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SOURCE ESTIMATION ALGORITHM IN NON COOPERATIVE BI-STATIC SONAR SYSTEM

Olga Sambataro[1*] **Riccardo Costanzi**[1] **Andrea Caiti**[1]
[1] Department of Information Engineering, University of Pisa, Italy

ABSTRACT

Research and surveillance at sea may benefit from the covertness of some of the involved platforms. Within this context, the paper focuses on a non-cooperative Bi-Static sonar configuration: a specific active sonar system in which the surface transmitter and the underwater receiver do not communicate with each other and the covert receiver has no information about transmitter source depth, course and speed, waveform and frequency spectrum, etc. Environmental conditions (bathymetry, sound speed) in the whole surveillance area are assumed known. Within this framework, several works have been proposed and this paper delves into the preliminary phase of one of these: a target detection algorithm based on the joint source-target localization at the receiver through matching the multipath arrivals with model based predictions. Such algorithm requires the application of an unknown source deconvolution processing to extract the multipath arrivals, plus the inversion of the arrivals times. Unknown source deconvolution is performed through a novel algorithm in the time-frequency domain, which aims to estimate the characteristics of the unknown transmitted signal. The algorithm is described and finally validated with synthetic acoustic signals and applied to real data. Tests on real data, though at a preliminary stage, confirm the theoretical and simulated analysis.

Keywords: *underwater acoustics, active sonar, inversion algorithm*

**Corresponding author*: *olga.sambataro@dii.unipi.it.*

1. INTRODUCTION

The algorithm proposed in this work fits into the context of a project aimed at designing and develop a system based on the principle of bi-static sonar in non-cooperative configuration. Bi-static sonar is a type of active sonar that employs a transmitter and a receiver which are positioned apart at a distance similar to the distance between the target and the transmitter. A more generalized form of bi-static sonar is a multi-static sonar system [1], which typically involves one projector and multiple receivers, but can also incorporate multiple transmitters emitting the signal alternately, and the received signals are processed together by the receivers. Bi-static sonars can be classified as either cooperative or non-cooperative systems [2]. In cooperative systems, the receiver has access to information related to the transmitter, such as its position and depth, course and speed, initial transmission time, waveform and frequency spectrum, and source level. In contrast, in non-cooperative systems, the receiver has either none or only a portion of the information mentioned above.

What we present in this work is a deepening of the preliminary part of a target detection algorithm based on matching the multipath arrivals with model-based predictions to achieve source-target localization at the receiver [3]. In that work a ray model for acoustic propagation is utilized and a comparison is made between temporal differences of multipath arrivals and a simulated database of arrival sequences. The localization algorithm flow is shown in Fig. 2. This paper focuses on the pre-processing phase, where the goal is to match the detected signal with the estimated source signal using onboard receiver information [4]. However, it cannot be assumed that the information about the transmitted signal, which is crucial for extracting the multipath at the receiver, is readily accessible. If all or part of the source information is not available, it needs to be extracted from the received signal itself: this is the goal of the new designed algorithm proposed in the paper.

The environmental conditions in the entire application area are assumed to be known and deep water situation is considered. A thorough description of environmental characteristics such as seabed depth, bathymetry, sound velocity profile, and temperature is essential for modeling acoustic propagation properly; variations in these parameters, in fact, significantly affect the the way sound travels in the water column. In deep water and in the high frequency range the most commonly used model is the ray model [5], which describes the sound as a series of beams propagating radially from the source and obeying Snell's law of refraction. The most widely used program for underwater acoustic beam propagation is Bellhop [6], a beam tracing program for predicting acoustic pressure fields in ocean environments.

Since this work focuses on the estimation of the source signal, Bellhop is not directly involved in the algorithm, but only to compare the multipath sequence obtained from the estimated signal and the simulated arrivals sequence in that particular conditions. This comparison is exploited for the validation of the effectiveness of the source estimation algorithm. The algorithm will be illustrated in the section 3 and finally applied to two scenarios, the first with simulated data (section 4) and the second one on real data (5).

2. ACOUSTIC CHANNEL MODELING

The modeling of the acoustic channel will be analogous to that described in [3]. The dimensions of the channel considered are $[0.5 - 70]$ km in range and greater than 50 m in depth. However, in deep water scenarios the source and target will be searched from the surface up to a maximum depth of 300 m.

The types of signal used during the study are Continuous Wave (CW) signals and Linear Frequency Modulated (LFM) signals. In the first case the signal is characterized by a constant frequency f_c and a specific time interval T. Frequency modulated signals are signals whose frequency varies over time and, in particular, LFMs are those in which this variation follows a linear law. Consequently the signal will be characterized, in addition to T, by an initial frequency f_0 and a final frequency f_1, which then give us the signal band Δf. In any case, the frequencies considered do not go below 1 kHz and do not exceed 10 kHz. The pulse repetition interval (PRI) need not to be constant, but it is assumed that there is a pause long enough between one pulse and the next to detect all energetically significant arrivals. As shown below, the estimation of this set of parameters will allow to simulate the source signal, apply the inversion algorithm and provide the multipath sequence.

For applications on real data the profiles have been supplied with data, and in the absence of these, they have been downloaded from the *Sound Speed Manager Toolbox* database, an open-source application developed by HydrOffice [7] in collaboration with NOAA (National Oceanic and Atmospheric Administration) and CCOM (Centre for Coastal and Ocean Mapping).

Similarly for bathymetric data. The simplest case is that of flat bathymetry, with which the first simulations were carried out. Subsequently more complex bathymetric profiles were used and finally, for the real data, these were downloaded from GEBCO database [8]. GEBCO is a non-profit making organisation that provides the bathymetric grid in the chosen area, with a resolution of 15 arc-second degrees.

The algorithm presented in this work simulates the acoustic propagation in the channel based on the *ray acoustic theory*. The sound is generated by the source and from this it propagates along rays normal to the wave fronts, obeying Snell's law of refraction.

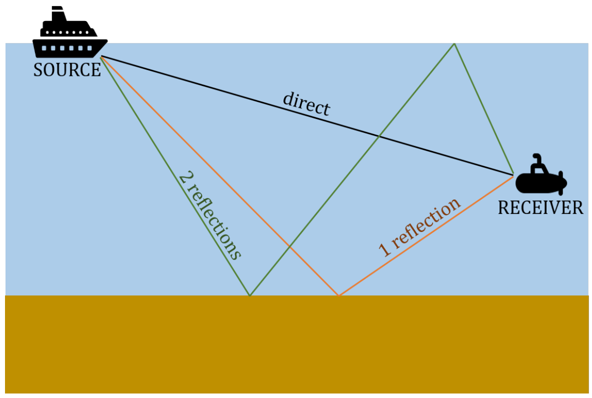


Figure 1. Acoustic rays frome source to receiver: direct, one or more reflections.

It is therefore clear that, depending on the geometry of the system, each ray, traveling a different path, will take a different time to reach a certain point. There are multiple paths that autorays can follow: direct rays, rays that are reflected from the seabed, from the surface or from both, one or more times (see Fig. 1). This is commonly referred to as multipath propagation of an acoustic signal.

What has been exploited in [3] is precisely the dependence of the multipath structure on the geometry of the system, and in particular on the relative position between source and receiver. The algorithm presented in this paper, however, is preliminary to the actual localization algorithm; the generation of the arrivals with Bellhop will then be used only as a comparison of the peaks extracted from the deconvolution on the real data with those simulated in the corresponding environment.

The program used to simulate the sequence of arrivals at a given point is Bellhop. The program is available in both Matlab and Python, but the core of the algorithm are particularly efficient libraries written in Fortran by Michael B. Porter and in the public domain.

3. ALGORITHM DESCRIPTION

A bi-static sonar in non-cooperative mode works in reception, listening to the acoustic signals that are propagated inside the water column. Typically the receiver is an array capable of composing n beams arranged to cover $360°$. The transducers of the array detect the pressure waves generated by the signals and convert them into n directional signals that correspond to each beam or channel.

The entire algorithm includes a pre-processing part, in which the received signals are filtered and cleaned of any disturbances, a second step in which a database of data relating to all the potential positions of the source (-target) is created and finally the estimation of the source position by mixing the time arrivals obtained in the pre-processing with those present in the database. The pre-processing step can include, in the event that the signal received is unknown, a further block for estimating the source parameters. We will focus on the pre-processing steps and in particular on the way in which the parameters of the source are obtained when this is unknown. For more details on the creation of the database and the localization algorithm see [3].

3.1 Pre-processing

Each input signal S_i will have to undergo a first filtering phase to eliminate all those external disturbances that could compromise the subsequent estimates. In this project, the frequency range of interest is between 1 kHz and 10 kHz. It will be necessary to implement a band pass

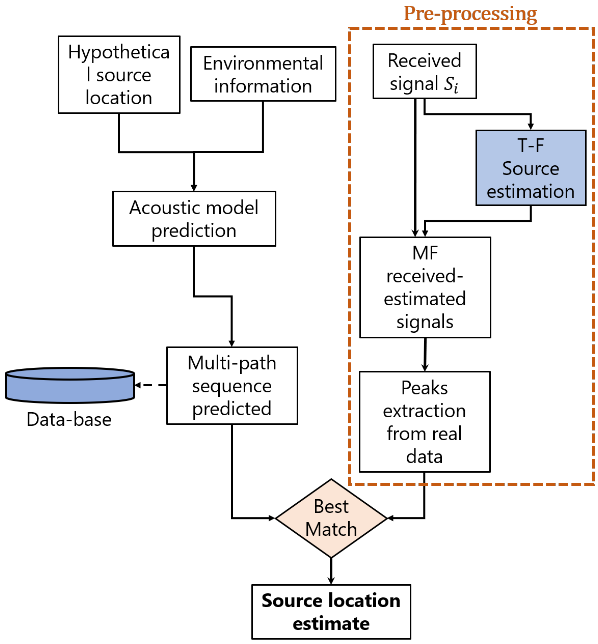


Figure 2. Algorithm flow-chart.

filter so as to eliminate frequency components outside the band of interest, limiting possible estimation errors.

At this point there are two paths that can be followed: carry out the matched filter (MF) between the received signal $S_i(t)$ with a known signal, or try to reconstruct the signal sent by the source starting from the one arriving at the receiver. The two methods, mutually exclusive, can be used in the first case, if the type of signal being transmitted by the source is known, while in the second, when there is no information on the signal emitted. The source reconstruction algorithm related to the second case is described in detail in the next section (section 3.2). The parameters estimated in this phase will be used as a reference signal for the matched filter operation.

The last step of the pre-processing is the detection threshold tuning on the sequence of peaks obtained with the MF. This will be done by the user by monitoring the results of the filtering on the display and selecting a reasonable threshold by hand.

At this point there will be at most n arrays (one for each beam) with the time instants in which the time signal has exceeded the detection threshold. Among these, the one containing the highest energy will be the input for the source estimation and target estimation blocks. Here, through research and optimization processes, an estimation of the position of the emitters ($\hat{R}_S$, $\hat{D}_S$) and of the targets ($\hat{R}_T$, $\hat{D}_T$) will be carried out.

3.2 Unknown source

In this section we will describe the algorithm that estimates the source when the emitted signal is unknown. In this case it is not easy to obtain information about the source and the acoustic transmission channel from the standard representations of the received signal, such as the temporal waveform and frequency spectrum. The temporal waveform provides information about the energy content of the signal over time, but not about the frequencies involved. Conversely, the spectrum provides a statistic of the frequencies present in the signal, but without any temporal information on when they occur.

A complete analysis of the signal can be performed by adding to the information obtainable from the standard representations those coming from an alternative representation: a time-frequency distribution (TFD), which offers simultaneous temporal information, through the structure of the signal arrivals, and frequency information, through the weighted replicas of the spectral content of the signal emitted by the source.

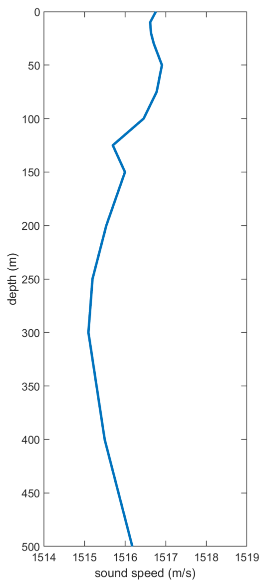
We will use the so-called Short-Time Fourier Transform (STFT) spectrogram. The spectrogram of the signal $x(t)$ is defined as the square modulus of the STFT

$$SP_x = |STFT_x(\nu, t)|^2$$
$$STFT_x(\nu, \tau) = \int_{-\infty}^{+\infty} x(t)\omega(t-\tau)e^{-i\nu t}dt \quad (1)$$

with $\omega(t)$ window function, of which the most commonly used are the Hann window and the Gaussian window.

The idea behind this approach is to exploit the time-frequency distribution, no longer to obtain the impulse response of the channel directly from it, but to obtain useful information for estimating the characteristics of the source.

The first step is to identify the frequency components of the received signal: central frequency f_c for CW signal and band Δf addition for LFM signals. This information can be easily obtained by looking at the spectrum of the total received signal or integrating the TF distribution over time. The frequency range chosen for the TF representation of the received signal will be considered as wide as possible in order to avoid missing fundamental parts of the signal. It will be limited only by the Nyquist frequency (and therefore by the sampling frequency which is related to the specific sonar system). To automate the process, what is done is to identify an adequate threshold that lies between the minimum and maximum power of the result and record its intersections with the latter (see Fig. 11). Since it is not expected to deal with LFM signals with bandwidth less than 200 Hz, if the difference between the maximum frequency and the minimum frequency is less than this value, the signal is identified as CW and the intermediate frequency between the two is indicated as the central frequency. The frequency values thus obtained represent the starting point for estimating the duration of the signal by integrating the time-frequency distribution.



Depth (m)	Sound Speed (m/s)
0.0	1516.76
10.0	1516.62
20.0	1516.64
30.0	1516.71
50.0	1516.91
75.0	1516.78
100.0	1516.46
125.0	1515.70
150.0	1516.00
200.0	1515.54
250.0	1515.20
300.0	1515.10
400.0	1515.50
500.0	1516.18

Figure 3. Sound speed profile for application to synthetic data.

After estimating the extreme frequencies of the transmitted signal, the time-frequency distribution is now integrated into the frequencies using the maximum and minimum frequencies estimated in the previous step as integration extremes. As explained previously, the integration for discrete signals reduces to the sum of all the frequency contributions for each instant of time, multiplied by a constant factor equal for all which in this context can be ignored. Similarly to what is done for the estimation of frequencies, once the signal corresponding to this integration has been obtained, an intermediate point is identified between the maximum and the minimum detected and the two extreme intersections are recorded. The difference between these two values will represent the first estimate of the duration of the signal. Around these first estimates, a bank of possible values will then be generated which will be used to further optimize the estimate. This process consists in defining a range of frequencies $[f_s - \Delta_{freq} : f_s + \Delta_{freq}]$ and times $[t_s - \Delta_{time} : t_s + \Delta_{time}]$ around the first estimate and dividing the interval in N elements separated by a step δf, and δt. Then, the matched filter operation is repeated for each combination of the two (or three in the LFM case) parameters and the optimal estimate will be given by the combination of values whose corresponding signal maximizes the MF with the received signal.

Note that this type of analysis allows bypassing the estimate of the Doppler effect. Any frequency shift at the receiver given by the relative motion with the source is inherently present in the received signal. Since the latter is used for estimating the source, the signal obtained already takes this effect into account. The MF operation is carried out between two corresponding signals, thus, the extracted multipath sequence is not modified by the Doppler.

In the next section we present two application of the unknown source estimation, one with simulated data and one with real data. For both we used the sound speed profile corresponding to the real scenario, shown on Fig. 8, and sandy bottom, with corresponding parameters presented in Tab. 1.

	Value	Unit
P-wave speed	1735	m/s
P-wave absorption	0.90	dB/wavelength
S-wave speed	437	m/s
S-wave absorption	0	dB/wavelength
Density	1.95	g/cm^3
Roughness (RMS)	0.013	m

Table 1. Sandy bottom parameters.

4. APPLYING THE ALGORITHM TO SYNTHETIC DATA

The algorithm described up to now has been applied to multiple tests using synthetic signals, one of which is presented below. The signal used is a LFM signal of 2 seconds duration, central frequency 7750 Hz and band 500 Hz. The signal received at the receiver was acquired by convolving the Bellhop arrivals with the source signal and introducing noise. Despite selecting a high signal-to-noise ratio (SNR) to facilitate the estimation process, this choice remained consistent with the SNR observed in real data (see Fig. 9 for a visual comparison). The received signal is shown in Fig. 4. The source and receiver depth are respectively 36.0 m and 17.0 m and these are 10.0 km apart.

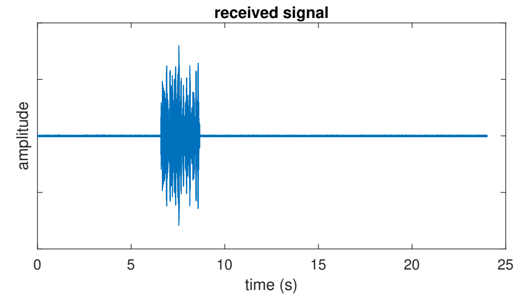


Figure 4. Simulation of the signal recorded by the receiver before starting the signal processing.

The sound velocity profile used is typical of the winter season and was downloaded from the Sound Speed Manager Toolbox in correspondence with a specific area of the Mediterranean Sea. The profile is shown in Fig. 8. The bathymetric profile was also extracted from real data and is represented in the Fig. 5. It is a seabed with a depth that varies between 100 m and 150 m.

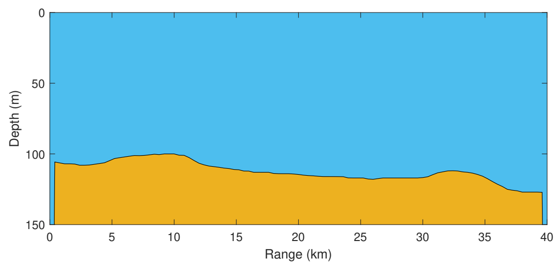


Figure 5. Bathymetric profile for synthetic data application.

As described in the previous section, after a filtering operation, the signal is represented via a time-frequency distribution. This will be the starting point for estimating, through an operation of integration, the temporal content

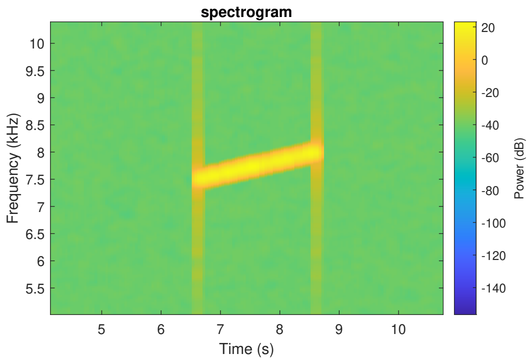


Figure 6. Spectrogram of the synthetic signal.

and frequencies of the transmitted signal. The distribution chosen is the STFT and is shown in Fig. 6. The colorbar's dynamic range is the default in Matlab, which is generated to comprise the entire power range of the spectrogram.

It is already possible by looking at the spectrogram that it is an LFM signal with increasing frequency in the interval between 7 kHz and 8 kHz, and about 2 seconds long. Integration over time and frequency separately, shown in Fig. 7, will allow us to estimate more precise values, which will act as central values for a filter bank in which an even more precise search for optimal values will be made.

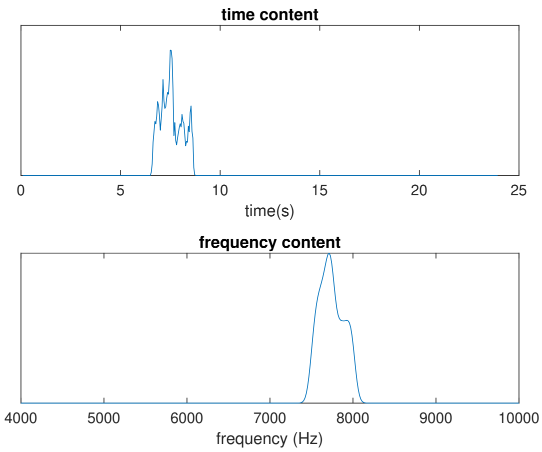


Figure 7. Time and frequency content extracted from the signal spectrogram.

The latter are the ones that maximize the MF with the

	T (s)	f_0 (Hz)	f_1 (Hz)	f_c (Hz)
Emitted	2	7500	8000	7750
Estimated	2.11	7474	8004	7739
Diff. (%)	5.50	0.35	0.05	0.14

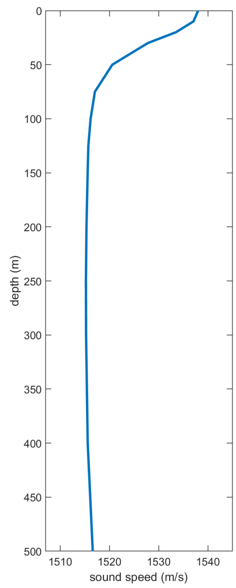
Table 2. Unknown signal estimation results for real data.

received signal and those obtained are shown in the Tab. 2.

The minimum cost functional was obtained in correspondence with an estimate of the source location at a depth of 26.47 m (error = 9.53 m) and a distance from the receiver of 9.15 km (error = 0.85 km).

5. APPLYING THE ALGORITHM TO REAL DATA

The application of the algorithm to real data requires data collection at sea in particular contexts. Preliminary studies have shown, indeed, that not all types of signals are suitable for this type of analysis, depending on their resolution and the characteristics of the propagation medium. However, some preliminary applications have been carried out and the first results obtained are presented below.



Depth (m)	Sound Speed (m/s)
0.0	1538.00
10.0	1537.05
20.0	1533.49
30.0	1527.80
50.0	1520.59
75.0	1517.05
100.0	1516.18
125.0	1515.72
150.0	1515.58
200.0	1515.34
250.0	1515.23
300.0	1515.26
400.0	1515.59
500.0	1516.61

Figure 8. Sound speed profile for application to real data.

The analyzed signal, shown in Fig. 9, corresponds to the sound recorded by the receiver along the propagation direction. This direction was obtained by carrying out the same analysis on all the beams that make up the receiver and looking for the one with the maximum intensity.

The transmitted signal is an LFM signal with a central frequency of f_T and a band Δf_T. Accordingly

$$\begin{aligned} f_0 &= f_T - (\Delta f_T)/2 \\ f_1 &= f_T + (\Delta f_T)/2 \end{aligned} \tag{2}$$

Its duration is τ. In this analysis, however, this is assumed unknown, therefore its characteristics will be obtained from the estimation procedure described in section 3.2.

The first step is to generate a time - frequency representation of the signal, shown in Fig. 10. Can already be seen by eye that it is an LFM signal as it has a linear behavior with increasing frequency around f_T. Looking at the spectrum of the signal and integrating the TFD over frequencies two curves are obtained, shown in the Fig. 11 from which it is possible to determine the time and frequency component of the signal.

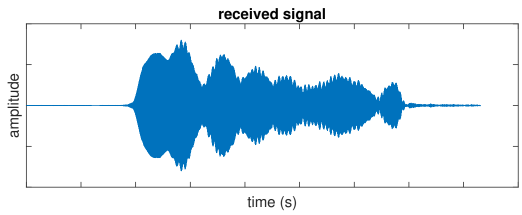


Figure 9. Received signal - experimental data.

The estimation results are very close to the real ones, showing that the estimation algorithm seems to work well even in real situations where the data is not always as clean as the simulated ones. The values obtained are shown in the Tab. 3 with relative discrepancies compared to the nominal values. Note that the three frequencies f_0, f_1, f_T are all underestimated and by a similar amount. This could therefore not be an estimation error, but a manifestation of the Doppler effect which, when source and receiver are in relative motion, causes a positive or negative frequency shift depending on the direction of motion.

These values were used as input for the matched filter procedure between the received signal and the estimated one. The result is shown in the Fig. 12. What is obtained

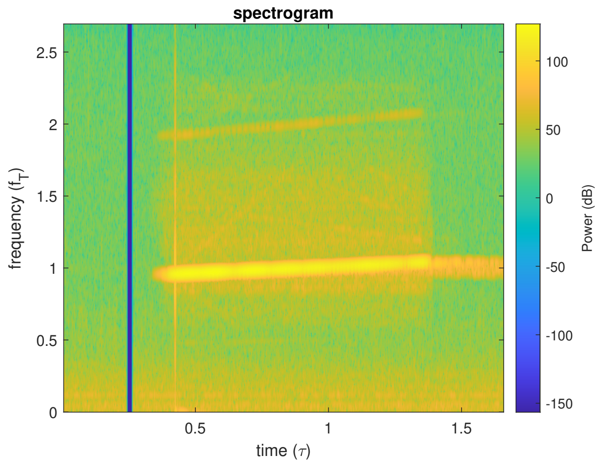


Figure 10. Spectrogram of the received signal.

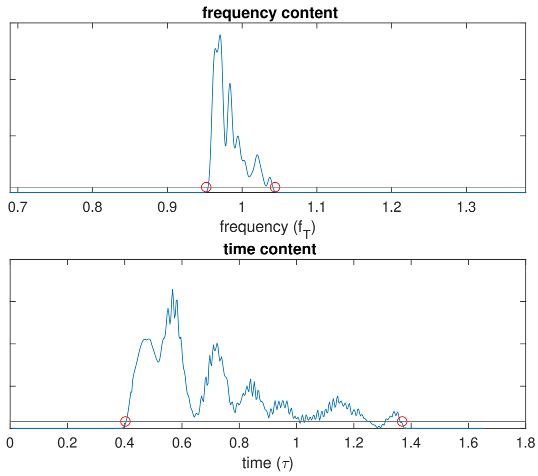


Figure 11. Time and frequency content obtained from spectrogram.

	T (s)	f_0 (Hz)	f_1 (Hz)	f_c (Hz)
Emitted	τ	f_0	f_1	f_T
Estimated	1.02τ	$0.997 f_0$	$0.996 f_1$	$0.997 f_T$
Diff. (%)	2.0	0.3	0.4	0.3

Table 3. Unknown signal estimation results for real data.

is a sequence of peaks, which will then be compared with the arrivals simulated by Bellhop in those specific environmental conditions. In order to highlight the temporal correspondence between peaks and arrivals, the amplitudes of arrivals were normalized with respect to the maximum of the cross-correlation. The agreement between these two sequences seems to be good.

Unfortunately, the number of arrivals is not sufficient to apply the inversion algorithm, so at this stage it is not yet possible to say whether the source location is successfully estimated. However, the good agreement between the two sequences seems to give good confidence not only in the goodness of the algorithm for estimating the characteristics of the source when this is unknown, but also in the good extraction of the sequence of arrivals through the matched filter process.

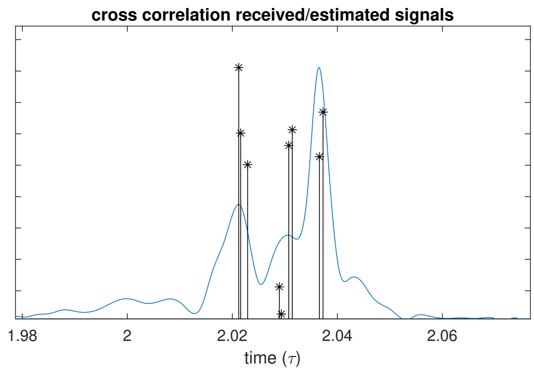


Figure 12. Cross correlation between real signal received and the estimated one, compared with the arrival train simulated with Bellhop. The amplitudes of arrivals were normalized with respect to the maximum of the cross-correlation.

6. CONCLUSIONS

In this work, an in-depth study of the source localization algorithm developed in [3] has been presented. The original contribution of the paper is to estimate the parameters of the source to be localized, when they are unknown a priori. The presented algorithm extracts this information by exploiting a time-frequency representation of the received signal. A validation through several scenarios has been carried out and two representative ones are here presented: one with synthetic data and one with a real signal. In the first case the characteristics of the source are correctly estimated, with an error of less than 1% for the frequencies and about 5% for the time duration. The obtained values have been used as input for the localization algorithm generating good results, which fall within the expected error. Also in the application to real data the source estimation results have been excellent. The discrepancy between the estimated values and the real ones is less than 1% for the frequencies and 2% for the time duration of the transmitted signal. Finally, the sequence of peaks resulting from the MF between the estimated signal and the arrivals simulated with Bellhop in that particular configuration were compared, obtaining an excellent agreement.

The analysis of additional experimental data will allow to validate the expectation (based on simulation results) that this algorithm allows to estimate the position of the source even when its characteristics are completely unknown.

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