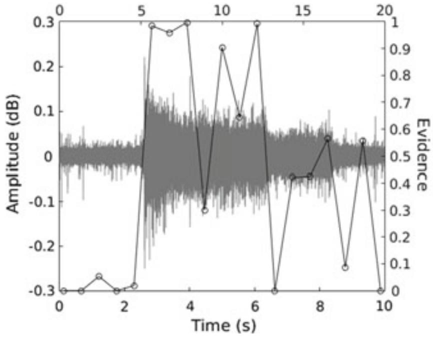

Fig. 5 Evidence values - $m = 7$ (LHS) and $m = 10$ (RHS)

3.1 Results

To test this model, we use a sample where it is known that small boats were passing.[1]

We calculate the evidence against H_0 (i.e. the evidence for the presence of a ship) using samples of 0.5 s. The hydrophone samples the signal at a 11.025 Hz, which gives us a total of 5.516 data points for each window. The results for a 10 s long signal, using non-overlapping 0.5 s samples, are shown in Fig. 5.

As we see in the left-hand side of Fig. 5, the problem of false positives was greatly reduced with the new model using $m = 7$. The first non-zero value for the evidence of a ship's passage is in the window starting at second 3, during which the signal first appears. After that, the evidence stays high for 3 s, falling to 0 again when the signal power falls considerably. After that we see evidence for the signal presence rise again. There is one possible false positive at the window between 8, 5 and 9 s, but auditive inspection of the signal shows a small occurrence of the engine sound at this point.

Using $m = 10$, the sensitivity of the test drops, and we see positive evidence for the presence of a ship only around second 3 in right-hand side of Fig. 5. This is due to the high dimensionality of the parametric space under H_0 (22 parameters) which allows for high posterior values under H_0.

Finally, we also applied our model in a sample of a large vessel, the one represented in the spectrogram Fig. 3. As expected, the evidence given by our model was less than 0.01 in all 0.5 s window extracted from that signal. This is another indication of the potentiality of our method in the detection of small vessels against other events, specifically against bigger boats in cruising speed.

[1]This was possible since touristic boats are allowed in the park for diving visits, and we happen to know that during weekends they are likely to be near the park.

4 Final Remarks and Future Work

The first goal of this paper was to evaluate the performance of the FBST framework in the task of signal detection. Being specially designed to calculate the evidence for sharp hypothesis, the FBST is a natural choice of tool for this job. Using simulated data, we confirmed that the FBST is a promising technique to be used in this kind of problems.

Our second goal was to apply the framework to a real data bank, namely audio recordings from a hydrophone. In this case, we wanted to design an algorithm that was able to preprocess subaquatic acoustic data, indicating sections of the audio that are highly likely to register the passage of small vessels. As we saw in the last section of the paper, by specifying a proper model for the ship's radiated noise, we obtained promising results with the FBST: the evidence values for our models are specially suited to detect the presence of rapidly moving vessels at a small distance from the hydrophone, which meets well the practical requirements for the problem at hand.

Also, the proposed framework is flexible: the models for the signal form can be modified to reflect different kinds of events, and the number of harmonics in the model can be used to adjust the evidence values for different values of signal power. Prior information can be incorporated easily in the model to adjust it for specific kinds of vessels, particularly by the previous estimation of the fundamental low-frequency of ships of interest using pre-annotated samples.

There are a few drawbacks, however; first of all, the algorithm relies on a MCMC technique, which in turn demands a large computing time until convergence. The computation of evidence for a 0.5 s window, with a model of 17 parameters, took roughly 15 min to complete (including both optimization and integration steps) in a Pentium Quadricore 1.6 GHz, 8 Mb RAM home computer, and with a serial algorithm running in a single core. However, since this method is aimed as a preprocessing tool, this is not a very serious drawback, and there are many ways to improve the performance of the algorithm, which we intend to investigate further on future works.

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