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# A THEORETICAL AND EXPERIMENTAL COMPARISON OF THE DECONVOLUTION METHODS FOR MOVING SOURCES

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## ABSTRACT

Acoustic array and imaging algorithms are a powerful tool for acoustic source ranking in pass-by noise analysis. The process comprises two steps: the first one is an adapted beamforming for sound source localization taking into account Doppler Effect and grid calculation displacement. The second is a deconvolution on beamforming results to get an equivalent source distribution and area contribution. Nevertheless the calculations can be very long when the Doppler Effect is important. To speed up calculations, some hypothesis can be done working with the averaged spread function and short time window.

In this paper, under these hypothesis, 3 iterative deconvolution methods will be presented and compared in the case of moving sources from simulations and experiments. Two of them have been largely published and used in industrial cases: DAMAS-MS (Deconvolution Algorithm for the Mapping of Acoustic Sources) from Gauss-Seidel algorithm and SDM (Sound Density Modelling) from gradient type non negative least-squares. More recently a new method SOOT (Smooth One-Over-Two norm ratio) uses a blind deconvolution without exact knowledge of the propagation model used in the beamforming. It takes into account here the sparsity of the source locations. The performances of the algorithms in terms of localization and quantification will be discussed.

A special attention will be paid to their sensitivity to model error and background noise. Simulations will test different signal to noise ratio and the experimental set-up consists of a model ship passing in front of a small array of 9 hydrophones with natural error model and background noise. It will prove the robustness of SOOT algorithm in complex environment.

## 1 INTRODUCTION

With the development of commercial activities between different continents, the ground, aerial and marine traffics have increased in such rate that the environmental impact is to be highly considered to preserve air quality and the acoustic pollution. Concerning noise reduction, first regularizations were created for automotive and aeronautic industries. Standard concerns noise level measured during pass-by testing. The criteria are based on noise level measured by single sound pressure sensors. These results guarantees the certification but does not help the constructor to reduce the noise sources. The acoustic array and imaging algorithms are a powerful tool for acoustic source ranking in pass-by noise analysis.

The linear movement of sources implies some adaptation of usual method used with fixed set-up. Many works have been published to present some algorithms for the pass-by noise. They are based on beamforming methods which results in the first localization maps. These results presents some artefacts: main lobes on the sources with variable size, secondary lobes with more or less level, qualitative level. The first part of the paper will briefly presents the Moving Sources Beamforming methods with some results in case of underwater pass-by.

To be able to get the area contribution in order to concentrate noise reduction efforts, some deconvolutions methods are applied on the beamforming results. Many algorithms have been developed in the past decades to face the need in different industry domain: in automotive, train and aeronautic. Two of them have been largely published and used in industrial cases: DAMAS-MS (Deconvolution Algorithm for the Mapping of Acoustic Sources) from Gauss-Seidel algorithm and SDM (Sound Density Modelling) from gradient type non negative least-squares. The second part of the paper briefly presents these methods. It will point out that they present good results in a high signal to noise ratio.

More recently some works have been published in the sub-marine domain because of the new regularization declared by the European Commission in the Marine Directive whose goal is to achieve Good Environmental Status of EU marine waters by 2020 and noise pollution is of interest. But in this specific environment with poor signal to noise ratio and model error, a new deconvolution method of beamforming results the variable metric forward-backward (VMF-B) and Smooth One-Over-Two norm ratio (SOOT) algorithms are proposed and will complete the second part of the article dedicated to deconvolution algorithm for moving sources.

The last chapter presents some results of these deconvolution methods. The set-up is the same than the one used for experiments carried out through a research project with DGA (French army general direction). Simulations permit to compare them with different background noise and prove the robustness of the new SOOT blind deconvolution method. Coming works and publications will present the experimental results.

# 2 BEAMFORMING FOR MOVING SOURCES

## 2.1 Formulation under Hypothesis of low Mach number

With moving sources, the Doppler Effect modifies the frequency content of sources measured on array pressure sensors.
In most application in ground transportation, the Doppler Effect is important and the beamforming is implemented in time domain to be able to resample the signal. In [Sijtsma 2012] it is applied for flight over. But [Fleury 2011] uses a frequency algorithm for the same application because of high speed over 360 km/h with large distance over 100 meters.
With low speed and with measurement in far field, a low Mach number implies to neglect the Doppler Effect on small time window, that is to say the frequency shift is within the spectral resolution. It simplifies beamforming for moving sources which is implemented in frequency domain. For example, this simplification is adapted to 30 meter modal marine surface vehicle whose speed is lower than 5 m/s and the antenna is 10 meters from sources.

Under the preceding hypothesis, [Oudompheng 2015] describes the frequency implementation. The measurements are sliced into snapshots which are individually processed to get instantaneous localization map. For each snapshot, the grid calculation moves with the trajectory and sources are considered fixed on each snapshots. For each calculation point $F$ of the grid and frequency $f$, the conventional beamforming $P_{BF}$ ($F_l$, f) is computed from the k-th snapshot, using the l-th calculation grid point. Finally, the beamforming-MS result is calculated by the averaging over all of the snapshots, which is energetically expressed as:

$$\Gamma_{BF}(F_l, f) = \frac{1}{K}\sum_{k=1}^{K} |P_{BF}(F_l(k), f)|^2$$

## 2.2 Results

The same measurement set-up is used for simulated results and experimental results which are presented in this paragraph for beamforming and later for deconvolution. The experiment takes place in a lake and a surface ship is tracked with some speeds between 2 m/s and 5 m/s. The sources are artificial ones from the model ship movement itself. Only 9 hydrophones are available for the measurements.

Accordingly the data are simulated in a water environment with 1500 m/s of celerity. The pressure sensor antenna is composed of 9 hydrophones, with regular 50 cm spacing. This array geometry has been preferred as detailed in [Oudompheng 2015]. The middle of the antenna is the origin of the x axis used to defined trajectory and calculation grid. Because of one dimension antenna, the source localization and contribution is only possible in the ship length. The calculation grid is a line of 301 points, 3 meters regularly spaced along x axis. The resolution is 10 Hz to respect hypothesis regarding Doppler Effect. The number of K block is 79, with 100 ms duration and 50% overlapping. With this set-up, the operating frequency range is to be known between 500 and 2000 Hz.

For these simulations dedicated to beamforming results analysis, two simulated white noise moving sources emits in this range, with a parallel movement to x axis or ship direction, with 2 m/s speed with a distance from the antenna represented by 2.5 m distance from antenna axis and 10 m over. The trajectory starts 6 m for first sources before array centre and ends 7 meter after. Their coordinate on the grid calculation are in meter -2 and 3. The Figure 1 represents the set-up.

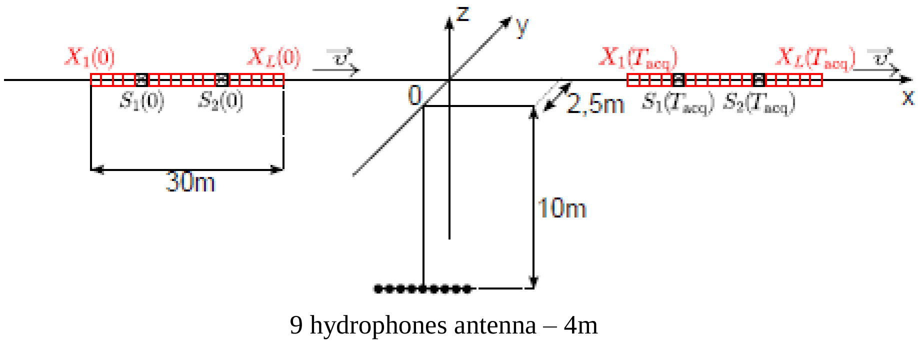


*Fig. 1. Measurement and calculation Set-up with simulated sources and experimental sources.*

Before applying the beamfroming MS on the set-up, the performances of the array answer or point spread function (PSF) of the used set-up are compared for beamforming MS and fixed source beamforming. The simulations are carried out with a mobile source and fixed source positioned in the grid centre. The grid calculation is still 30 meter length. The results are displayed on figure 2 on maps with the x-axis and frequency dimensions.

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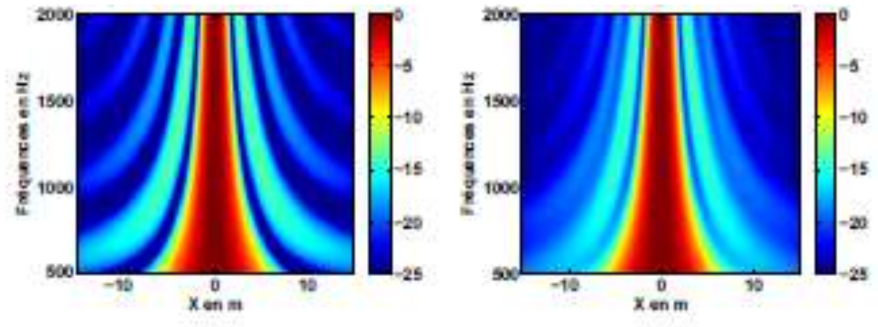



*Fig. 2. Point spread function for classical beamforming (left) and moving source (right)*

This results proves that the averaging PSF for moving source has a similar resolution (main lobe size at -3dB) but the secondary lobes are smoothed and lower with a better dynamic.

The results from two sources as previously described are displayed on two maps in Figure 3. The two maps present results with two Signal to Noise ratio: no noise and 5 dB. The resolution observed in PSF in Figure 2 leads to two main lobes that are superimposed in low frequencies. It proves that resolution is an important parameter to improve because when two sources are close they cannot be separated.

Moreover, the dynamic keeps low secondary lobes level with no additive noise and with two sources. But this dynamic is quickly degraded in noisy environment like underwater.

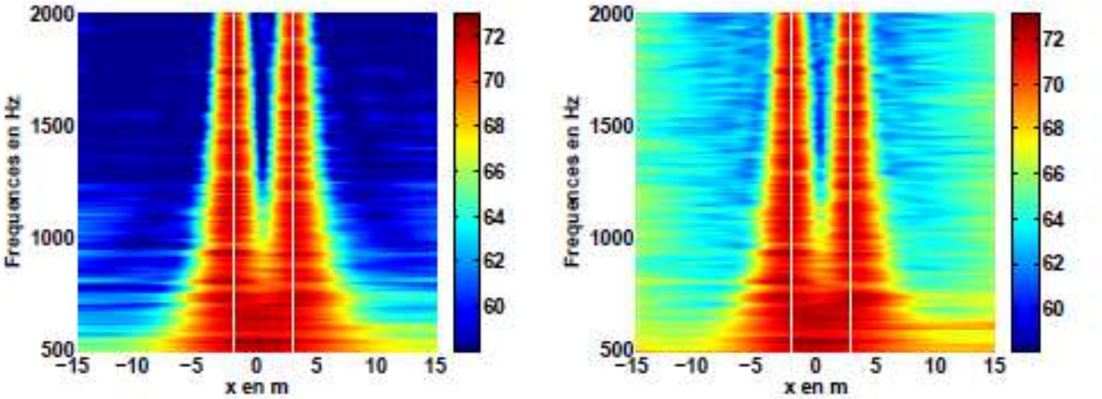



*Fig. 3. Beamforming LS results without noise (left) and with 5 dB SNR (right) for 2 moving sources at 2 m/s*

To conclude on Beamforming-MS, it is a first quick processing applied in frequency domain in this case allowing to get a direction of source localization. Nevertheless, its spatial resolution is limited, as the image of a point source is the array transfer function, which is comprised of a main lobe and secondary lobes. Consequently, improvements have been proposed to overcome this problem, among which there are deconvolution methods.

## 3 DECONVOLUTION OF BEAMFORMING RESULTS

### 3.1 The least square solutions: DAMAS-MS and SDM

In order to estimate the accurate source localization and contribution from beamforming results, the deconvolution methods try to estimate the unknown uncorrelated source autospectra Γs associated to a distribution of S monopole source distribution. These sources would be localized on the same calculation points than beamforming grid. We set the following assumptions:

- The sources are random variables that are mutually independent and stationary;
- The number grid calculation points F is greater than the number S of sources, and these S sources are sparsely distributed on the calculation grid;
- The noise components are Gaussian with zero mean, mutually independent, and independent of the sources.

On this basis, we can model the beamforming output at a given:

$$\Gamma_{BF}(F_l, f) = |PSF(F_l(k), s, f)|_a^2 \Gamma_s(s_l, f) + F[\Gamma_b(a, f)]$$

Where

PSF is the Point Spread Function matrix of F × S size

$F[\Gamma_b]$ is the realization of a zero-mean white Gaussian noise

The deconvolution methods consist in removing the point spread function from the beamforming results and access to source autospectra. This estimation is possible inverting the linear system. The inverse problem is solved with the least square solution with a constraint of non-negativity expressed as:

$$\tilde{\Gamma_s}(F_l, f) = \arg min \, \|\Gamma_{BF}(F_l, f) - |PSF(F_l(k), s, f)|_a^2 \Gamma_s(F_l, f)\|_2^2$$

$$\Gamma_s(F_l, f) > 0, \forall l \ \in [1, M]$$

This article firstly presents two iterative deconvolution algorithms solving this least square problem which take into account the positivity of unknown autospectra and have been applied to beamforming-MS: DAMAS-MS and SDM.

DAMAS-MS, for Deconvolution Algorithm for the Mapping of Acoustic Sources for Moving Sources is inspired from the original DAMAS deconvolution for fixed source in aeroacoutsic application domain [Brooks 2006b]. It has been then extended to moving sources by [Fleury 2011] for in flight pass-by case, by [Courtois 2012] for train pass-by and more recently by [Oudompheng 2015] for low speed sources for marine application.

It is based on the Gauss-Seidel algorithm which consists in formulating the theoretical value of beamformer estimator without noise component and successively considering one of the source component. It is formulated by the following equation:

$$\tilde{\Gamma}_s(s_l, f) = \Gamma_{BF}(F_l, f) - \sum_{m!=l} |PSF(F_l(k), s_m, f)|_a^2 \, \Gamma_s(s_m, f)$$

Another iterative algorithm to solve a least square problem with positivity constraint is the iterative gradient error. This mathematical method has been initially developed by [Bruhl 2000] and named SDM for Sound Density Modelization for moving sources and adapted to snapshot beamforming-MS in [Oudompheng 2015].

At each iteration, the autospectra are estimated by the following formula:

$$\tilde{\Gamma}_s(s_l, f)^i = \tilde{\Gamma}_s(s_l, f)^{i-1} + 2\mu |PSF(F_l(k), s_m, f)|_a^{2,H} \left(\tilde{\Gamma}_{BF}(F_l, f) - |PSF(F_l(k), s_l, f)|_a^2 \tilde{\Gamma}_s(s_l, f)^{i-1}\right)$$

The μ parameter is the velocity parameter of the iteration.

In both methods, the estimation of source autospectra is made by iteration. The first iteration is initialized from the beamforming results. The stop criteria is defined form the reconstruction error. To difference between DAMAS and SDM deconvolution methods is that the first one works on each source individually while the second SDM one tries to find a global solution.

## 3.2 VMF-B (variable metric forward-backward) and SOOT (Smooth One-Over-Two norm ratio)

The preceding DAMAS-MS and SDM algorithms are frequently used in Beamforming deconvolution, but it needs the knowledge of transfer matrix or point spread functions. Moreover, the PSF matrix is bad-conditioned regarding the high calculation grid point number compared to source one. It means that array frequency answer have similar shape. Solving this problem shall implies errors if model error and measurement noise are not correctly taken into account. It has been previously demonstrated in preceding chapter that a bad SNR modifies the expected Beamforming MS result and then these results could not match any source distribution and would lead to add “ghost” sources, not physical ones.

The robustness of methods is usually achieved by adding appropriate assumptions on the input and/or the impulse response to restore the output. The strategy is to formulate the inverse problem as an optimization problem with constraints derived from the physical context:

- data-fidelity term accounts for the noise characteristics, with the least-squares objective function like DAMAS and SDM,
- the smoothed L1/L2 ratio [1] promotes sparsity in the moving-source locations,
- the knowledges of some physical properties on the sources and on the blurring kernel: source amplitude between 2 limits: non negative value and maximum corresponding to maximum of Beamforming,

In the case of source identification, it takes into account the sparsity or parsimony of the input signal, that is to say source distribution. The L1/L2 ratio regularization function has shown good performance with the variable metric forward-backward (VMF-B) algorithm proposed in [Chouzenoux 2014] for retrieving sparse signals in underwater pass-by noise application [May 2015].

Moreover, in the context of their application in pass-by in sub-marine, the ocean environments to perform deconvolution leads to uncertainties on propagation. Beyond the determination of the source distribution, the evaluation of the true transfer function instead of using the PSF becomes a blind deconvolution problem.One class of popular solutions to this problem is the alternating minimization algorithm by iteratively performing the two following steps: (i) updating transfer function given source distribution, (ii) updating source distribution given transfer function. The solution is solved then using the SOOT algorithm proposed in [Repetti 2014].

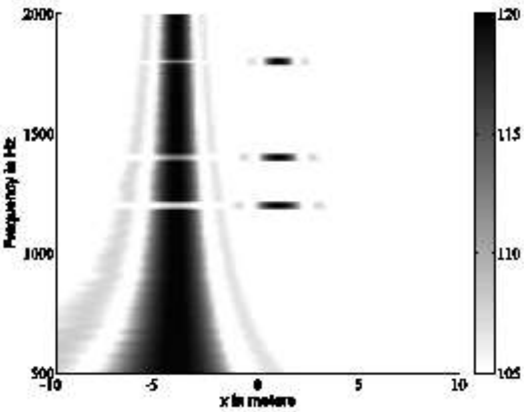
# 4 RESULTS

## 4.1 Simulated data

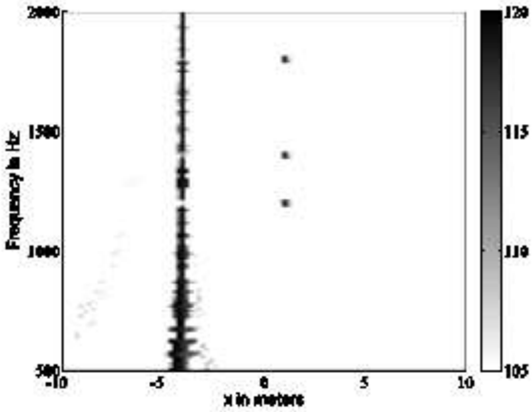
The same set-up as previously described for beamforming results is reused. But the sources are of different types : one at -4 m emitted white noise in frequency range 500-2000 Hz and the second one at +1 m emitted 3 tones: 1200, 1400 and 1800 Hz.

In Figure 4, without additive background noise, the beamforming results is firstly presented as the initial state of the deconvolution algorithms. Then the 4 algorithms presented in preceding chapter: DAMAS, SDM, VMF-B and SOOT are applied on this result.

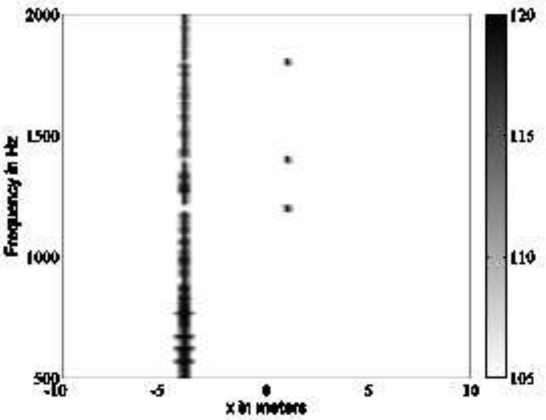
These maps in frequency/space dimensions point out that all methods correctly localized the sources and with good accuracy with deconvolution methods. There are some “ghost” sources formed by secondary lobes in beamforming results. Few ghost sources appear with DAMAS MS deconvolution on map especially located on beamforming MS secondary lobes. The SDM and DAMAS methods presents some larger source distributions on the wide range source location than SOOT and VMF-B. SOOT algorithm presents the best results with a perfect source location.



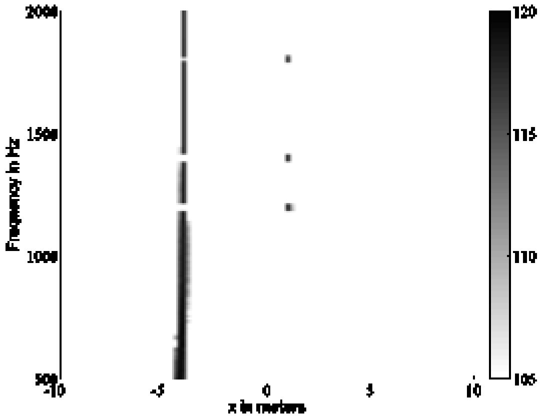

(a) beamforming-MS



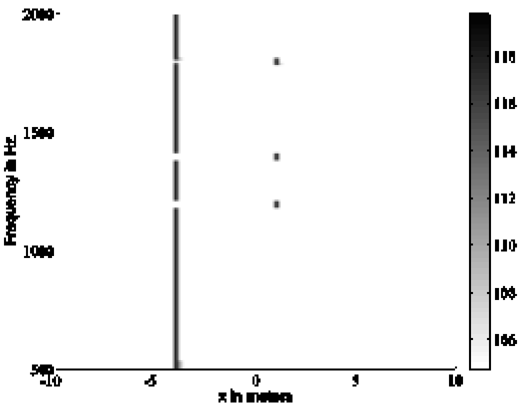

(b) DAMAS




(c) SDM

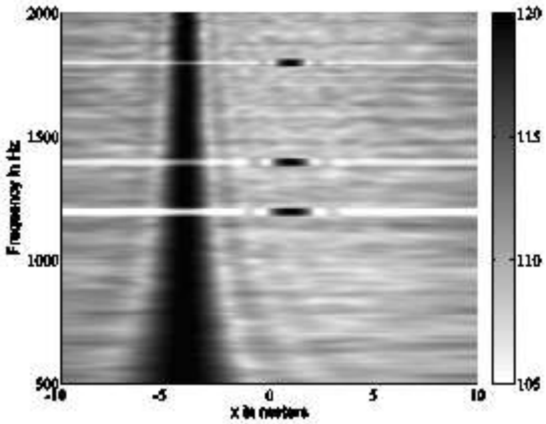



(d) VMF-B

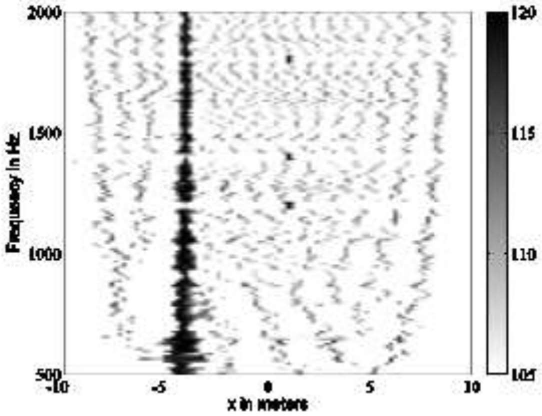



(e) SOOT

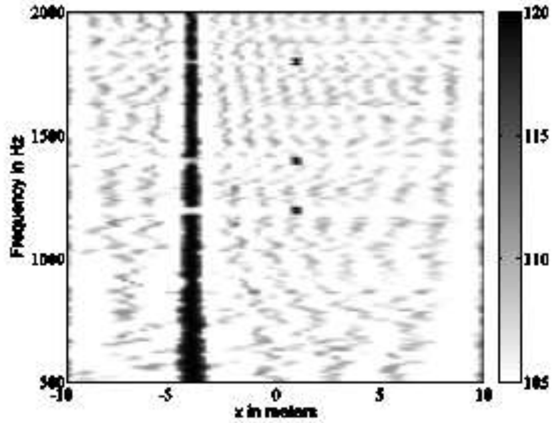
*Fig. 4. Beamforming MS result (a) and its deconvolution results with 4 methods (b,c,d,e) for 2 moving sources at 2 m/s without noise .*



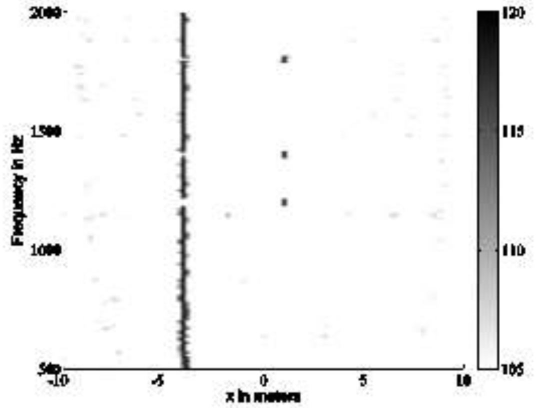

(f) beamforming-MS



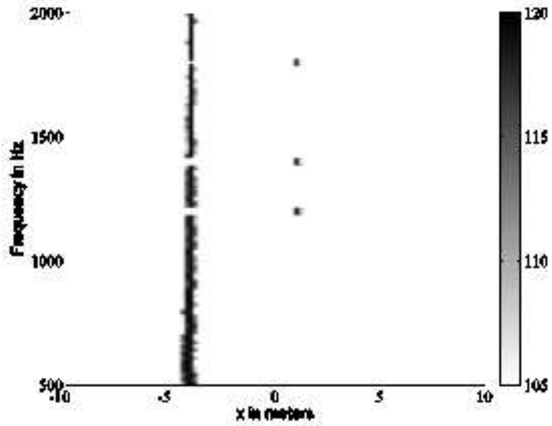

(g) DAMAS




(h) SDM




(i) VMF-B




(j) SOOT

*Fig. 5. Beamforming MS result (f) and its deconvolution results with 3 methods (g,h,i,j) for 2 moving sources at 2 m/s with -5 dB SNR .*

In Figure 5, the same configurations are presented with higher background noise level with -5 dB SNR. The beamforming result presents a main lobes on each source but with a very bad dynamic. As a consequence, this background noise power is distributed on ghost sources during the deconvolution with the least square solutions (DAMAS-MS and SDM). Few alarms appear with VMF-B and SOOT proves in this very hard environment its robustness with very good results.

## 5 CONCLUSIONS

This paper presents 4 deconvolutions method adapted to beamforming for moving sources. They have been applied in the specific environment of underwater pass-by testing with simulated data. Some assumptions have been made in this specific context with uncorrelated sources, and uncorrelated noise, low speed and constant Doppler Effect on small time window to be able to apply a simplified beamforming for moving sources in frequency domain.

The deconvolution of beamforming results permit to improve source localization in order to calculate their contribution in noise emission. 4 algorithms used on beamforming for moving sources have been presented and compared. 2 of them, DAMAS and SDM solves the inverse problem with least square solutions. It is known to be robust when the propagation model is valid and signal to noise ratio is high. The third and fourth ones, VMF-B and SOOT help to better consider error model, forcing the sparsity of the solution in both case. The SOOT blind deconvolution has proved its robustness with noisy environment.

Their application on simulated cases with true experimental set-up and the results comparison has proved their sensitivity to measurement context. Further publications will present results from true experimental data and research are ongoing to be able to also consider the signal to noise ratio as an input data that can improve the problem solution.

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