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Compressive sensing based underwater channel estimation

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Abstract

Underwater communication is a research area of great relevance for naval applications. The proposed work explores the state of the art channel estimation techniques for underwater communications in the context of compressed sensing. A communication model with popular techniques like QPSK, QAM, OFDM etc are simulated for transmission and reception in underwater scenario. This paper considers OFDM channel estimation as a compressive sensing problem since underwater channels are characterized by sparse multipath. It is demonstrated that compressive sensing based methods give more efficient channel estimation for OFDM based underwater communication systems than conventional methods.

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Keywords: Compressive sensing(CS); Channel estimation; Compressive Sampling Matching Pursuit(CoSaMP); Orthogonal Matching Pursuit(OMP); Orthogonal Frequency Division Multiplexing (OFDM) .

1. Introduction

Underwater communication between nodes using acoustic waves is becoming more and more relevant in the scenario of global strategic policy changes where underwater warfare gain more prominence. Both autonomous underwater vehicles and static surveillance systems bank on communication via acoustic means, as electromagnetic

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waves get attenuated rapidly in water. The medium is hostile, characterized by severe multipaths and large time delays[9]. The number of propagating modes and complex mode values depend on the frequency of the acoustic source and the seasonal channel characteristics. The underwater acoustic channel is also band limited due to the frequency dependent absorption in the water. Since the channel parameters are varying rapidly with time and space, it is essential to estimate the channel coefficients, at regular intervals, in the case of underwater applications. The motivation to use compressive sensing in channel estimation is the sparsity of multipath arrivals in the channel[4].

Compressive sensing is a relatively recent paradigm in the field of signal processing, regarded as an efficient signal acquisition framework for sparse signals. This is based on the principle that, through optimization, the signal can be recovered from far fewer samples than required by the Shannon-Nyquist sampling theorem[5].

2. Compressive sensing

Compressive sensing (CS) is a technique for efficiently acquiring and reconstructing a signal, by finding solutions to underdetermined linear systems. The basic difference between CS and Nyquist sampling lies in the way they achieve the reconstruction of signals. Nyquist theorem demands the sampling frequency to be greater than or equal to twice the maximum signal for signal recovery, while CS says, signal recovery is possible with much less number of samples for certain class of signals. CS is based on two principles: Sparsity and Incoherence. A signal is sparse if it has compact representation in some basis $\boldsymbol{\psi}$. Let a discrete signal, $\mathbf{f} \in R^N$ be sparse in somebasis $\boldsymbol{\psi}$. Then we can express the signal $\mathbf{f}$ as[1],

$$\mathbf{f} = \boldsymbol{\psi}\mathbf{x} \tag{1}$$

where x is the K- sparse signal. A signal is K-sparse if it has at most K non-zero components; $K<<N$. Since the signal has only less number of non- zero components in basis $\boldsymbol{\psi}$, we can throw away large number of coefficients without much loss. Let $\boldsymbol{\Phi}$ be the sensing matrix used to obtain the measurements, then the incoherence property says that $\boldsymbol{\Phi}$ and $\boldsymbol{\psi}$ must have low coherence value. The coherence between the sensing basis $\boldsymbol{\Phi}$ and the representation basis $\boldsymbol{\psi}$ can be obtained from [1]

$$\boldsymbol{\mu}(\boldsymbol{\Phi}, \boldsymbol{\psi}) = \sqrt{N}.max\left|\langle \boldsymbol{\Phi}_k, \boldsymbol{\psi}_j \rangle\right| \tag{2}$$

where $1 \leq k, j \leq N$, and $\boldsymbol{\mu}(\boldsymbol{\phi}, \boldsymbol{\psi}) \in [1, \sqrt{N}]$

Considering M linear measurements $\mathbf{y}$ of the signal $\mathbf{f}$,

$$\mathbf{y} = \boldsymbol{\Phi}\mathbf{f} + \mathbf{w} \tag{3}$$

where $\boldsymbol{\Phi} \in R^{M\times N}$ represents the measurement system, $\mathbf{w} \in R^M$ represents additive measurement noise, and $\mathbf{y} \in R^M$ represents the measurement vector.

Let $\boldsymbol{\psi} \in R^{N\times N}$ be the sparsifying basis, the measurement vector $\mathbf{y} = \boldsymbol{\Phi}\mathbf{f} = \boldsymbol{\Phi}\boldsymbol{\psi}\mathbf{x}$ or $\mathbf{y}=\mathbf{A}\mathbf{x}$; where $\mathbf{A}=\boldsymbol{\Phi}\boldsymbol{\psi}$. CS theory states that $\mathbf{f}$ can be recovered using $M = KO\log(N)$ non-adaptive linear projection measurements of the compressed array data vector y, on to a random matrix namely $\boldsymbol{\Phi} \in R^{M\times N}$ sensing matrix[6].

3. Greedy algorithms

To solve $\mathbf{x}$ from $\mathbf{y} = \mathbf{Ax} + \mathbf{w}$, is an underdetermined problem, where unique signal reconstruction is not possible, in general. Solutions based on traditional l_1 norm convex relaxation methods are computationally expensive leading to implementation issues. Hence an alternate strategy is to use greedy family of algorithms like Orthogonal Matching Pursuit, Compressive Sampling Matching Pursuit etc. The algorithm is called greedy because the optimal solution to