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CONSTRAINED CHANNEL ESTIMATION METHODS IN UNDERWATER ACOUSTICS

by

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A thesis submitted in partial fulfillment of the requirements
for graduation with Honors in the Electrical Engineering

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Spring 2017

All requirements for graduation with Honors in the
Electrical Engineering have been completed.

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Constrained Channel Estimation Methods in Underwater Acoustics

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Honors Engineering Thesis

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May 10, 2017

Abstract

Underwater acoustic signal processing aims to reconstruct the shallow water acoustic channel from both direct arrival and delayed multipath reflections. This enables accurate acoustic communications in shallow water, such as between underwater autonomous vehicles (UAVs), which are essential for coastal surveillance and other applications. In this work, we take a previously implemented algorithm for channel estimation and apply practical constraints motivated by shallow water acoustic physics. We base our estimation constraints on the physical properties of the rapidly fluctuating reflections from the moving sea surface and rough sea bottom. Our work aims to reduce the computation time and prediction error in the channel estimation using our constraints for real time applications.

Contents

1	Introduction	3
2	Foundations	4
2.1	Mixed Norm Optimization	4
2.2	Boyd L1-Least Squares Optimization	5
3	Methodology	5
4	Constraint Implementations	7
4.1	Static Single-Band Mask	8
4.2	Static Multi-Band (Three-Piece) Mask	8
4.3	Threshold Mask	8
4.4	Dynamic Mask	8
5	Results	9
6	Future Directions	10
7	Acknowledgements	10
	References	11

1 Introduction

Underwater acoustic signal communication requires real-time solutions. As such, optimization in channel estimation methods for sparse reconstruction opens the door for lower estimation delays and lower prediction error. In this work, we attempt to demonstrate the potential in applying channel constraints to a mixed norm channel estimate [3] to achieve this. For comparison, the channel constraints are also applied to a popular sparse-sensing ℓ_1 -regularized least squares estimation method [2].

We'll be considering a shallow-water system with a transmitter-receiver distance of 200 meters and a depth of 15 meters. Figure 1 shows the mixed-norm channel estimation applied a sample of our experimental data collected during the SPACE08 experiment (courtesy of James Preisig, Woods Hole Oceanographic Institution), also used in [1]. It shows the banding structure created by the physical system of the ocean, wherein the number of surface bounces increase the delay along the y-axis. The x-axis represents the time snapshot of the data samples.

The band with the lowest delay is the narrow, bright direct arrival, which has no surface bounces whatsoever. From bottom to top, there is also a band which represents a single-surface bounce delay band and a faint band with the highest delay which represents multi-surface bounces. The surface is moving and this leads to fluctuations in arrival times, as can be seen in Figure 1.

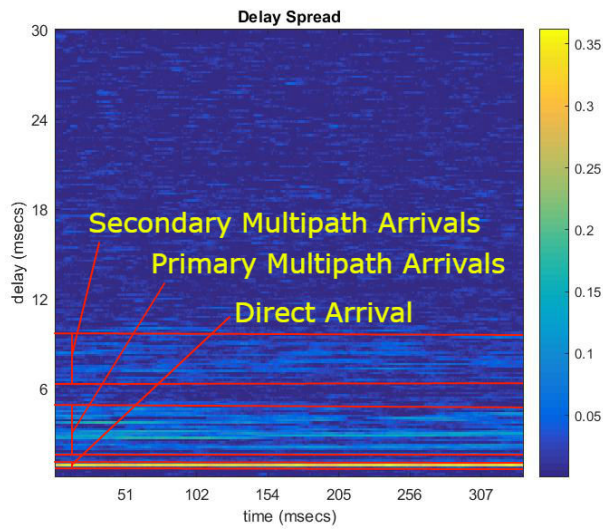


Figure 1: Delay incurred in experimental field data collected at 15 meters depth and 200 meters range under moderate sea conditions during SPACE08 experiment. Multipath bands from bottom to top: (i) direct arrival, (ii) single surface reflection, and (iii) multi-surface reflection between moving sea surface and sea bottom.

2 Foundations

The literature covering different channel estimation methods are extensive, but in this work we focus on the mixed norm optimization method as presented by Professor Ananya Sen Gupta [4]. Other channel estimation methods [2] will be mentioned alongside their relevance to future work.

2.1 Mixed Norm Optimization

The mixed norm optimization models the multiple arrivals in the following form, as:

$$y(i) = \sum_{k=0}^{K-1} h(i, k)x(i - k) + n(i) \quad (1)$$

where $y(i)$ represents our current received signal at time instant i , while $x(i)$ represents our current transmitted signal. K is the number of delay taps, and $x(i - k)$, $K > 0$ gives us the past transmitted signals with their corresponding channel impulse response, $\{h(i, k)\}_{k=0}^{K-1}$. This delay is caused by both reflection as well as refraction.

While [4] also considers the frequency shifting in the form of the Doppler spread with L Doppler frequencies, this work only considers the K time delay taps when $L=1$.

The signals are stacked over an averaging window of M where the u vector of coefficients to be estimated are assumed constant. C represents the matrix of time delayed and frequency-shifted versions of the transmitted data. n is the observational noise modeled statistically as $\mathbf{n} \sim \mathcal{N}(\mathbf{0}, \sigma^2 \mathbf{I})$. The receiver signal may also be expressed as

$$\mathbf{y} = \mathbf{C}\mathbf{u} + \mathbf{n} \quad (2)$$

The optimization algorithm described in [3] can be best described with the equation

$$\mathbf{u}_{opt} = ((1 - \lambda)\|\mathbf{u}\|_1 + \lambda\|\mathbf{C}\mathbf{u} - \mathbf{y}\|_2^2) \quad (3)$$

It is implemented as a Non-Convex Mixed Norm Solver (NCMNS) solver with design parameter λ in MATLAB[®]. The code setup for the estimation methods as written in conjunction with [4] and [3], the mathematical premise of which is detailed above. The constraints were added within the code.

Figure 1 above is a plot of the delay spread of the u coefficients calculated by NCMNS over about 3.5 seconds of samples, where our sample rate is 6510.4 samples/sec. The number of delay taps, K , is 200. We constrain these delay

taps according to our knowledge of the physical model, which expects the banded structure visible in 1.

2.2 Boyd L1-Least Squares Optimization

While the NCMNS optimization varies the λ design parameter, we compare this to a L1-Least Squares solver presented by [2]. We use this solver for comparison because it is not built to take physical properties of the system into account. It emphasizes using the overall channel taps for estimation while NCMNS considers each separately, and will be impacted by channel delay tap masking differently.

3 Methodology

The research methodology focuses on visualization of data for analysis. Meteorological cloud reflection points were the starting point, used as a toy data set for analyzing the way things change with time through frequency analysis. Figure 2 highlights examples of this analysis through use of more advanced plotting techniques. They were created in addition to GIFs which more fully showed change over time or frequency.

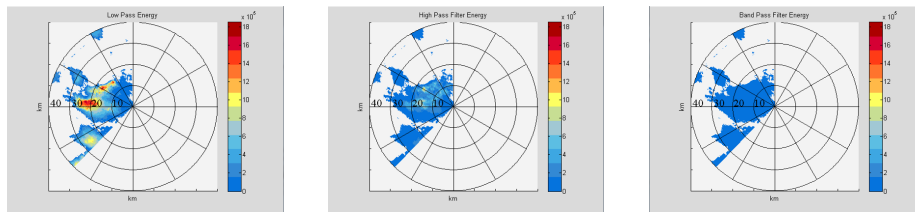


Figure 2: Frequency analysis of cloud movement using low-pass, high-pass, and band-pass filters. Cloud reflection Fourier energy summed over filtered frequencies.

After creating a basis in visualization practices, we shifted into underwater acoustic signal processing with a visualization of the delay taps to find the non-zero coefficients. Figure 3 shows a bar graph of the absolute value of the coefficients across the 200 delay taps, and is one of a larger set used for quantifying the behavior of the delay response.

The image shows that the main delay activity occurs between $L = 1$ and $L = 80$, which we took advantage of when first designing constraints and will be further discussed in the following section.

Before implementing constraints, we wanted to simulate our shallow-water ocean system. The signal paths within the ocean system are modeled as a linear combination of multipath reflections. They are traced by different eigenrays bouncing off the moving sea surface and stationary sea bottom. The ocean surface itself is a combination of surface waves such that each point of reflection

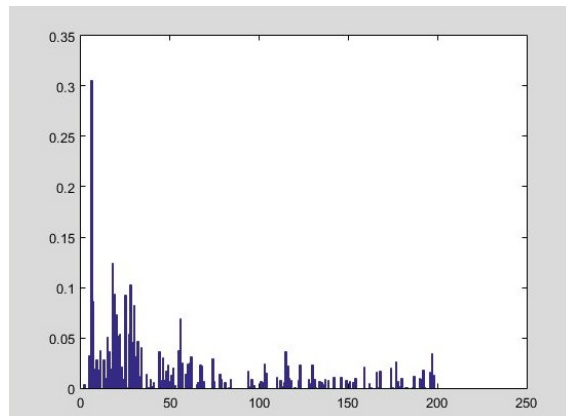


Figure 3: Bar graph representing absolute valued channel delay tap coefficients with $K = 200$.

on the ocean surface can be modeled as linear combinations of one or more simple harmonic motions induced by waves.

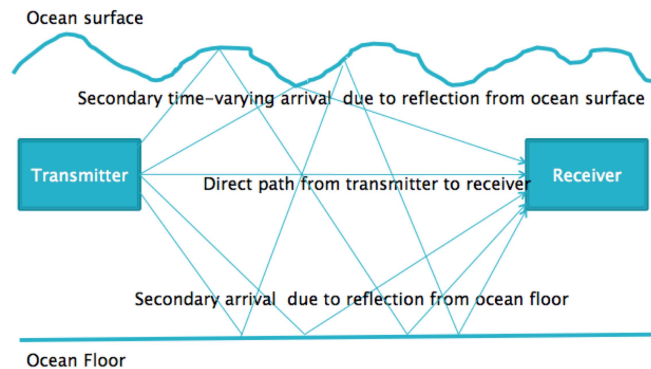


Figure 4: Model of possible signal channel paths with varying number of bounces between transmitter and receiver.

Fig 4 shows potential paths that a signal could take to incur different delays. The straight path from transmitted to receiver is the direct arrival.

To further our understanding of the channel paths, we also modeled the channel by creating ray traced paths. Their arrival times are geometrically described by the types of paths they take from transmitter to receiver and whether they bounce on the surface waves or along the ocean bottom. These can include:

- Direct arrival (no bounces)

- Single surface bounce
- Single bottom bounce
- Surface to bottom bounce
- Surface to bottom to surface bounce

This list can be extended onwards, but this will suffice for our model. After modelling the paths mathematically, we were able to simulate arrival times and create Figure 5. This too shows the banding structure of the channel paths in an underwater system, and though a simplified system, describes it in a mathematical way.

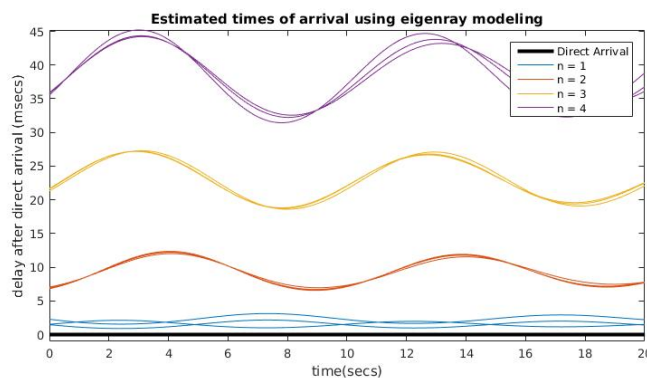


Figure 5: Model of direct arrival and up to four surface bounces. Number of surface bounces is represented with n . Simulated with three waves of time periods 11, 9, and 10 seconds, amplitudes 2, 1.5 and 1 meters and wave numbers 100, 110 and 90 radians/meter.

Figure 5 shows that the delay banding happens with respect to the number of surface bounces, without regard for bottom bounces. After gaining a better understanding of the system itself, we began designing our various constraints for lower prediction error in estimating the channels.

4 Constraint Implementations

A challenge in creating constraints is keeping track of their effect across a variation of external parameters such as observation window and the number of samples which the algorithm runs over. We attempt to vary these as well to view their impact on the constraint methods.

The constraints are created such that they mask out channel taps by multiplying their initial channel coefficients for the delay tap by 0 before estimation.

4.1 Static Single-Band Mask

Figure 3 best represents the usefulness of the one-piece mask. Most of the activity in the 200 channel delay taps exist between taps 1 through 80. The one-piece mask imposes a single band on the channel structure from Figure 1.

4.2 Static Multi-Band (Three-Piece) Mask

Observation of the time-varying channel delay characteristics in Figure 1 reveal a tri-banded structure. To incorporate this tri-banded physical structure of the delay response, we refined the mask to capture the nature of the delays occurring from different bounce patterns. Figure 1 illustrates the delay spread of the experimental data taken across about 500 milliseconds. The lowest part of the delay spread represents the direct arrival, which manifest as a narrow bright band at the bottom of Figure 1. The middle primary multipath band represents the delay spread due to multipath arrivals from single surface bounce, and the top secondary multipath band represents multipath arrivals due to multiple bounces between the moving sea surface and static bottom.

4.3 Threshold Mask

While the static mask gave improved results as compared to not using a mask, in reality, the sparsity of the channel response may also vary dynamically. To account for this variability, we created a threshold-driven mask which tracks all high-amplitude taps of channel activity. It leaves unchanged the locations of the top 35% preliminary estimated channel values and zero out the rest. As each estimation was made, it would update the mask again with the updated locations of the 35% value threshold. As such, a shift in the behavior of the waves over time would also create a shift in the mask and keep low prediction errors in the results. Although it will be affected by random noise, it will not be limited by the static boundaries of the masks.

4.4 Dynamic Mask

Due to changing surface wave dynamics, the boundaries of the multipath bands themselves may also change with time. As a comparison, we created a dynamic mask which would use the banding structure of the channel and adapt to changes over time. In particular, we designed the mask to adapt to the activity in the primary interference band. It tracks the prediction error of the estimate at the end of each averaging window. If the error has increased, the boundaries of the band are shifted. The intent is to respond to change over time by tracking the performance to show its relationship to the locations of the masking boundaries.

The algorithm was designed in two ways - one which used a round robin technique for switching the boundaries and another which checks whether coefficients

higher than 0 exists near the edges and adjusts. The first allows the boundary shift to be arbitrary and changes to new boundary values when the prediction error worsens. It is marked as Dynamic in the results. By comparison, the other method, marked as Dynamic 2, checks the edges to decide whether to shift.

5 Results

To test the impact of our constraints, they are run over the experimental data also from the SPACE08 experiment over 200 samples. We vary the observation windows to analyze how short-term fluctuations in the channels impact the results of our constraints.

Figure 6 below contains four graphs to compare the observation windows. Each sub-figure is a plot of the varying design factor and the prediction error computed from comparing the received signal to the original transmitted signal to see how accurate the channel estimation's reconstruction is.

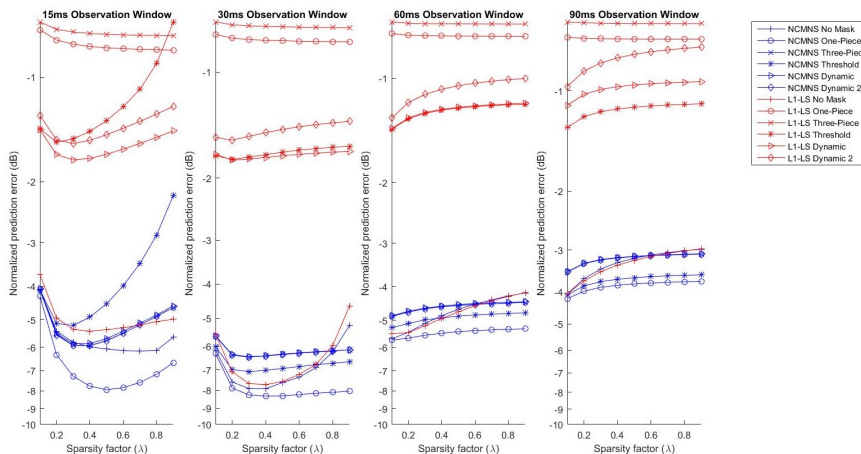


Figure 6: These results are run over the experimental data with 15, 30, 60 and 90 ms observation windows. They were run over 200 samples with $K=200$ delay taps. It is meant to compare the performance of the constraints over two different estimation methods.

Our results show that, as predicted, the Boyd solver will not perform as well when constrained. It is negatively impacted by the constraints since it considers the entire set of channel delay taps for estimation. By comparison, NCMNS is able to take advantage of the masking of the delay taps in which noise was present for better prediction error.

Overall, the static one-piece mask outperformed the rest. This can be explained by the activity viewable in Figure 3 for the first 80 delay taps. It also is also immune to the shifting boundaries of the interference paths and the noise present

in high-delay paths.

The constraints are impacted by the observation window as high observation windows mean that rapid fluctuations are averaged out. The threshold mask is indifferent to the banding structure and did well. This indicates that though the banding-based constraints have potential, the possibility of overlapping bands and relevant channel information also being zeroed out negatively impact the prediction error.

6 Future Directions

Our results show promise in the premise of constrained estimation but there is more investigation to be done. This would include a comparison of applying our constraints to other popular sparse sensing channel estimation algorithms, as well further analysis of constraint implementations which can adapt to fluctuations. We would also like to extend our work into Doppler spread analysis for $L > 1$ Doppler frequencies to see their impact on prediction error.

7 Acknowledgements

Special thanks go to Professor Ananya Sen Gupta for her mentoring throughout this research projec, as well as for the partial sponsorship by the Iowa Center for Research by Undergraduates (ICRU)for this project.

We'd also like to thank Dr. James Preisig, Woods Hole Oceanographic Institution, for providing experimental field data from the SPACE08 experiment and related consultation.

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