Tracking the underwater acoustic channel using two-dimensional frequency sampling

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***Abstract*—Rapidly fluctuating multipath arrivals along with unpredictable surface wave focusing events render the shallow water acoustic channel difficult to track using sparse or least-squared error (LSE) optimization techniques. This fundamental bottleneck is primarily due to the time-varying nature of the underlying distribution. In this work, we propose a complementary channel tracking technique that exploits the dual representation of the acoustic channel in the Fourier domain and employs two-dimensional frequency sampling using an application-inspired input dictionary. Specifically, we reformulate the time-varying channel tracking problem on a MIMO framework and design training symbols that sample the channel in its dual Fourier domain. Ground truths based on experimental field data are presented.**

Keywords—underwater acoustics; Doppler; channel estimation.

I. INTRODUCTION

The fundamental bottleneck in undersea acoustic communications and sonar target detection is tracking and compensating for the rapidly fluctuating shallow water acoustic channel impulse response. Multipath arrivals from the transmitter to the receiver undergo non-stationary reflections at the moving sea surface and rough sea bottom [1,2]. Moreover, surface focusing events lead to unpredictable surges of energy in secondary delay taps [3], which are challenging to predict or compensate for. Figure 1 shows the channel impulse response as a function of time for a shallow water acoustic channel over experimental field data collected at 15 meters depth and 200 meters range over moderate to rough sea conditions. Delay refers to the delay taps constituting the channel impulse response at a given point in time point on the x-axis. We note that there are two bands of interference besides the direct arrival: (i) the primary multipath interference dominated by single surface reflections, and (ii) secondary multipath interference dominated by multiple bounce reflections between moving sea surface and rough sea bottom. Additionally, sparsely distributed high-energy events such as surface wave focusing render tracking the dynamic shallow water channel exceptionally difficult.

Sparse sensing techniques (see e.g. [4-13]) for tracking sparse phenomena has largely met with limited success in the undersea paradigm because of three related challenges: (i) the underlying energy distribution among the delay taps is non-stationary, (ii) sparsity of the distribution itself fluctuates over time [5], and (iii) the build-up to high-energy events, which may involve smaller components, gets suppressed by sparse optimization techniques, and often contain crucial information that classify and thereby, identify and compensate for high-energy events.

In this work, we propose a complementary approach to the acoustic communications and sparse sensing literature. We formulate the underwater channel estimation problem as a spectral sampling problem in the dual domain to the delay spread versus time representation in Figure 1. This dual representation has been investigated as the Delay-Doppler spread function and well-known to follow a banded sparse representation [13,14]. We extend the Delay-Doppler representation, which only considers the Fourier transform of the delay spread to consider the two-way Fourier transform in delay and time. This novel representation allows designing suitable input signal dictionaries for MIMO transmission and signaling recovery. Depending on context, we will use the terms delay spread and channel impulse response interchangeably in this work.

II. CHALLENGES TO APPROPRIATE BASIS SELECTION

Selecting a basis representation to track the non-stationary channel delay spread is an open challenge in shallow water acoustics. The unpredictable nature of high-energy focusing events, as well as the rapidly fluctuating channel delay spread due to non-stationary multipath evolution renders most adaptive representations ineffective for successful channel tracking. For example, wavelet representations fall short of sufficient representation due to the unpredictable distribution of oceanographic phenomena [3]. Figure 2 illustrates the time-frequency representation of the same channel shown over two different observation window lengths: (i) 1.5 seconds, and (ii) 7.63 seconds. Each window captures the shallow water acoustic channel over a quasi-stationary time-frequency window, commonly referred to in the acoustics literature as the Delay-Doppler spread function [1, 2, 4]. Delay-Doppler spread function is the one-dimensional Fourier transform of the Delay-Time channel representation (Figure 1a) across the time domain (x-axis). The direct arrival manifests as the bright dot at the bottom and the two multipath bands generally manifest as sparse clouds of energy in the Delay-Doppler representation.

From Figure 2, we note that the longer observation window, having more observed samples, shows higher

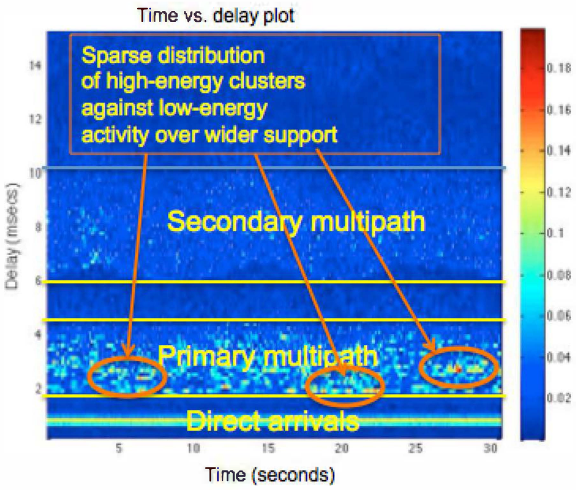

Figure 1(a): Delay vs. time plot

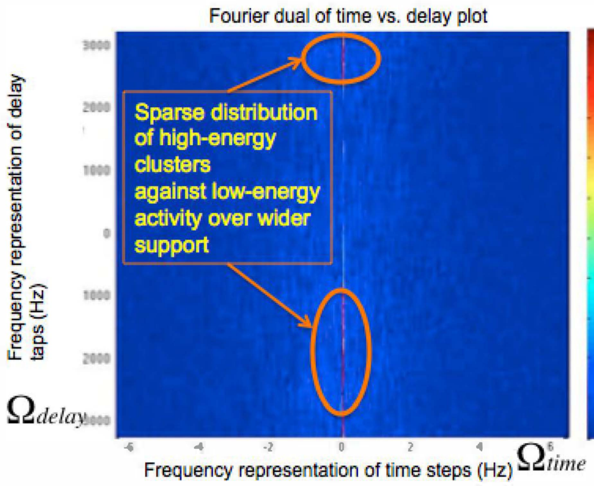

Figure 2

Figure 1(b): Dual representation of Figure-1

Figure-1(a) and Figure-1(b) correspond to an underwater acoustic channel over experimental field data collected at 15 meters depth, 200 meters range, at moderate to rough sea conditions (Data courtesy: Dr. James Preisig, Woods Hole Oceanographic Institution).

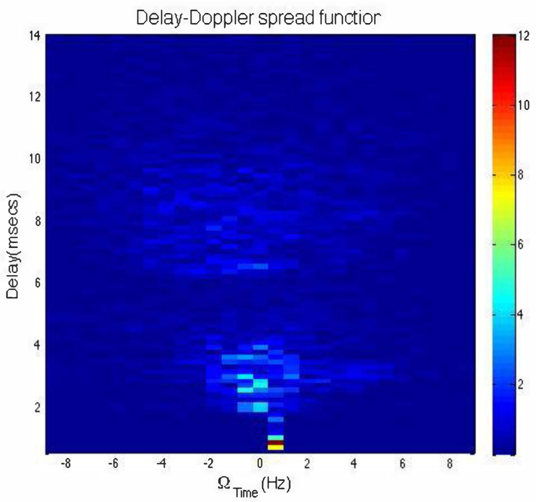

Figure 2(a): Delay-Doppler spread function of underwater channel estimated over an observation window of 1.5 seconds

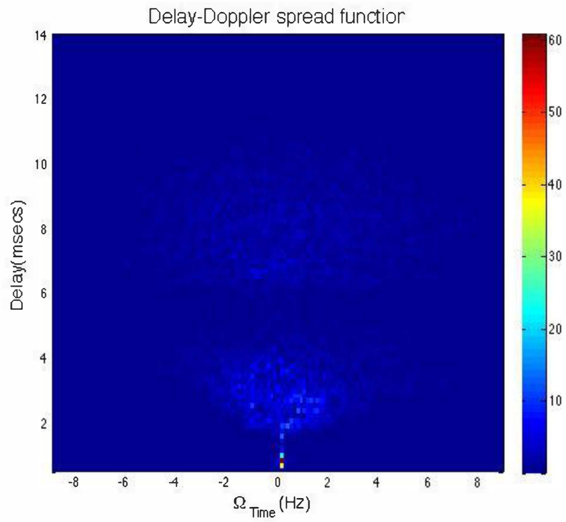

Figure 2(b): Delay-Doppler spread function of underwater channel estimated over an observation window of 7.63 seconds.

resolution. Moreover, the two different windows will exhibit different degrees of sparsity as different aspects of the time-varying channel get localized.

Resolution issues may be fixed by sampling more densely over the shorter observation window. However, choosing one window over the other leads to focusing on either the more transient aspects of the channel, e.g. the high-energy activity in the primary multipath band in figure 2(a) or the relatively steady components of the channel delay spread centered around the main arrival (bright spot at the bottom) and the time-averaged activity over the primary and secondary multipath bands. From an acoustic communications perspective, both these feature types are important to localize, as they carry information on key aspects of the channel. However, due to the uncertain nature of oceanographic reflections, it is hard to predict where the transient activity might occur, and if so, how frequently and for how long.

Moreover, as explored in [14] the underlying sparsity of the channel itself may vary over time. This indicates that incoherence criteria for precise reconstruction [7] need to be adaptive over time as the observed channel changes. The intricate interplay between time-frequency localization and observed sparsity as well as its implications on measuring the actual sparsity are explored in more detail in [14] and outside the scope of this work. Local time-frequency sampling has been recently investigated in the sonar target detection literature [16] but have been largely unexplored in underwater acoustic communications.

III. TECHNICAL APPROACH

The key idea behind our approach is to setup the channel estimation problem as a spectral sampling problem in the two-dimensional space where each dimension represents the Fourier dual of delay spread and time as illustrated in Figure 1(b). Let us consider the MIMO framework where input signal is a complex exponential $x[i,f_k]=e^{j\frac{2\pi i f_k}{K}}$, sampling K possible delay frequencies $\{f_k\}_{k=0}^{K-1}$ across parallel sub-channels. These K sub-channels may be easily designed in baseband using appropriate frequency selective techniques. Let us further assume a granularity of L Doppler frequencies $\{f_l\}_{l=0}^{L-1}$ for sampling the channel in the Doppler domain (dual to time domain). Therefore, if we model the channel impulse response to have K delays and L Doppler frequencies, then the received signal $y[i, f_k]$ at time instant i in sub-channel f_k is given as:

$$\begin{aligned} y[i, f_k] &= \sum_{k=0}^{K-1} h[i,k]x[i-k], \\ &= \sum_{k=0}^{K-1} h[i,k] e^{j\frac{2\pi(i-k)f_k}{K}}, \\ &= e^{j\frac{2\pi.i.f_k}{K}} \sum_{k=0}^{K-1} h[i,k] e^{\frac{-j2\pi.k.f_k}{K}} \end{aligned} \tag{1}$$

where is the K-tap length time-varying channel specified at different time instants i. We can rewrite equation (1) as below:

$$Y[i, f_k] = y[i, f_k] e^{-j\frac{2\pi.i.f_k}{K}} = \sum_{k=0}^{K-1} h[i,k] e^{\frac{-j2\pi.k.f_k}{K}} \tag{2}$$

On performing the 1-dimensional Fourier transform along the first dimension (corresponding to the time variable i), we obtain

$$U[f_l, f_k] = \sum_{k=0}^{K-1} \sum_{f_l=0}^{L-1} h[i,k] e^{\frac{-j2\pi.i.f_l}{L}} e^{\frac{-j2\pi.k.f_k}{K}} \tag{3}$$

Thus, we stack the received signal across an L-length observation window to set up an L x K observation matrix $\mathbf{Y}$, where the column k of $\mathbf{Y}$ consists of modified (as in (2)) L temporal observations received through sub-channel k. On performing one-dimensional Fourier transform of $\mathbf{Y}$ across the first dimension, we obtain the estimate of $U[f_l, f_k]$. The two-dimensional inverse Fourier transform of this will yield the channel estimate $h[i,k]$.

In the case of noise free scenario, this will yield perfect channel recovery. In the noisy scenario, the problem can be modeled as below:

$$\mathbf{U} = \mathbf{FH} + \mathbf{N} \tag{4}$$

where $\mathbf{U}$ is the matrix representation of $U[f_l,f_k]$, $\mathbf{H}$ is the matrix representation of $h[i,k]$, $\mathbf{F}$ is the two-dimensional Fourier transform operator, and $\mathbf{N}$ is the complex white Gaussian noise matrix. Since the channel $\mathbf{H}$ is sparse, the problem can be formulated as BPDN (Basis Pursuit Denoising) problem [16] and mathematically given by:

$$\min \|\mathbf{H}\|_1 \quad \text{subject to: } \|\mathbf{U}\text{-}\mathbf{FH}\| \le \sigma \tag{5}$$

where $\|\mathbf{z}\|_1$ denotes the sum of the absolute values of the vector $\mathbf{z}$, $\|\mathbf{z}\|$ denotes the l^2 norm of vector $\mathbf{z}$, and σ is the standard deviation or the measure of the noise level. The problem can be solved with the MATLAB solver SPGL1, which can be downloaded from [17].

The advantage to this approach is that no feedback is needed between the transmitter and the receiver. In addition to the above, one may employ prior knowledge of acoustic physics to densely sample in the region where we expect more oceanographic activity. Such physical constraints were considered in related research on mixed norm optimization [13]. The input signal dictionary can be designed to detect more activity around the direct arrival and primary band, with loose sampling along the secondary band and sparse sampling elsewhere.

IV. Results

In this section, we present results on the Delay-Doppler spread and its dual based on channel estimates [4] derived from experimental field data collected using BPSK-signaling (fig-1).

We provide (Figure 3) a representative channel estimate employing non-convex mixed norm optimization [4] as the kernel solver to sample the non-stationary channel at several points in time spaced 23 milliseconds (approximately one channel length). We note that despite similar bands of activity there is noticeable distinction between the four temporal snapshots. We also note that despite areas of high activity, the channel itself is not very sparse, but nonetheless exhibits significant spikes that dominate over lower and diffused spread of smaller taps. These channel values are used as ground truths to simulate the received signal when the proposed signaling scheme (ref. Section 3, eqns. (1) to (3)) is

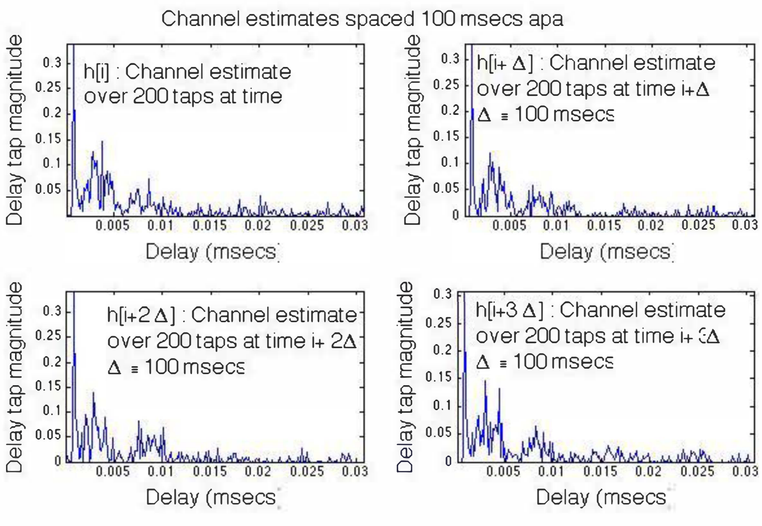

Figure 3: Representative channel estimates using [4] as kernel solver.

used. Figure 4 shows the difference between the recovered channel $\widetilde{h}[i,k]$ and the ground truth $h[i,k]$ in the case of noise free scenario.

In the noisy scenario, additive white complex Gaussian noise is added to equation (1). The variance of the added noise (in dB) and the signal-to-noise ratio (SNR) of the estimated channel are given in Table-1.

Table-1: Channel Recovery under Noisy Scenario

S.No.	Variance of noise	SNR of the received noisy signal (in dB)	Mean Squared Error (MSE) of the estimated channel
1.	0.03140	3.8112	0.0060
2.	0.01000	9.6451	0.0033
3.	0.00320	14.5597	0.0018
4.	0.00099	18.9340	9.8202e-004
5.	0.00031	23.6967	6.0524e-004

We ran simulations over 50 iterations for each noise level. All experiments are performed on MATLAB platform on a 2.60 GHz i5 processor with 16 GB RAM.

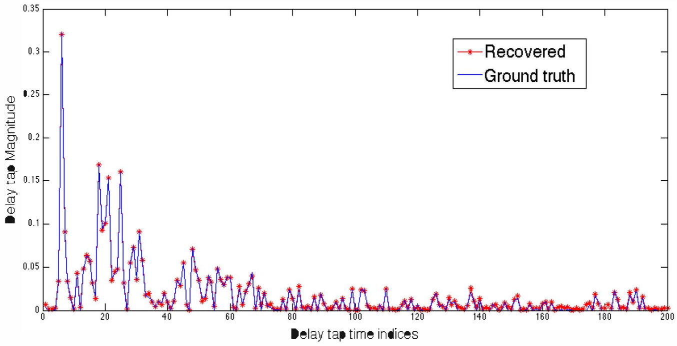

Figure 4: Recovered channel and ground truth at time instant i in noise free scenario

V. CONCLUDING REMARKS

We present a formulation to estimate underwater acoustic channel by constructing a specific pre-defined input signal (signal dictionary) and presenting the received signal in the form of input received over Delay-Doppler spectrum of the time-varying underwater acoustic channel. The advantage to this approach is that no feedback is needed from the transmitter. In fact, this 2-dimensional frequency domain representation via input signal dictionary design in MIMO framework is similar to k-space representation in MRI. Similar to k-space MRI, the frequency domain representation of Delay-Doppler channel spread is sparse. Channel recovery under noisy scenario is shown by formulating the proposed framework in the context of constraint optimization problem.

Currently, we are working on designing a pre-selected input signal dictionary based on acoustic channel physics and employing an adaptive input signal dictionary that adapts sampling density around changing channel activity.

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