Adaptive Bayesian sparse representation for underwater acoustic signal de-noising

Mark Barnard and Wenwu Wang

Centre for Vision, Speech and Signal Processing, University of Surrey, Guildford, GU27XH, United Kingdom.
Emails: {mark.barnard; w.wang}@surrey.ac.uk

Keywords: acoustics, underwater, source separation, de-noising, source localisation

Abstract

In this paper we specifically address the problem of de-noising and localisation/separation of underwater acoustic sources. There have been a number of approaches to this problem. Here we evaluate a recently proposed adaptive sparse sequential Bayesian approach. This approach extends sparse reconstruction methods to sequential data. This is achieved by extending the classic Bayesian approach to a sequential *Maximum a Posterior* (MAP) estimation of the signal over time. A sparsity constraint is enforced through the use of a Laplacian like prior at each time step. An adaptively weighted LASSO cost function is sequentially minimised using the new measurement received at each time step. This algorithm was tested on the very challenging Portland03 dataset. This dataset was collected at Portland harbour in the UK using two linear hydrophone arrays laid on the sea floor. The target, a small fishing boat, then performed a number of transits in the harbour in various directions. This dataset is particularly challenging with a lot of noise from both natural and man-made sources. Therefore an effective method of de-noising and localisation is expected to significantly improve the results on this dataset. Our preliminary results show that the Bayesian sparse representation technique is effective in source localisation and denoising on this dataset.

1 Introduction

The problem we address here is that of using passive sonar to detect and track the direction of moving underwater targets, as can be seen in Figure 1. In passive systems one or more receiving sensors or hydrophones are used to record the ambient acoustic signal. Unlike active sonar systems there is no control over the strength of the received signal from the object we wish to track. Therefore there is a potential that a very high level of noise may be presented in the signal recorded.

One early approach to estimating the direction of arrival (DOA) of an underwater acoustic source was using time delay methods. These methods exploit the different arrival time of the acoustic wavefront at different sensors in the array. An

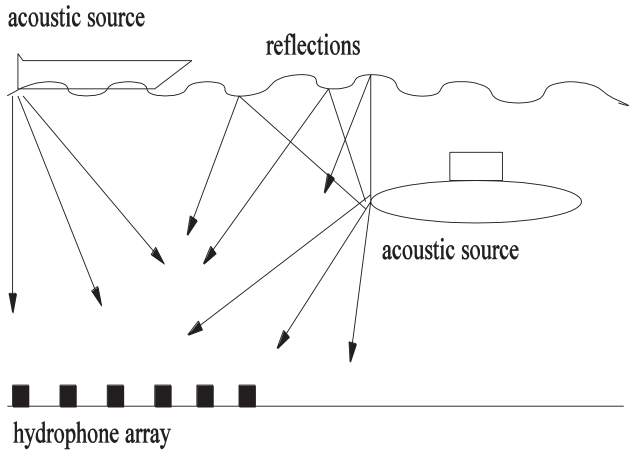


Figure 1 Underwater acoustic environment

early demonstration of this method is provided by Carter [1] and tested using a simulated linear array and also Watkins and Schevill [2]. Indeed, the use of time domain techniques in the area is still an open area of research [3].

There have been a number of approaches to the problem of de-noising and separation of underwater acoustic sources using so called spectrum based methods. Some methods rely on the specific nature of the underwater acoustic environment such as match field (MF) methods of beamforming [4]. These methods combine sophisticated acoustic models and the ocean environment to isolate narrowband and broadband signals [5]. Other more general methods of source localisation have also been used for underwater acoustic signals. These include adapting the traditional MUSIC algorithm as proposed by Wong and Zoltowski [6] and using Basis Pursuit de-noising [7]. These methods perform poorly in environments with high levels of reverberation and noise.

Here we evaluate the adaptive sparse sequential Bayesian approach proposed by Mecklenbruker et al [8], where a sequential sparse Bayesian approach is used for underwater source separation and tracking. We give an overview of this approach in the next section, which is followed by detailed description of the Portland03 dataset and finally we present experiments and results on this dataset.

2 Method

In the problem of estimating the DOA of underwater acoustic sources we have a series of Fourier transformed

measurements from our sensor array at each time step k, $\mathbf{y}_k=(y_{k1}, y_{k2}, \ldots y_{kN})$, where N is the number of sensors. We also have at each time step a vector of possible angles for the DOA $\mathbf{x}_k=(x_{k1}, x_{k2}, \ldots x_{kM})$, where M is the number of potential source directions. We also have a matrix $\mathbf{A}$ that has dimensions $N \times M$ where $N \ll M$, the m^{th} column of $\mathbf{A}$ is an steering vector for the sensor array corresponding to the m^{th} source direction in the vector $\mathbf{x}_k$. This gives us the following linear model
where $\mathbf{n}_k$ is additive noise.

$$\mathbf{y}_k=\mathbf{A}\mathbf{x}_k+\mathbf{n}_k \quad (1)$$

Given a sequence of inputs over time from the sensor array at time k we have, $\mathbf{Y}_{k-1}=(\mathbf{y}_1, \ldots \mathbf{y}_{(k-2)}, \mathbf{y}_{(k-1)})$ and the current observation $\mathbf{y}_k$. We wish to find the *Maximum a Posteriori* (MAP) estimate of $\hat{\mathbf{x}}_k$, thus providing an estimate of the DOA for a number of sources at each time step k.

The approach presented by Mecklenbruker et al [8] extends sparse reconstruction methods to sequential data. This is done by extending the classic Bayesian approach to a sequential MAP estimation of the signal over time. A sparsity constraint is enforced through the use of a Laplacian like prior at each time step. An adaptively weighted LASSO cost function is sequentially minimised using the new measurement received at each time step. A function φ is derived to give a source estimate at each time step k,

$$(\hat{\mathbf{x}}_k, \boldsymbol{\lambda}_{k+1})=\varphi(\mathbf{y}_k, \boldsymbol{\lambda}_k) \quad (2)$$

Sparsity is enforced through $\boldsymbol{\lambda}_k=(\lambda_{k1} \ldots \lambda_{kM})^T$ which is the Laplacian prior where M is the number of possible source DOAs and $\mathbf{y}_k$ is the current sensor array output.

The LASSO cost function is generalised by weighting the regularisation parameters. So the Laplacian prior can be updated based on the past history of observations. The weighted LASSO cost function, ς_k [9] to be minimised is given by

$$\zeta_k(\mathbf{x}_k)=\frac{\|(\mathbf{y}_k-\mathbf{A}\mathbf{x}_k)\|_2^2}{\sigma^2}+\mu \sum_{m=1}^{M} w_{km}|x_{km}| \quad (3)$$

where σ^2 is the noise variance, $\mathbf{w}_k$ is a vector of weighting coefficients of length M and μ is a parameter that controls the level of sparsity of the estimates $\mathbf{x}_k$. The parameter μ and the adaptive weight vector $\mathbf{w}_k$ are related through the Laplacian like prior given by

$$\boldsymbol{\lambda}_k=\mu\mathbf{w}_k \quad (4)$$

Full details of the algorithm can be found in Mecklenbruker et al [8] and Panahi and Viberg [9].

3 Dataset

Here we present results on the Portland03 dataset. This data was collected at Portland harbour on the South coast of England in December 2003[1]. The recordings were made with two parallel 32 element hydrophone arrays. The target source in this data set is a small fishing vessel. In the first set of recordings the vessel transits a number of times broadside to the arrays, tracks T1-T5 (Sequence 1), then in the second set of recordings the vessel transits end-fire to the linear arrays, tracks T8-T9 (Sequence 2). The engines of the vessel were turned off between tracks, so there are portions of the data where the target acoustic source is not present. Additionally Sequence 2 consists of only two tracks end on to the array, as shown in Figure 2, recording was halted some time after a large ocean going vessel entered the harbour, the track of this vessel can be seen in the data. Sequence 1 is approximately 3300 seconds long and Sequence 2 is approximately 2400 seconds long.

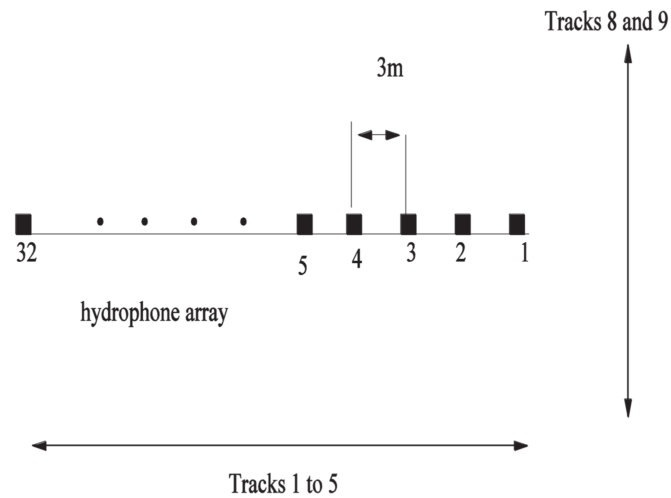


Figure 2: Layout of the hydrophone array and tracks of the target vessel.

The sensors in the arrays were placed at equally spaced 3m intervals on the sea floor. In practice the data from only one array was used as two hydrophones failed on the other array. On the array that was used only 31 of the sensors were used as the first sensor in the array failed, however the remaining 31 sensors could be used and preserve the equal spacing

[1] This dataset was provided by the Defence Science and Technology Laboratory of the UK and permission has been obtained with respect to the publication of the results obtained on this dataset as presented in this paper

constraint of the sensors in the array. The design frequency of the array is 240 Hz and the data was sampled at 2604.17 Hz.

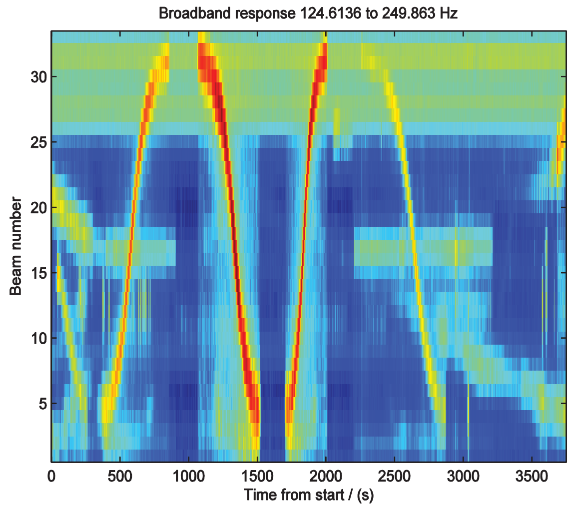
4 Experiments and Results

We evaluate the performance of the sequential sparse Bayesian algorithm proposed by Mecklenbruker et al [8] outlined in Section 2 on the Portland03 dataset described in the previous section. The original time domain data was transformed into the frequency domain by using a Fast Fourier Transform (FFT) with a window size of 128 and an overlap between successive windows of 25%. We only processed the first 2750 seconds of Sequence 1 due to time constraints and the fact that there is little activity in the sequence after this point. This produced two sequences of 220000 and 196500 data samples for Sequence 1 and Sequence 2, respectively.

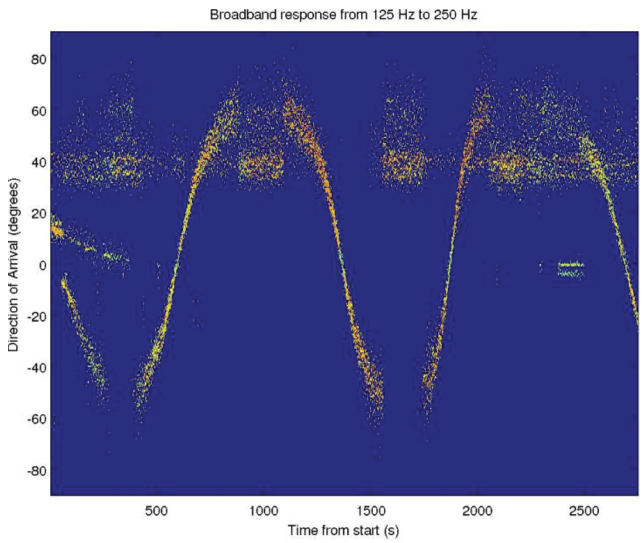
In our first set of experiments we set the parameter μ in Equation 3, that controls the level of sparsity in the output vector, $\mathbf{x}_k$, to two. This enforces the constraint that the maximum number of non-zero entries, i.e. possible target DOAs, in $\mathbf{x}_k$ is two. This was done due to the prior knowledge that there should be only one acoustic source of interest in the data.

In Figure 3 and Figure 4 we show the overall broadband response for Sequence 1 and 2, respectively, as the array of hydrophones is steered through 33 beam angles. This provides a reference for comparison with our source localisation and de-noising results. In Figure 3, we show our results from 125 Hz to 250 Hz for Sequence 1, it can clearly be seen that the DOA of the target acoustic source is accurately localised and tracked through most of the sequence. There is a stationary noise source in the data at approximately +40 degrees and at a number of places in the sequence when we track this source, however this is always between the tracks (at approximately 300 sec, 1000 sec, 1600 sec and 2200 sec) when the engine of the target vessel was turned off. It can also be seen that the angular resolution of the DOA estimate is most accurate when the target source is directly abeam of the array in the middle of each track.

In Figure 4 we show our results for Sequence 2. It can be seen these are far less clear than for Sequence 1. There are a number of possible reasons for this, tracks 8 and 9 are end-fire to the array as shown in Figure 2, so accurately resolving the DOA is more challenging and also it can be seen in Figure 4 that the signal energy of the target source is much lower than in Sequence 1. At approximately 1700 seconds the large vessel enters the harbour and it can be seen that we accurately track the DOA of this source.

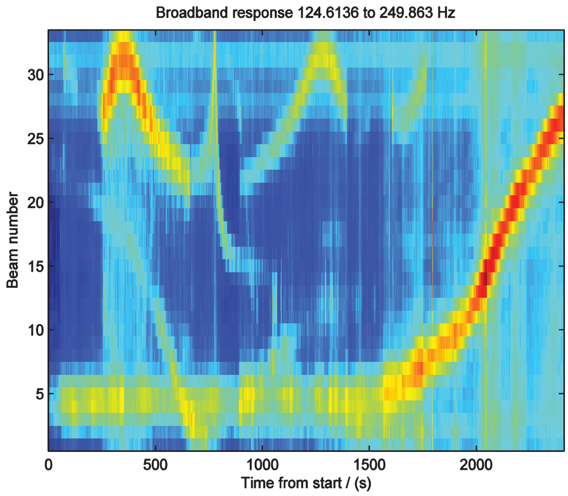


(a) Broadband response from sensor array

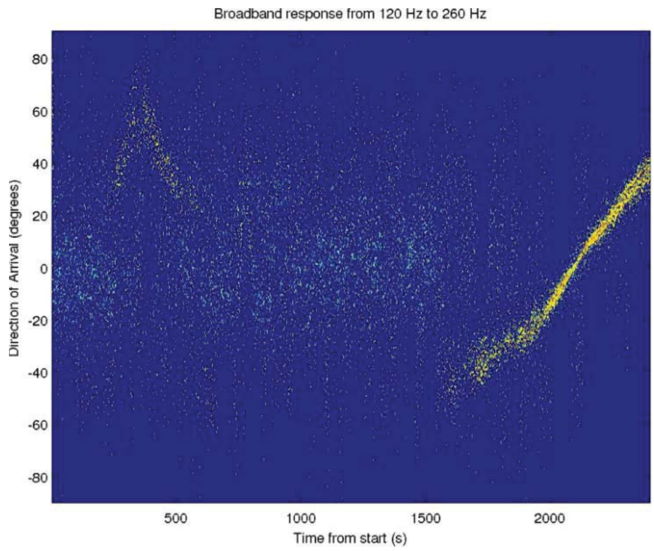


(b) Broadband beamforming results

Figure 3: The broadband response from the array as compared to the broadband localisation and de-noising results for Sequence 1.



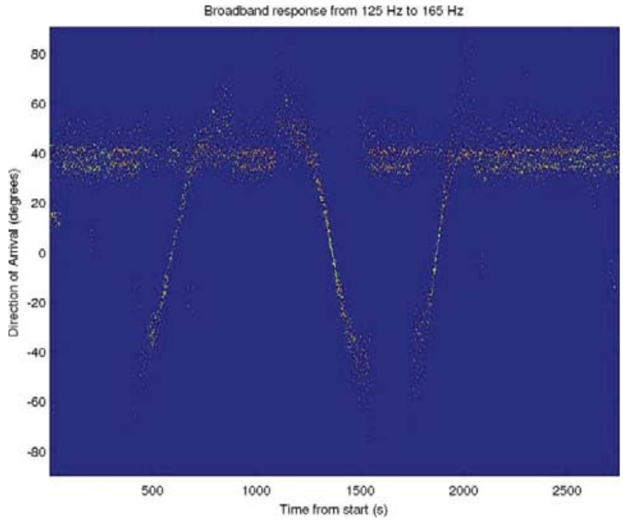
(a) Broadband response from sensor array



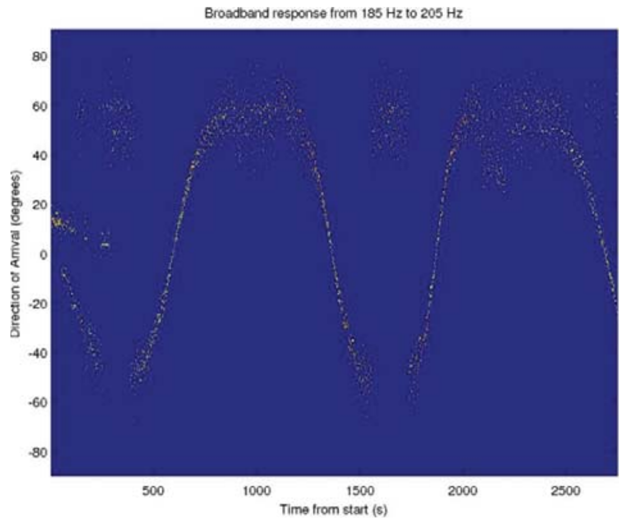
(b) Broadband beamforming results

Figure 4: The broadband response from the array as compared to the broadband localisation and de-noising results for Sequence 2.

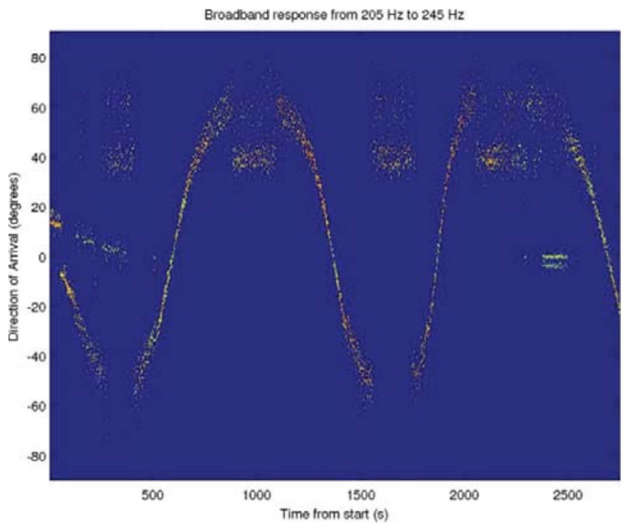
In order to investigate the performance within different frequency bands Figure 5 shows our results for Sequence 1 on three different frequency bands. Figure 5(a) shows results for the lower frequency band 125 Hz to 165 Hz it shows the tracking does not perform as well in this frequency band and also the stationary noise source with a DOA of +40 degrees is more dominant at these frequencies. It can clearly be seen in Figure 5(b) and Figure 5(c) that as the frequency increases the accuracy of the tracking improves and the effect of the stationary noise source is decreased.



(a) Results in band 125 Hz to 165 Hz



(b) Results in band 165 Hz to 205 Hz



(c) Results in band 205 Hz to 245 Hz

Figure 5: Beamforming results for each frequency band.

In a final set of experiments we look at the effect of decreasing the sparsity of $\mathbf{x}_k$ by increasing the value of the parameter μ from two to four, thus increasing the number of potential target sources to four. However, as the sparsity level is reduced the computational cost increases making it prohibitive to run on such long sequences, so only Sequence 1 was used in this experiment. The result of increasing the number of potential sources is shown in Figure 6, the increased amount of noise in the result can clearly be seen. This shows the advantage of applying sparsity in the estimation, however some prior knowledge about the number of sources is required in order to select the optimal level of sparsity.

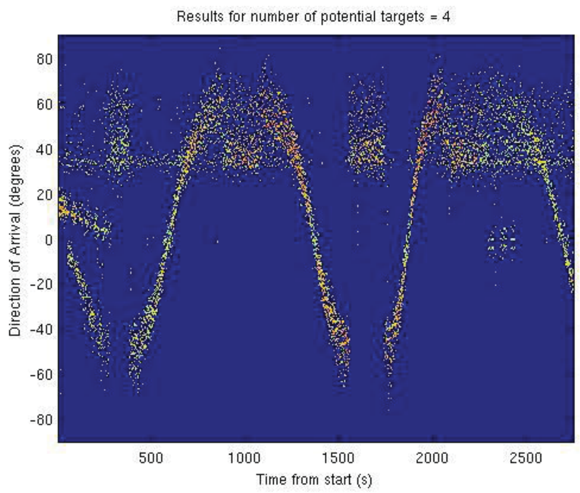


Figure 6: Beamforming results for Sequence 1 with sparsity parameter set to four.

5 Conclusion

We have demonstrated that an adaptive Bayesian sparse representation can be used to accurately estimate and track the DOA of underwater acoustic sources. We have shown results on the real and very challenging Portland03 dataset, which was collected in a working harbour using a boat as a moving target source. The results of these experiments show that imposing a sparsity constraint on the DOA can greatly reduce the amount of unwanted noise in the final result.

Acknowledgements

This work was supported by the Engineering and Physical Sciences Research Council (EPSRC) Grant number EP/K014307/1 and the MOD University Defence Research Collaboration in Signal Processing.

References

[1] G. C. Carter, "Time delay estimation for passive sonar signal processing," *IEEE Transactions on Acoustics, Speech and Signal Processing*, vol. 29, no. 3, pp. 463–470, June 1981.

[2] W. A. Watkins and W. E. Schevill, "Sound source location by arrival-times on a non-rigid three-dimensional hydrophone array," *Deep Sea Research and Oceanographic Abstracts*, vol. 19, no. 10, pp. 691 – 706, 1972.

[3] W. Fan, X. Zhang, and B. Jiang, "A new passive sonar bearing estimation algorithm combined with blind source separation," in *IEEE Third International Joint Conference on Computational Science and Optimization (CSO)*, 2010, vol. 1, pp. 15–18.

[4] A.B. Baggeroer, W.A. Kuperman, and P.N. Mikhalevsky, "An overview of matched field methods in ocean acoustics," *IEEE Journal of Oceanic Engineering*, vol. 18, no. 4, pp. 401–424, Oct 1993.

[5] H. P. Bucker, "Use of calculated sound fields and matched field detection to locate sound sources in shallow water," *The Journal of the Acoustical Society of America*, vol. 59, no. 2, pp. 368–373, 1976.

[6] K. T. Wong and M. D. Zoltowski, "Self-initiating music-based direction finding in underwater particle velocity-field beamspace," *IEEE Journal of Oceanic Engineering*, vol. 25, no. 2, pp. 262–273, 2000.

[7] C. Liu, Y. V. Zakharov, and T. Chen, "Broadband underwater localization of multiple sources using basis pursuit de-noising," *IEEE Transactions on Signal Processing*, vol. 60, no. 4, pp. 1708–1717, 2012.

[8] C. Mecklenbruker, P. Gerstoft, A. Panahi, and M. Viberg, "Sequential bayesian sparse signal reconstruction using array data," *IEEE Transactions on Signal Processing*, vol. 61, no. 24, pp. 6344–6354, 2013.

[9] A. Panahi and M. Viberg, "Fast candidate points selection in the lasso path," *IEEE Signal Processing Letters*, vol. 19, no. 2, pp. 79–82, 2012.