A Survey On Channel Estimation Technique Based On Compressed Sensing For Uwa Communication

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Abstract—In past years there has been a growing interest in the study of underwater acoustic channel as the physical layer for communication systems, ranging from point-to-point communications to underwater multicarrier modulation networks. Recently, compressed sensing (CS) has achieved a fast-growing interest by exploiting the sparse nature of UWA channels in OFDM communication networks. This paper studies selected characterizations of the UWA channels, and reviews several mathematical UWA channel models in the literature. We try to provide an overview of the key developments, both theoretical and applied, in the particular topics regarding multicarrier communication for underwater acoustic communication such as the channel and Doppler shift estimation.

keywords—Underwater Communication; Multicarrier Communication, Compressed/compressive sensing, ,time-varying systems, orthogonal frequency division multiplexing, pilot-based sparse channel estimation

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INTRODUCTION

Under Water Acoustic (UWA) Communication is actually transmission of signals successfully between nodes, or from the node into the cluster head by utilizing the acoustic signal as a carrier under the water. Acoustic propagation in the underwater channel influenced by three factors: signal attenuation, multipath propagation, and low speed of sound propagation. So, designing of a reliable communication system is needed for proper understanding of underwater acoustic channel, and the challenging part of it is that no standard fading model for underwater acoustic channel has been established . Though continued research over the years has resulted in improved performance and robustness as compared to the initial communication systems[19]. Underwater wireless information exchange and networking are one of the demanding areas of research and development for numerous applications in terms of ocean-monitoring systems. These systems may include the exploration of marine research, oceanography, marine commercial operations, the offshore oil industry and defense marine life, image broadcasting from remote sites, environmental monitoring, seismic alerts, collection of scientific data both, pollution control, object detection in sea floor, control of AUVs and other security/military based applications. Terrestrial and airborne Wireless Sensor Networks rely on radio frequencies as their communication medium for transmitting data and information. However, sensing and subsequent transmission in sub-sea environment e.g. deep sea. Most commonly , method of using Experimental method supported with measurement data is as a first step in modeling of channel properties for underwater applications in sensor network . As an example (Fig -1) A group of sensor nodes mounted on the seabed and several anchors are use to observe environmental conditions such as temperature, pollution data, or the other environment data. Data from sensor node are collected by using underwater sinks (uw-sinks) which is equipped with the ability to perform the data received from sensor nodes observations, then be sent to a surface station. The next step is sending the information to the offshore sink for data processing. Delivery of data to offshore of sink through horizontal transceiver with surface sink, or vertical transceiver with satellite technology. Exploration requires all together a different approach for communication that has to be done under water. There's no escaping the fact that a huge amount of unexploited resources lies in the 70% of the earth covered by oceans. Generally, there are two research topics..

NEED OF CHANNEL ESTIMATION IN UWA COMMUNICATION:

The first step of underwater communications includes channel estimation, equalizations & modeling ,which tends to the next step for multi-carrier & spatial modulation. The second relates to underwater networking that includes the data link layer and networking topology, clustering and AUV networking. Characteristic of acoustic signal propagation in the underwater channels and problems in realization an underwater communication system by using acoustic signals as career waves was presented in[19]. Channel characterization begins with a measurement of acoustic signal propagation parameters in the various configurations[25]. In communications, compressive sensing is largely accepted for sparse channel estimation and its variants. Mostly multipath channels are sparse and lead to much sparser channel representations and better estimation performance, so due to the arrivals of sparse channel features , each characterized by its distinct delay and Doppler scale factor. Considering practical systems, several modifications need to be made to the compressive sensing framework as the channel estimation error varies with the detailed channel modeling, and how data and pilot symbols are mixed in the signal design.
OFDM is adapted vastly for efficient spectral utilization and ability to cope with multipath fading as severe noise, narrow bandwidth and large timing delays, high data rate are the specific feature of UWA communication. In coherent digital wireless systems, it is critical to obtain accurate estimates of the Channel State Information (CSI) at the receiver because reflections from the moving ocean surface as well as the sea bottom considered as functions of diffuse reflector which lead to

multipath arrivals from the transmitter to the receiver. This results in a non-stationary time-varying channel impulse response, popularly referred to as the delay spread, which typically stretches over 100–200 delay . Insertion of pilot tones into certain subcarriers of each OFDM symbol, or all subcarriers of OFDM symbols prevent frequency and phase shift errors. Conventional methods for estimation of channel state information, such as Least Square (LS) and Minimum Mean-Square (MMSE), lead to the excessive-utilization of the spectral and energy resources and cannot exploit the sparsity of the wireless channels. As opposed to the traditional methods, channel estimation exploiting the sparsity of the channels effectively improves the spectral and energy efficiency by reducing the required number of pilots. Advances in the field of CS have gained a fast-growing interest in signal processing and can be applied to sparse channel estimation. Orthogonal Frequency Division Multiplexing (OFDM) is a multi-carrier system. It utilizes a number of sub-carrier parallel transmitting data, effectively raising the transmission rate, and combating the frequency selective fading.. OFDM channel estimation can be divided into Blind estimation and non-Blind estimation (based on the Pilot). Though its very difficult to adapt to the fast time-varying channel. Blind estimation, which of the high efficiency to transmit effective data, the complex computation and slow convergence.

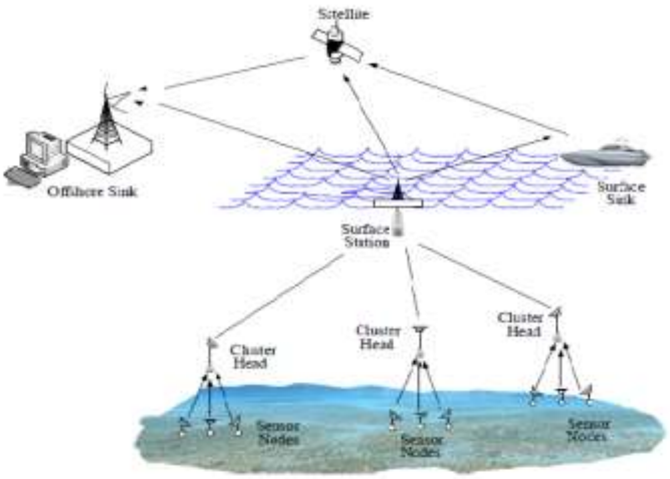

Figure 1. Under Water Acoustic Sensor Network System

Need of compressed sensing for channel estimation

The transmission signal need to travel through different fading paths and tends to multipath fading which results fluctuations in receiver power , as the received signal is the sum of the transmitted signals on multiple paths with varying damping and delays time. In the wideband system, if the transmission bandwidth is wider than the coherent bandwidth, then the signal will experience frequency selective fading, i.e the signal will experience different treatment (response) by the channel for each frequency spectrum, either the phase or amplitude response. Mostly , detection using MIMO systems done by Zero-Forcing (ZF), Minimum Mean Square Error (MMSE), Matched Filtering (MF), Block-iterative Generalized De- cision Feedback Equalization (BI-GDFE), Likelihood Ascent Search (LAS), etc. Usually, inserting pilot symbols into subcarriers, and calculating by Interpolation method channel state information (CSI) is performed. The drawback of Interpolation method is, it needs plenty of a number of pilots to achieve better performance where as, Compressed Sensing uses a small number of pilots but increase the performance. CS algorithms can achieve higher correctness of channel status using a small number of pilots [24] though it has high complexity. In CS, the measurement matrix should have a small correlation to achieve low complexity. This survey is to compare various Compressed Sens- ing based Channel Estimation Algorithm for MIMO-OFDM Systems to achieve good performance with low complexity.

BASIC PARAMETERS OF COMPRESSED SENSING

Compressive sensing is applied in various areas, such as imaging, radar, speech recognition, and data acquisition. Before discussing the mathematical model of Compressed Sensing (CS), it is necessary to discuss the terminology associated with CS. These terminologies include signal sparsity, measurement matrix, and restricted properties of isometric property.

Sparse Signal: signal is considered to be sparse in a known transform domain can be acquired with much fewer samples than usually required by the dimensions of this domain. To achieve this, the sampling process need to be “incoherent” with the transform that achieves the sparse representation and “sparse” means that most weighting coefficients of the signal representation in the transform domain are zero. Sparse signal states the number of nonzero elements in the signal. This sparsity level is expressed by sparsity k that the signal contains 3 nonzero values. Fig-2 shows an example of a sparse signal in the time domain with sparsity k =3.

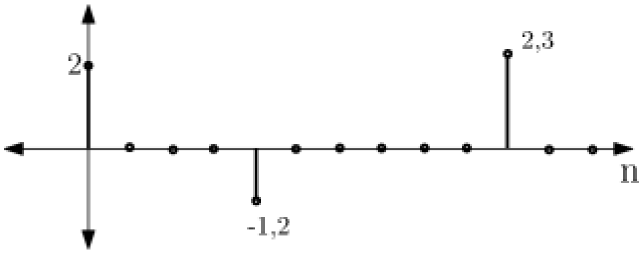

Fig-2 - A sparse signal having sparsity k=3

Measurement Matrix: Measurement matrix is also known as sensing matrix. This matrix serves to reduce the number of samples to be the original signal. If the original matrix **x** consists of **n** elements, then to reduce the number of samples matrix **y** into element m (m < n), then measurement matrix **A** dimension m × n is required. The resulting signal **y** is obtained by multiplying the **x** signal by measurement matrix **A**, i.e
y = A . x, where signal y dimension m × 1, matrix **A** dimension m × n, and matrix **x** dimension n × 1. The signal **x** is called the sparse signal and the signal **y** is called the measurement signal

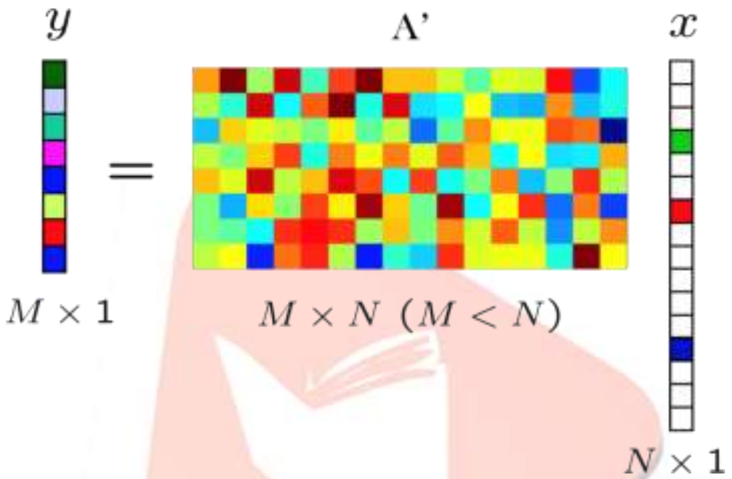

Fig-3- Illustration of Compressed Sensing

Restricted Isometric Property (RIP). Another important issue in CS is to select a measurement matrix **A** such that the original **x** signal can be returned from the **y** measurement. A measurement matrix **A** is said to be RIP if it meets the following conditions: With δ_s is a small number

$$(1-\delta_s).|x|_2 \le |A.x|_2 \le (1+\delta_s).|x|_2 \qquad \text{Eq-1}$$

LITERATURE SURVEY

Though undersea communications and related signal processing techniques have been rigorously developed over the last few decades still, phenomenal advancements in underwater acoustic (UWA) propagation models and related channel representations, tracking the UWA channel in shallow water depths in real time remains an active challenging problem. While several complementary approaches have been suggested toward shallow water acoustic channel estimation, the fundamental challenges to real-time channel tracking remain a bottleneck. The possible reason may be considered as a signal that is sparse in a certain basis can be fully represented by determining the coefficients are non-zero would usually involve calculating all coefficients, which requires an index specifying the basis vectors corresponding to non-zero weighting coefficients plus the coefficients at leastas many samples as there are basis functions. This drawback can be overcome by incoherence property with a feasible sampling scheme computationally tractable algorithms that can reconstruct the original signal from these samples . Thus this paper states various approaches of channel estimation techniques for UWA Communication.
V. Nagendra Babu[6] proposed efficient pilot placement, for Compressed Sensing (CS)-based sparse channel estimation based on Sparsity Adaptive Matching Pursuit (SAMP) in Orthogonal Frequency Division locations when the signal is sparse on the unitary Discrete Fourier Transform (DFT) matrix by minimizing the mutual coherence of the measurement matrix. Here a novel pilot pattern selection scheme which relies on the concatenated CDS with an iterative tail search (C-CDS with TS). Because the proposed design is deterministic and more efficient than any other search-based methods. Hence AS-SAMP with the proposed pilot allocation scheme provides the best BER performance among all the estimation algorithms with the considered pilot placement schemes.Multiplexing (OFDM) communication systems. The priori knowledge of the sparsity is not the prime requirement of this algorithm, and to approach the true sparsity, the step size is adjusted adaptively. Furthermore, different pilot arrangement leads to different measurement matrices in CS, which affects the estimation accuracy arrangements. It is known that, the Cyclic Difference Set (CDS) is the optimal setoff pilot .

Chenhao Qi [2]proposed that to compensate for the Doppler effect application of orthogonal frequency division multiplexing (OFDM) and receiver preprocessing should be employed in UWA communication system before channel estimation. For channel estimation , Homotopy algorithm is used which considers only for real-valued signals to the complex field, as in practical application the channel taps of each path are usually complex-valued. Then to exploit UWA channel temporal correlation two enhancements are done for the compressed-sensing(CS)-based channel estimators . The first one is based on a first-order Gauss-Markov (GM) model which uses the previous estimated channel to assist current one. The other is to use the recursive least-squares (RLS) algorithm together with the CS algorithms to track the time-varying UWA channel. The sparse recovery algorithms can be roughly divided into two classes, i.e a) the convex optimization algorithms & Simulation results show that the Homotopy algorithm can estimate the UWA channels in faster and more accurate manner than other sparse recovery methods, and the proposed enhancements offer further performance improvement.
Christian R. Berger[3] proposed basis expansion model (BEM) to approximate the time-varying UWA channels, so that the number of unknowns reduction will be done in channel estimation. In path-based channel model, where the channel is described by a limited number of paths, each characterized by a delay, Doppler scale, and attenuation factor, and derive the exact inter-carrier-interference (ICI) pattern. For channels that have limited Doppler spread show that subspace algorithms from the array processing literature, namely Root-MUSIC and ESPRIT, can be applied for channel estimation. For channels with Doppler spread, compressed sensing approach may be adopted , in form of Orthogonal Matching Pursuit (OMP) and Basis Pursuit (BP) algorithms, and utilize over complete dictionaries with an increased path delay resolution. Numerical simulation and experimental data of an OFDM block-by-block receiver are used to evaluate the proposed algorithms in comparison to the conventional least-squares (LS) channel estimator as subspace methods can tolerate small to moderate Doppler effects, and outperform the LS approach when the channel is indeed sparse. On the other hand, compressed sensing algorithms uniformly outperform the LS and subspace methods. Coupled with a channel equalizer mitigating ICI, the compressed sensing algorithms can effectively handle channels with significant Doppler spread.
Jie Huang [15] proposes a block-by-block iterative receiver for underwater MIMO-OFDM that couples channel estimation withmultiple-input multiple-output (MIMO) detection and low-density parity-check (LDPC) channel decoding. For this MIMO-OFDM system Nt transmitters are used to transmit Nt parallel data streams using spatial multiplexing. Specifically, within each OFDM block, Nt independent bit streams are separately encoded with a nonbinary low-density parity-check (LDPC) code. Here the MIMO detector consists of a hybrid use of successiveinterference cancellation and soft minimum mean-square error (MMSE) equalization, and channel coding uses nonbinary LDPC codes. The decoder outputs the decoded information symbols and updates a posterior/extrinsic probabilities. These posterior/extrinsic probabilities are used in the next iteration of channel estimation and equalization. During the decoding process, the decoder declares successful recovery of this data stream if all the parity check conditions of one data stream are satisfied . In this case all symbols of this data stream are considered as known without uncertainty. To use feedback in channel estimation or MIMO detection, the unknown data are estimated and uncertainty measurement is left behind. Based on the previous round of decoding, the LDPC decoder outputs a posterior probabilities for each symbol, as well as probabilities based on extrinsic information only. While the extrinsic information is used in the MIMO symbol detection. the a posterior probabilities are used to improve channel estimation. For receiver processing , the authors made fer consideration such as, Non-iterative", "Turbo-equalization", controlled soft decision feedback", "full hard decision feedback". This channel estimation in the iterative loop provides significant gains in performance. These gains are more pronounced even-if less pilots are available for channel estimation.
Lakshmi K [4]considers the estimation problem as an optimization problem of the form of a Basis Pursuit De Noising and as a solution sparse reconstruction methods is proposed . In addition to giving good sparse solution, iterative nature of solution methodology is used to reduce the computational complexity, compared to traditional estimation methods like Least Square Estimation (LSE) and Minimum Mean Square Error Estimation(MMSE). The iterative sparse reconstruction algorithms which are used in this work are- 1. FISTA (Fast Iterative Soft thresholding Algorithm), 2. DALM (Dual Augmented Lagrangian Method) and 3. Fast DALM Algorithm are demonstrated to be effective in the estimation of sparse channels. Also, their computational complexity is less compared to traditional methods like MMSE, LSE etc. The efficacy of iterative algorithms in sparse channel estimation has been demonstrated with an original OFDM dataset and the estimated result has been compared with the results from traditional methods like LSE and MMSE is shown in a proper manner . The iterative solutions trace the response from other methods almost perfectly; the slight difference could be neglected when the reduction in computational complexity is taken into account. IN UWA communication systems, due to scarcity of computational resources, this reduction of computational complexity could be a marked advantage.
Nina Wang [5] proposed that for coherent receiving and channel equalization at the receiver, accurate channel state information (CSI) is an indispensable part , thus, channel estimation becomes a huge challenge under such execrable multicarrier underwater acoustic (MC-UWA) channel conditions. In recent years, numerous channel measurements have shown that the MC-UWA multipath channels tend to exhibit sparse structures in form of OFDM structure and estimate the channel for every OFDM symbol. Sparse channels are probed by sending known data (pilots) on the pilot subcarriers. The proposed compressive channel estimation method with compressive sampling matching pursuit (CoSaMP) is used for sparse multipath MC-UWA channels. The proposed method allows an even faster implementation than OMP. Simulations show that the running time is only less than a quarter of that of OMP, while the estimation performance is only slightly poorer than BP. Therefore, the CoSaMP algorithm combines the high performance of accuracy and the low computational complexity for MC-UWA systems. This proposed method offer a good compromise between high spectral efficiency, good practical performance guarantee and low computational complexity but the experiments are performed assuming the channel sparsity as known factor.
Samar Kaddouri [7] proposed a time-varying MIMO single carrier channel estimation technique based on the orthogonal matching pursuit (OMP) algorithm and analyze its performance in an experimental MIMO setup, where a test tank of length L

= 9:14 m, width W = 7:62 m and height H = 3:81 m is used for keeping Two sources placed at 0.15 m below the surface and separated by a length of W=2 and two receivers r1 and r2 are placed 1.5 m vertically below the sources. The signals transmitted are 873.8 ms pseudo noise (PN) sequences phase- modulated using Binary Phase Shift Keying (BPSK), pulse shaped using a conventional Root raised cosine (RRC) _lter and transmitted between 253 kHz and 347 kHz. Doppler spread [4] is introduced by modulating the source signal, so that the channel impulse response now depends both on time and time delay. the proposed MIMO-OMP algorithm closely estimates the Doppler spread present in the main echo of the channel impulse response with an estimated 0.93 Hz for a theoretical value of 1 Hz.
Andreja Radosevic[7] proposed selective decision directed channel estimation (CE) method based on hard and soft selection of data subcarriers for underwater acoustic (UWA) orthogonal frequency division multiplexing (OFDM) based communications. Particularly, in the process of hard selection sub-carriers having high signal-to noise ratios (SNR) is chosen , while for soft selection data sub-carriers are weighted for reliable channel estimation. Here combination of the CSI from the pilot sub-carriers, and the reliable a priori CSI from previous OFDM blocks is used to selectively choose data sub-carriers for decision directed Channel estimation. The latter approach is shown to be advantageous since the channel state information (CSI) from all data sub-carriers is exploited. From a comparative study of selective decision directed CE techniques with different channel reconstruction methods such as least-squares (LS) with thresholding, orthogonal matching pursuit(OMP), and basis pursuit denoising (BPD) the results indicate good performance improvements as compared to the block-by-block pilot-assisted CE with a uniform pilot grid for high spectral efficiency communications. Moreover, the trade-offs resulting from using a varying number of pilots and/or decision directed data sub-carriers in terms of the overall system throughput and bit error rate (BER) is explored here through an experimental set up . Experimental results are obtained using real data measurements from the Mobile Acoustic Communication Experiment 2010 (MACE'10), conducted off the coast of Martha's Vineyard.
Milica Stojanovic [3] proposed A phase synchronization method, which provides non-uniform frequency offset compensation needed for wideband OFDM [1], is coupled with low-complexity channel estimation in the time domain. Sparsing of the channel impulse response leads to an improved performance, while adaptive synchronization supportsdecision-directedoperation and yields lowoverhead. System performance is demonstrated using experimental data transmitted over a 1 km shallow water channel in the 19 kHz 31 kHz band.
Yi Zhang [11] proposed recovery algorithm based on sparsity adaptive matching pursuit (SaMP) and a new near optimal pilot placement scheme, for compressed sensing (CS)based sparse channel estimation in orthogonal frequency division multiplexing (OFDM) communication systems. Compared with other state-of-the-art recovery algorithms, the proposed algorithm possesses the feature of SaMP of not requiring a priori knowledge of the sparsity level, and moreover, adjusts the step size adaptively to approach the true sparsity level. Here main stress is given in pilot pattern design in sparse channel estimation. Although a brute-force search guarantees the optimal pilot pattern, it is prohibitive to examine all possibilities due to high computational complexity still an efficient near-optimal pilot placement scheme is designed by minimizing the mutual coherence of the measurement matrix when the signal is sparse on the unitary discrete Fourier transform (DFT) matrix, where CDS does not exist. This proposed channel estimation algorithm, with the new pilot placement scheme, offers a better trade off between the performance—in terms of mean-squared-error (MSE) and bit-error-rate (BER)— and complexity, when compared to other estimation algorithms

APPLICATION OF UWA COMMUNICATION

Acoustic waves are not only used as a carrier for wireless communication underwater, rather it is the only one that can travel over longer distances because to cover a longer distance, a lower frequency has to be used. Acoustic waves is the single best solution for communicating underwater,as tethering is not acceptable in application field in under water. In contrast with to acoustic waves, radio waves that propagate over longer distance through conductive sea water , have extra low frequency ones (30 Hz-300 Hz) which require large antenna and high transmitter powers [19], while higher-frequency signals will propagate only over very short distances (few meters at 10 kHz) and requires small size antenna [25]. Optical waves propagate best in the blue-green region, but in addition to attenuation, they are affected by scattering, and are limited to distances on the order of a hundred meters [6]. Narrow laser beams are power-efficient but require high pointing precision, while simple light-emitting diodes are not as power-efficient. Underwater wireless sensing systems can be engaged for stand-alone[23] applications and control of autonomous underwater vehicles (AUVs) and cabled systems. For example, cabled ocean observatories are being built on submarine cables to deploy an extensive fibre-optic network of sensors (cameras, wave sensors and seismometers) covering miles of ocean floor [21]. These cables can support communication access points, very much as cellular base stations are connected to the telephone network, allowing users to move and communicate from places where cables cannot reach. Another application for UWA communication is cabled submersibles, also known as remotely operated vehicles (ROVs).. Acoustic communications offer longer ranges, but are constrained by three factors: limited and distance-dependent bandwidth, time-varying multi-path propagation and low speed of sound . These challenges result in a communication channel of poor quality and high latency, thus combining the worst aspects of terrestrial mobile and satellite radio channels into a communication medium of extreme difficulty.

CONCLUSION

From the review it is quite apparent that The low speed of sound used for communication in water leads to multipath propagation, thereby resulting in a long delay spread. Also, the slow movement of seaborne vessels (or even the sea surface), produces a manifestation of pronounced Doppler shift in the frequencies used. Both the effects together make the underwater channel doubly dispersed. In addition the underwater acoustic (UWA) channel exhibited a limited number of echoes so that the channel could be classified as a sparse channel. Pilot-assisted channel estimation (CE) is used as a standard method to obtain necessary channel state information (CSI) for reliable coherent communications. For OFDM systems a uniformly spaced pilot grid is shown to be a robust pilot allocation strategy for CE under various conditions if the channel is time-invariant, i.e. without inter-carrier interference. For time-invariant channels, both OMP and BP can reduce the estimation error relative to a conventional LS estimator. Intuitively, the advantage of sparse channel estimation relative to its LS counterpart comes from the fact that by exploiting sparsity in the estimate, sparse channel estimation can effectively reduce the number of unknowns. Therefore a basis that leads to a sparser representation of the channel can further reduce the number of unknowns. • while in case a time-varying channel, there are too many unknown channel parameters for a LS estimator to handle with a reasonable amount of pilots. So, using compressive sensing identification of the relevant parameters and reconstruction of a channel matrix with many more unknowns than the pilots used in equalization , can be resolved. While the drawback of compressive sensing is to estimate the channel with sufficient accuracy, so it can make sense to limit the number of unknowns in the channel matrix using a banded structure. In this case BP seemed to continually outperform OMP. So to overcome these drawbacks sophisticated CoSaMP channel estimation algorithm to sense the channel feature, or MIMO-OFDM may be used for higher frequency transmission. it is clear that a number of challenges still remain to be solved. With the flurry of new approaches to communication, medium access, networking and applications, effective analysis, integration and testing of these ideas is paramount—the field must develop fundamental insights, as well as understand what stands up in practice. For these reasons, we believe that the development of new theoretical models (both analytical and computational) is very much needed, and that greater use of testbeds and field experiments is essential; such work will support more accurate performance analysis and system characterization, which will feed into the next generation of underwater communications and sensing. In addition, integration and testing of current ideas will stress the seams that are often hidden in more focused laboratory research, such as total system cost, energy requirements and overall robustness in different conditions.

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