UNDERWATER ACOUSTIC CHANNEL ESTIMATION USING STRUCTURED SPARSITY

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Abstract: *A novel framework for collaborative estimation of multiple underwater acoustic (UWA) communication channels, considering the high correlation of received signals in a linear hydrophone array, is developed and evaluated. Throughout this work, the channel is assumed to be a time-variant linear system and is represented by its 3D delay-Doppler-depth function (DDDF), an extension of the 1D impulse response of LTI systems. To jointly estimate the DDDF coefficients for all hydrophones in a linear receiver array, sparse estimation techniques such as Orthogonal Matching Pursuit (OMP) and Basis Pursuit (BP) are used. A new structured dictionary matrix is introduced to encompass the linear structure of energetic parts of the DDDF corresponding to wavefronts impinging upon the array. The over-complete structured dictionary is built by concatenating small blocks, each defining a candidate wavefront in the 3D DDDF image. Blocks are swept according to a grid of slopes, delay and Doppler shifts. To reduce the problem size and increase the performance, lines are replaced by Gaussian tubes in the structured dictionary. These can accommodate wavefronts that deviate slightly from the linear assumption. For near-field scenarios where wavefronts are more markedly nonlinear, an additional step is applied to fully retrieve the evolution pattern in the DDDF by solving a fast BP problem with narrow delay/Doppler support. The collaborative framework makes it possible to leverage the spatial dimension to detect arrival patterns across the array whose estimation would be too unreliable based on a single hydrophone, while retaining reasonable computational complexity. The practical feasibility of the developed schemes is assessed for various channel configurations using both simulations and experimental data collected during the CALCOM'10 sea trial in Faro, Portugal, 2010.*

Keywords: *Underwater Acoustic Communication, Channel Estimation, Structured Sparsity, Group Matching Pursuit, Basis Pursuit, Delay Doppler Depth Function (DDDF)*

1. INTRODUCTION

Time-varying channel responses may be modeled by (2D) Delay-Doppler Spread Functions (DDSF), a generalization of the concept of time-invariant channel impulse response to the time-frequency plane that introduces a Doppler dimension [1]. The received signal is considered as a sum of replicas of the transmitted signal, each associated with a given delay and Doppler shift that are assumed persistent over an averaging span [2]. Nearly all DDSFs of practical UWA are sparse with most of the energy localized in several small regions [2]. Exploiting sparsity is a key insight for attaining a generic delay-Doppler representation of underwater channels with manageable complexity using sparse estimation methods.

This work presents a framework for identifying UWA time-varying channels using a 3D delay-Doppler-depth function (DDDF). Fig. 2a shows thresholded coefficients of a DDDF in a volumetric plot which may be viewed as the spatio-temporal "skeleton" of the acoustic field, comprising several wavefronts that impinge upon a receiver array, after interacting with the surface and/or bottom. Such functions are represented by a potentially large set of coefficients, but sparsity ensures that most of them are zero, except for a small subset that explains how the observed channel outputs are produced from an input signal.

The main contribution of this work is developing collaborative approaches for channel estimation of multiple UWA communication links, focusing on high correlation of received signals in a linear array. Orthogonal Matching Pursuit (OMP) and Basis Pursuit (BP) are used to jointly estimate the DDDF coefficients for all hydrophones. A new concept for building the over-complete dictionary matrix is presented to leverage the linear structure of energetic parts of the DDDF corresponding to wavefronts impinging upon the array. In addition to fast channel estimation, this approach detects the key "skeleton" of the acoustic field contained in DDDFs and contributes to improve the robustness of subsequent detection algorithms that utilize that structure.

2. TIME-VARYING CHANNEL MODEL

A sampled baseband representation of a time-varying channel, for the transmitted signal, *x(n)*, and the received signal, *y(n)*, is adopted with the following discrete-time input-output model,

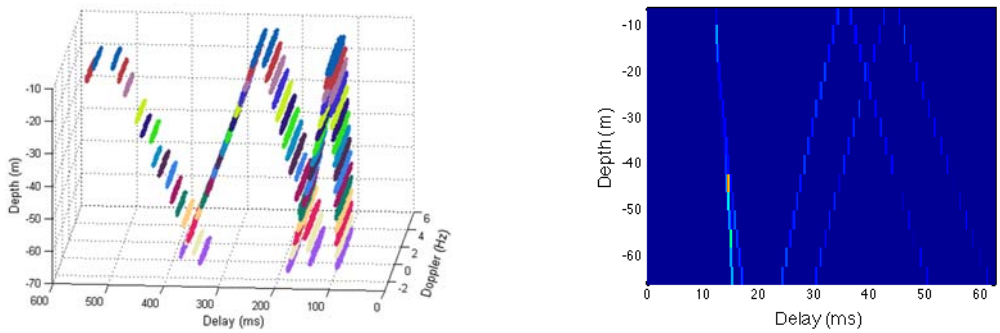
$$y(n) = \sum_{k,l} u_{k,l} x_l(n-k), \qquad x_l(n) = x(n) e^{j2\pi \upsilon_l n}, \tag{1}$$

where the sampling frequency, f_s, is a multiple of the input signal bandwidth and $\upsilon_l = l/(Tf_s)$ for an input block of duration T. The DDSF, whose samples $u_{k,l}$ appear in (1), is the Fourier transform of the channel impulse response along the time variable. In a multipath channel the (continuous) DDSF comprises a set of impulses in delay-Doppler,

$$U(\tau,\upsilon) = \sum_{p=1}^{N_p} \alpha_p \delta(\tau - \tau_p)\delta(\upsilon - \upsilon_p). \tag{2}$$

The channel model (1) is linear in the DDSF coefficients, and may be written in matrix form as **y** = **Xu**, where **y** denotes a vector of M observed samples, **u** holds the DDSF

coefficients to be determined, and **X** is the known dictionary matrix. To address the collaborative channel estimation problem, the channel model is represented as **Y** = **XU**, where **Y** and **U** are, respectively, the matrix of *M* received samples and the matrix of unknown DDSF coefficients for all hydrophones.



(a) (b)

Fig. 1: (a) A sample Delay-Doppler-Depth Function (DDDF) for an array of 16 hydrophones with equal spacing. (b) Arrival time delay vs. hydrophone depth.

2.1. Individual Channel Estimation Through Basis Pursuit Methods

Basis Pursuit (BP) techniques are used to find sparse approximate solutions to large underdetermined linear systems of equations. According to the original BP principle, a signal is decomposed into a superposition of highly redundant dictionary signals, and an optimal set of weights is found such that the resulting coefficient vector has minimum l_1 norm. Among several variations of BP that have been proposed [3], we are mainly interested in solving unconstrained l_2-l_1 optimization problems of the form

$$\min_{\mathbf{u}} \frac{1}{2}\|\mathbf{y}-\mathbf{X}\mathbf{u}\|_2^2 + \tau\|\mathbf{u}\|_1, \tag{3}$$

where the first term measures how well the candidate solution fits the observed data while the second one acts as a regularizer for setting zero for small coefficients. The regularization parameter τ controls the relative weight of the two terms.

Sparse Reconstruction by Separable Approximation (SpaRSA) and Two-step Iterative Shrinkage/Thresholding (TwIST) [4] are two elegant methods for solving unconstrained l_2-l_1 optimization problems with complex variables and data [5].

3. STRUCTURED CHANNEL ESTIMATION

Matching Pursuit iteratively decomposes a signal into a linear expansion of waveforms that are selected from a redundant dictionary. Both MP and OMP sequentially select dominant taps of the DDSF that maximize the projection of the residual observation vector onto the corresponding symbol vector and then calculate tap coefficients. The difference is that MP calculates each tap coefficient directly from the projection, while OMP derives a joint LS solution for the coefficients of all the selected taps [2].

To jointly estimate the DDSF for all hydrophones in the receiver array, a new Group Matching Pursuit approach is introduced. This is more efficient and accurate than independently processing each hydrophone in the array to obtain the set of (correlated)

channel estimates. In this scheme the structured dictionary matrix encompasses the linear structure of energetic parts of the DDDF corresponding to wavefronts impinging upon the array (see Fig. 1). As Fig. 2 illustrates, the over-complete structured dictionary, *D*, is built by concatenating small blocks, each defining a candidate wavefront in the 3D DDDF image. Blocks are swept according to a grid of slopes, delay and Doppler shifts. To reduce the problem size and increase the performance, lines are replaced by Gaussian tubes in the structured dictionary. These can accommodate wavefronts that deviate slightly from the linear assumption.

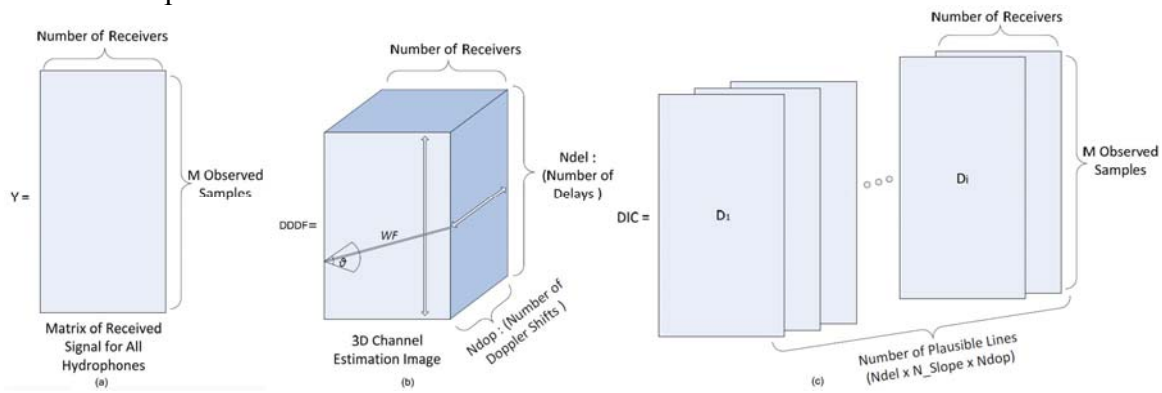


Fig. 2: (a) Matrix of M observed samples for all hydrophones. (b) 3D delay-Doppler-depth matrix. (c) Structured dictionary matrix

The proposed joint channel estimation technique consists of two main steps. At each iteration, the first step detects the active wavefront from the structured dictionary matrix ***D*** that correlates best with the approximation residual from the previous iteration, $\boldsymbol{R}_{t-1}$,

$$p_t = \arg\max_{s \notin I_{t-1}} \frac{\left| D_s^H R_{t-1} \right|^2}{\left\| D_s \right\|_2^2}, \tag{4}$$

where I_{t-1} is the index set of all previously selected blocks. The initial residual is the observation vector, $\boldsymbol{R}_0 = \boldsymbol{Y}$. At each iteration, the residual matrix, ***R***, is built by attaching the residual vectors, *r*, computed for each receiver. When the same structured dictionary matrix is repeatedly applied to different observation vectors, the online computation of inner products can be eliminated by precomputing a table with all inner products with blocks of the dictionary matrix. Estimation of the unknown coefficients is done in the second step of this *Group Matching Pursuit* (GMP) approach. For near-field scenarios where wavefronts are more markedly nonlinear, an alternative step is applied to fully retrieve the evolution pattern in the DDDF by solving a fast BP/OMP problem with narrow delay/Doppler support, defined by a local over-complete dictionary matrix for each receiver. This is termed here *Group Matching/Basis Pursuit* (GMBP).

The stopping criterion can be based on evaluating p_t at each iteration, comparing to p_0 for the first selected wavefront. The whole proposed collaborative channel estimation scheme can be summarized as follow:

1. Initialize $\boldsymbol{R}_0 = \boldsymbol{Y}$
2. Select a block from the structured dictionary matrix as in (4)
3. Estimate the coefficients for each hydrophone using narrow delay/Doppler support applying the BP method as described in section 2.1 with local dictionary matrix X_l.
4. Update $I_t = I_{t-1} \cup p$ and $r_t = r_{t-1} - X_l u_p$ for each receiver.

5. If the stopping criterion is not met go to the 2nd step

In [6] a robust approach is presented to deal with wavefront classification and assign the appropriate number of surface and bottom bounces to a propagation path detected in the 3D channel response, considering possible omission or duplication of some paths.

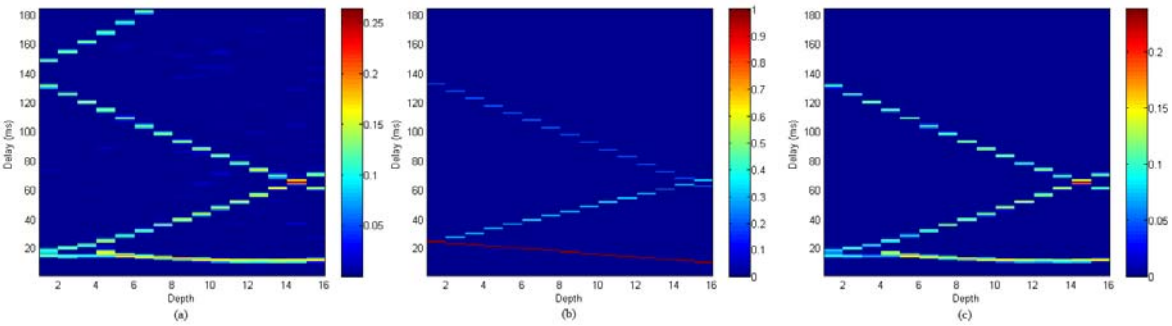


Fig. 3: Simulation results on channel estimation. (a) Individual channel estimation using BP methods (TwIST). (b) Group Matching Pursuit (GMP). (c) Group Matching/Basis Pursuit (GMBP).

4. PERFORMANCE ASSESSMENT

Performance evaluation of the collaborative estimation of sparse DDDF in single-carrier (QPSK) transmissions over simulated and real underwater channels is presented in this section.

Simulation results are obtained using an underwater acoustic simulator developed by the University of Algarve. The transmission uses 5.5 kHz carrier frequency, 4.5 kHz bandwidth, root-raised-cosine (RRC) pulse shapes, and total duration 1 s. The baseband received signal is sampled at 4 times the symbol rate, f_s=12 kHz.

Fig. 3 shows the DDDF estimation results for this channel using simulated data. Comparing to individual channel estimation presented in Fig. 3.a it is seen that both structured sparsity techniques detect the major structure of the DDDF. However, GMBP provides better channel estimates than GMP.

The experimental results are based on data collected during the CALCOM'10 sea trial which was conducted south of Faro, Portugal, on June 2010. The receiver was a vertical drifting array with 16 uniformly-spaced hydrophones from 6 m to 66 m depth and the source was attached to the boat at 10 m depth. We focus on QPSK packets at 5.6 kbit/s, with 4.5 kHz bandwidth, 5.5 kHz carrier frequency (refer to [6] for more details).

As the experimental channel estimation results of Fig. 4 illustrate, GMBP (Fig. 4.b) captures the effective support region for the DDDF reasonably well. In this case, due to the high noise level in the experimental data, GMBP fails to detect the topmost wavefront shown in Fig.4.a. Also due to the same noise issue in practical situations, GMP was found to provide poor performance for collaborative channel estimation in CALCOM’10 data.

5. CONCLUSION

This work addresses the problem of collaborative channel estimation of multiple underwater acoustic (UWA) communication channels in a linear receiver array, applying sparse estimation techniques such as Orthogonal Matching Pursuit (OMP) and Basis Pursuit (BP).

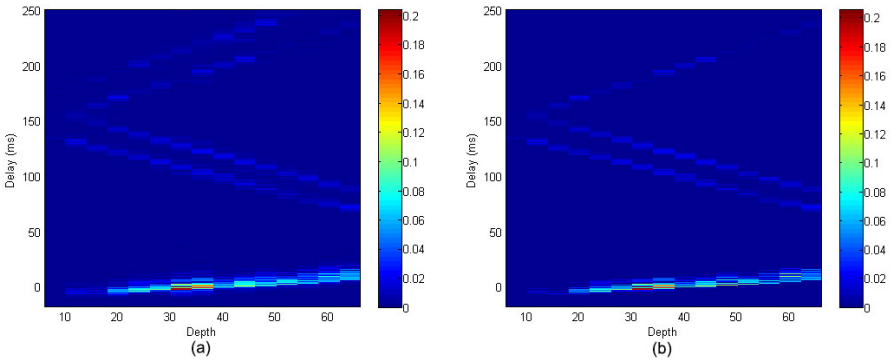


Fig. 4: Channel estimation results using experimental data. (a) Individual channel estimation using BP methods (TwIST). (b) Group Matching/Basis Pursuit (GMBP).

Comparing to individual channel estimation, the presented collaborative scheme makes it possible to leverage the spatial dimension to detect arrival patterns across the array whose estimation would be too unreliable based on a single hydrophone, while retaining reasonable computational complexity.

Using both simulated and real data, the performance of the developed collaborative channel estimation approach is compared to the individual Basis Pursuit approach which has been proposed previously for similar purposes. Not only does this approach lead to fast channel estimation, but the induced structured sparseness also detects the "skeleton" of the acoustic field contained in DDDFs and thereby contributes to improve the robustness of subsequent detection and estimation algorithms that exploit that structure.

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