Arab Academy
for Science , Technology and Maritime Transport

13 Marlog 2024

The International Maritime Transport and Logistics Conference

“MARLOG 13”

Towards Smart Green Blue Infrastructure

3-5 March 2024 - Alexandria, Egypt

Pilot-assisted underwater acoustic channel estimation for MIMO OFDM systems using sparse Bayesian learning algorithm

Outline

- Objectives.
- Underwater Acoustic Communications.
- Characteristics of the Underwater Acoustic Channel (UWA).
- MIMO-OFDM Communication System.
- UWA Channel Modeling.
- Proposed Channel Estimation Approaches.
  - Traditional Method
    1. least squares (LS)
  - Compressed Sensing
    1. Compressive Sampling Matching Pursuit (CoSaMP).
    2. Sparse Bayesian Learning (SBL).
- Simulation Results.
- Conclusion and future directions.

Objectives

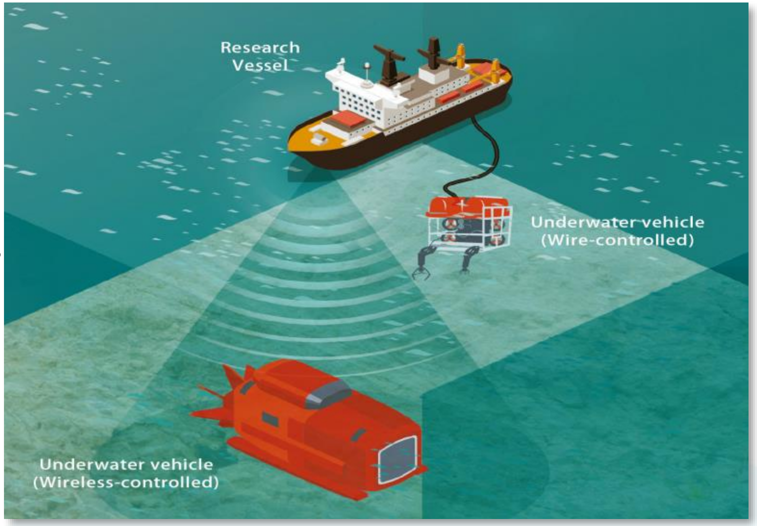
Objectives

- UWA channel modeling
- UWA channel estimation
- Compare between different channel estimation algorithms

Underwater Acoustic Communications.

- **Underwater acoustic communication systems play a crucial role in several applications and fields, such as:**

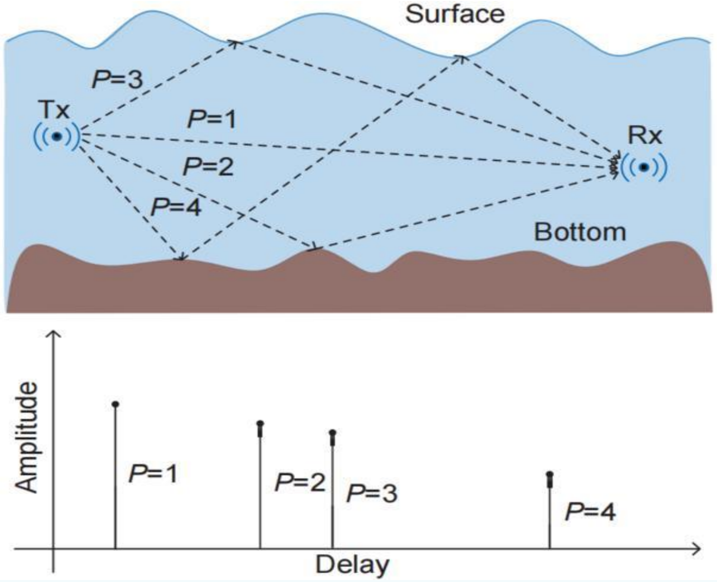
1. Ocean Exploration.
2. Commercial and Industrial Applications.
3. Submarine Communication.
4. Environmental Monitoring and Disaster Prevention.
5. Underwater Infrastructure Maintenance.



Characteristics of Underwater Acoustic Channel.

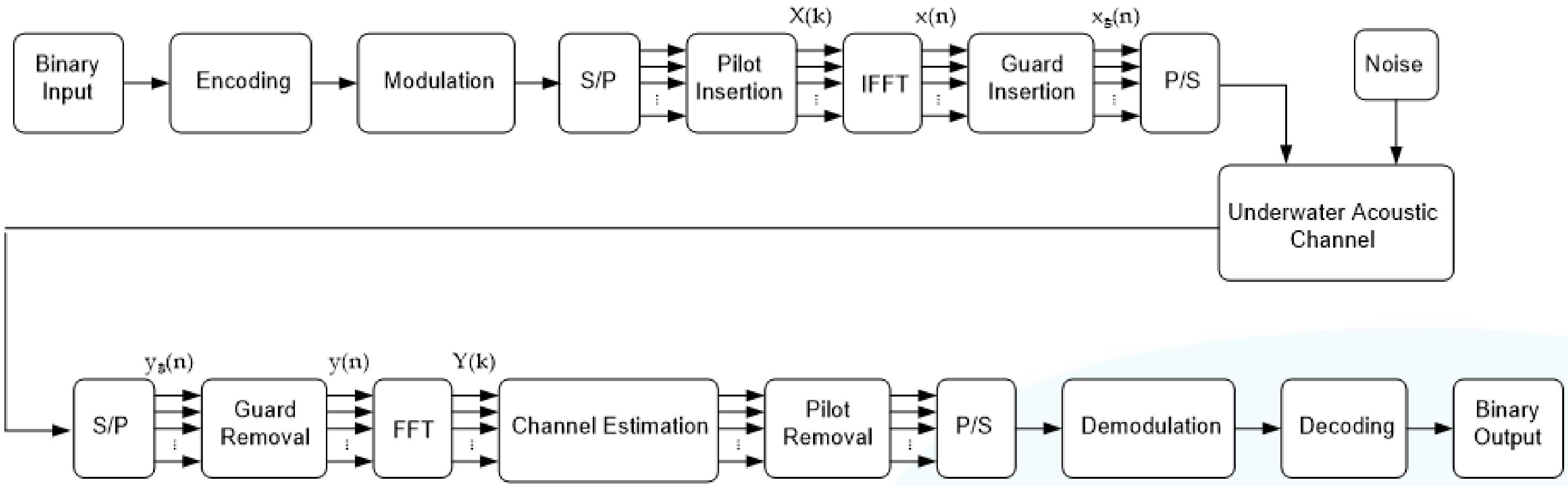
- **Studying underwater acoustic communication systems comes with a set of challenges, here are some examples:**

1. Propagation Loss and Attenuation.
2. Limited Bandwidth.
3. Multipath Propagation.
4. Sparsity.



MIMO-OFDM Communication System

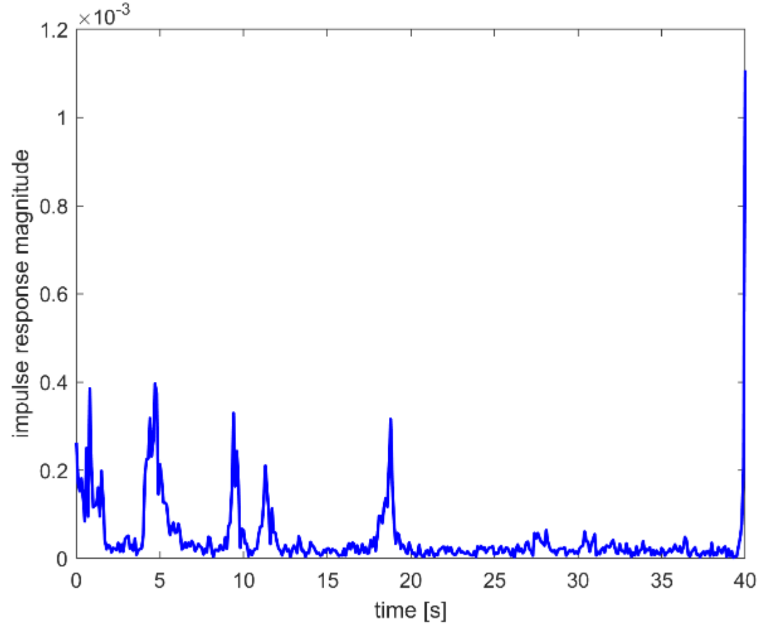
- Enhanced Spectral Efficiency.
- Improved Data Rate.
- Multipath Mitigation.



UWA channel modeling

- The approximate channel impulse response based on measured data obtained from the Kauai AComms Multidisciplinary University Research Initiative (MURI) (KAM), conducted proximate to the shoreline of Kauai Island, HI, and USA.

Parameter	Value	Parameter	Value
Bandwidth	10KHz	No. of intra paths	20
Central frequency	13KHz	Surface Variance	1.125
Channel distance	3000m	Bottom variance	0.563
Water depth	100m	Mean of intra paths amplitudes	0.025V
Transmitter height	58m	Variance of intra paths amplitudes	$1\mu v^2$
Receiver height	59m	PSD of intra-path delays 3-dB width	5×10^{-4}



Proposed Channel Estimation Approaches

- **Traditional Method**
  1. **least squares (LS)**

$$\widehat{H}_{LS} = (A^H A)^{-1} A^H . y$$

  - Large number of samples required for channel estimation.
  - Discards the sparsity of the UWA.

- **Compressed Sensing**
  1. **Compressive Sampling Matching Pursuit (CoSaMP).**
  2. **Sparse Bayesian Learning (SBL).**
  - Sparse signal can be estimated using few significant coefficient.

Compressive Sampling Matching Pursuit (CoSaMP)

Algorithm 1 CoSaMP

Input: the measurement matrix (A), the measurement vector (y), the sparsity level (k), threshold, number of iterations

Output: an estimate $\hat{x}$

Procedure:

1) Initialize the residual vector $r = y$

2) Establish the support set S as an empty set.

3) Set an iteration counter $i =$ number of iterations.

4) Compute the correlation vector $c = A^T r$

5) Identify the indices j corresponding to the top $2k$ of the absolute values in c

6) Augment S with j

7) Solve the least squares problem

$$\min \|A_s x_s - r\|_2 \text{ to drive } x_s$$

8) Select the indices corresponding to the top k of the absolute values in x_s

9) Refresh S with the new indices

10) Update $r = y - Ax_s$

11) Decrement i by 1

12) If $i \neq 0$ or $\|r\|_2 <$ threshold, Return to Step (4)

11) Output $\hat{x}(S) = x_s$

Sparse Bayesian Learning (SBL)

Algorithm 2 SBL

Input: the measurement matrix (A), the measurement vector (y), threshold, number of iterations

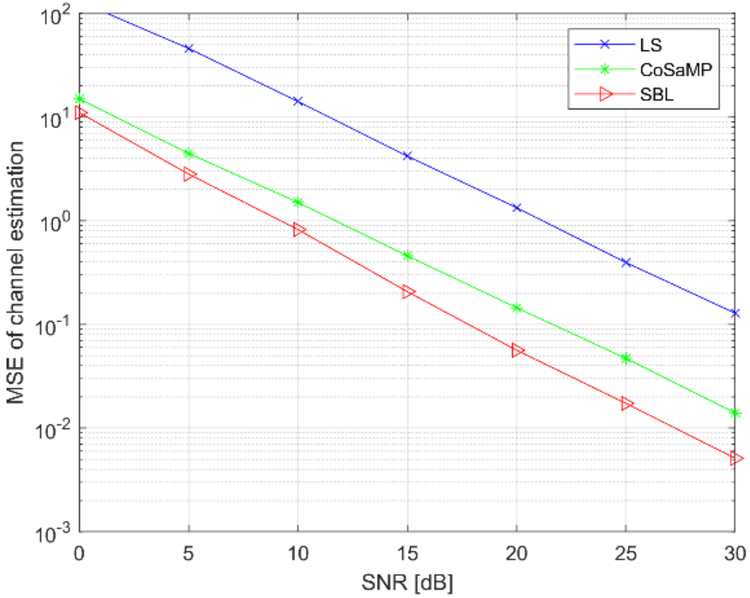
Output: an estimate $\hat{x}$

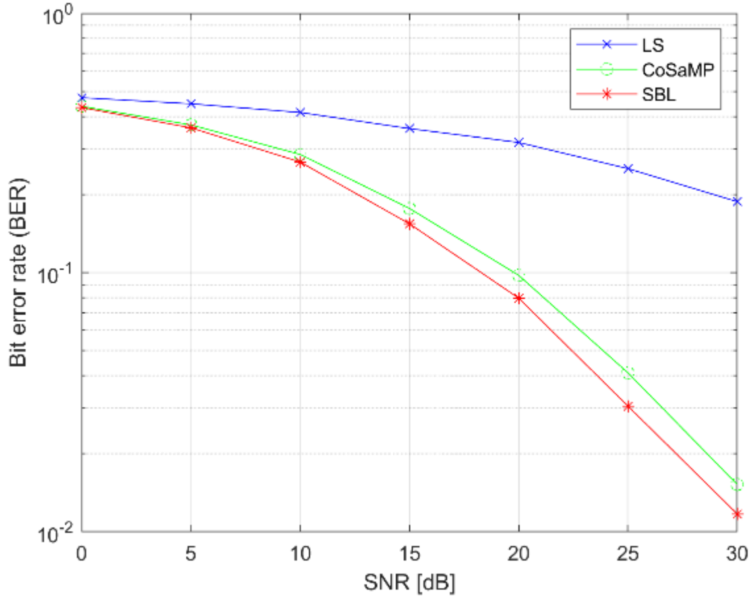
Procedure:

1) **Initiate the hyperparameters**
2) **Set an iteration counter $i = 0$**
3) **Compute the posterior covariance σ**
$\sigma = (\alpha + \beta A^T A)^{-1}$
4) **Compute the posterior covariance μ**
$$\mu = \beta \sigma A^T y$$
5) **Update the hyperparameters**
$$\alpha_i = \frac{|\mu|}{\sigma}$$
$$\beta_i = \frac{\|y\|_2}{\|y - A\mu\|_2^2}$$
6) **Increment i by 1**
7) **Return to Step (4) if** $i <$ number of iterations **and** $\|\alpha_{i+1} - \alpha_i\|_2^2 >$ **threshold**
8) **Output $\hat{x} = \mu$**

Simulation Results

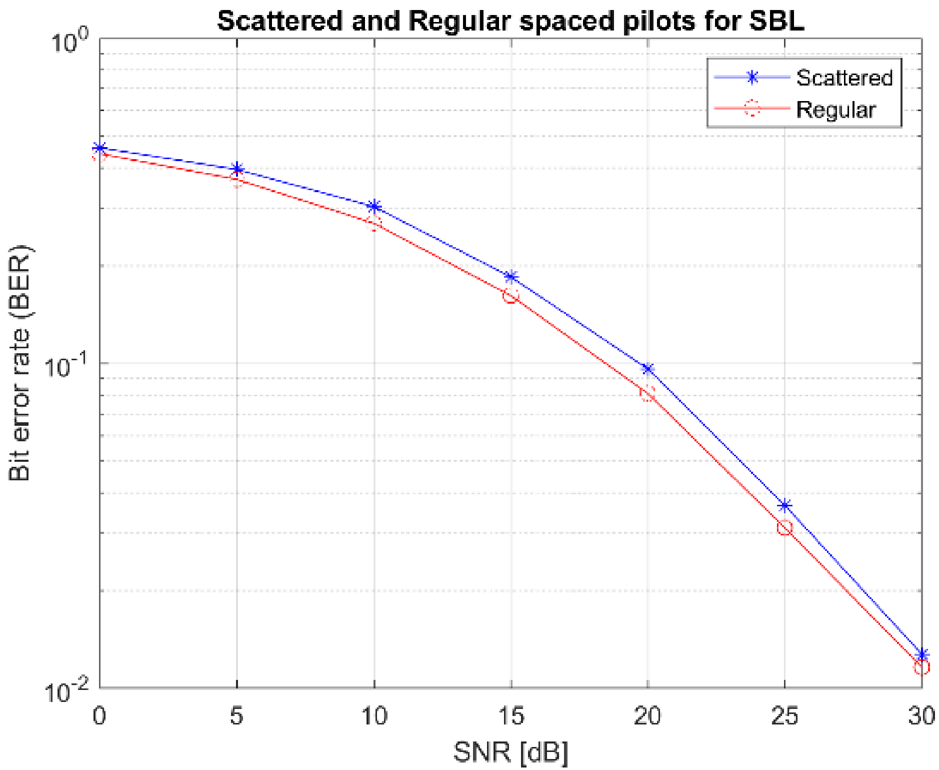
- BER and MSE performance of LS, CoSaMP, and SBL:





Simulation Results

- The effect of pilot's arrangement on the BER performance:



Conclusion and Future Directions

- The findings illustrate that the compressed sensing algorithms, CoSaMP and SBL, outperform the conventional LS method in the context of Underwater Acoustic channel estimation.
- positioning SBL as the optimal compressed sensing candidate as it doesn’t need the sparsity degree of the channel.
- For the SBL algorithm, a regular pilot arrangement proves to be more efficacious for UWA channel estimation compared to a scattered arrangement.

- Future research will focus on further exploration of Bayesian-based compressed sensing algorithms for UWA channel estimation.

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