

A Modified Normalized Channel Estimation Method for Efficient Compressive Sensing Based SWA by 2D Frequency Characterization

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Abstract -Shallow or Deep-water acoustic (SWA) is widely being used for under water marine communications. The most essential part of the SWA is multipath channel modeling. Due to the huge data and limited bandwidth under water environment the compressive sensing based channel estimation is widely adopted for communication. In this paper a SWA channel estimation method is presented using modified compressive sensing (CS). The new method assumes the higher SNR values and respective higher window sizes maintaining the compressive time and frequency sparsity. Paper in first pass validates the existing SWA channel estimation methods using CS methods. Then during second pass performance is evaluated under the modified channel normalization based non uniform multipath fading based channel estimation and space recovery. The numbers of iteration counts are also compared for performance evaluation. It is found that modifying the channel realization can improve the efficiency of CS based channel estimation for SWA environment.

Key words: Shallow Water Acoustic, Channel Estimation, Compressive Sensing, Sparsity Frequency characterization.. Multipath fading

I. INTRODUCTION

Shallow Water Acoustic (SWA) is also known as Under Water Acoustics (UWA). Acoustics based communication systems are common in under water environments [1]. As the underwater environment is not uniform with depth thus there are various multipath components between the transceivers. Due to the presence of the energy transients the channel suffers from the huge frequency sparsity in the underwater conditions. This frequency diversity in this paper are modeled at higher Doppler frequencies using compressive sensing techniques.

The SWA channel can be modeled using the sparsity as it contains few non-zero samples over larger sample space. Due to the sparse nature the underwater channel can be easily modeled using compressive sensing [2], [3] Due to the increasing data transmission demand the sparse solutions became popular over last two decades. The main advantages of sparse CS are that it is highly scalable over huge data dimensions and therefore less susceptible to noise. The challenges under the multipath fading water environments are given in the Figure 1.

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Multipath components in underwater are present due to the reflection scattering or refraction of acoustic signals as shown in Figure 1. This is significant to reduce signal strength.

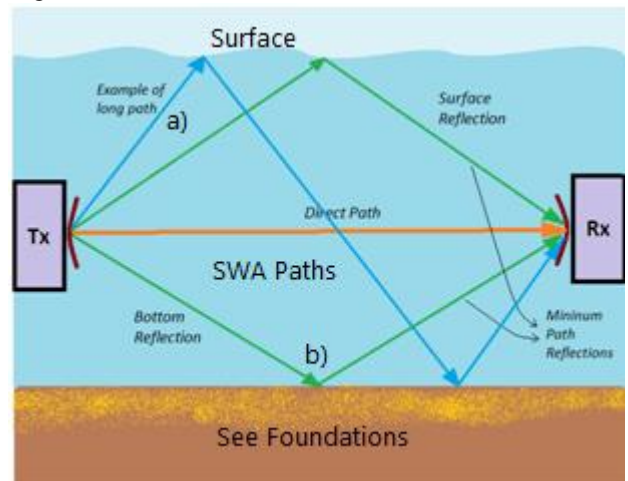


Fig.1. Multipath fading scenario in the underwater environment,

The acoustic waves are reflected back due to the bouncing of waveform the surface or foundation of the ocean. The surface of the ocean behaves like a diffuse reflector. These reflections may reduce the acoustics strengths due to dynamic multipath channel response at the receivers. These reflections are common and certain under the shallow or deepwater environments. This phenomenon is more complex in shallow water as frequency of light follows greater diversity in this environment with depth. The multipath delay spread is exceeded to wide range of around 200 delay taps. To understand the SWA scenario the Figure 2 explains phenomenon of delay spread in underwater environments.

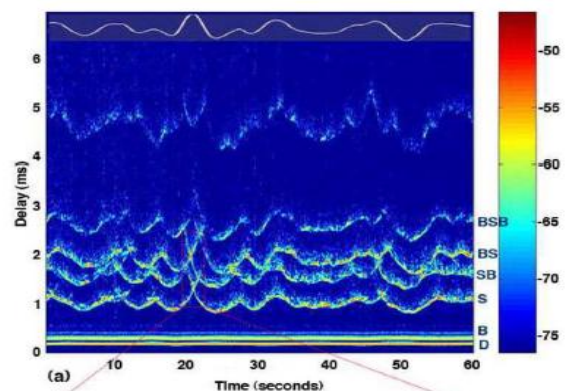


Fig.2.Delay spread in Shallow water environment

Due to these phenomenon's the SWA study is still a challenging problem in hand. There were numerous modeling methods available in the literature for shallow or under water acoustic channel estimation [1, 6]. Enhancing the accuracy of the SWA for CS based channel estimation is still a challenging problem in hand. Therefore this paper addressed problem of SWA under the higher expected SNR performance of existing methods over wide window dimensions without changing the CS rates.

In this paper the experimental modeling and study is presented for evaluating the effect of higher noise level and the varying the window size of the sample space over the compressive sensing based channel estimation based methods.

Rest of the paper is organized as follows: In Section II reviews of existing SWA methods of Channel estimation are discussed. Section III mathematical model for frequency selective space channel estimation method is presented. In section IV the validation of the MSE for the Existing channel estimation in CS sparse channel is presented. Section V the proposed channel modeling is presented using the normalization. Then VI section results of proposed modified CS based channel estimation method for SWA communication are presented. Section VII concludes the work and future prospects are discussed.

II. RELATED WORK

There were many related research found for the estimation of the SWA channel efficiently. Numerous methods are available in the literature for modeling the shallow or under water acoustic channel estimation [1, 2 and 6]. The classifications of the SWA channel modeling methods are given in the Figure 3.

The history of the SWA started long back during World War 2, when army engineer's noted that shallow water sonar broadband waves had frequency dispersion over the strange curve. This was noted that there is delay based on low medium and high frequency at the receiver. Low frequencies arrives first them followed by other two, thus making the scenario difficult to model, There are three ways of channel modeling based on time frequency and Doppler spreads as shown in the Figure

3.Naushad Ansari et al [1] have defined the three different concept of the Compressive Sampling (CS) based 2D frequency characterization for SWA channel estimation. They have presented the mathematical modeling of SWA channel using the frequency characterization model. They stated that using 2D frequency domain is advantageous to distinguish between slow varying and highly transients SWA channel at higher frequencies. They have demonstrated non uniform compressive sensing in 2D domain.

Naushad Ansari et al [3] have recently presented the energy efficient method for the SWA channel estimation using the 2D Frequency modeling. They have explained the modeling of CS based 2d frequency modeling then demonstrated the energy efficient approach of estimation. Samar Kaddouri et al [3] have presented an estimation method for high frequency sparse and dynamic underwater acoustic channel (UWAC) considering MIMO transceiver. They stated that due to time varying nature of UWAC the data rates are significantly limited. José S. et al [8] have presented the underwater noise model as case of the SWAC system. They have presented the SER estimation for noise models.

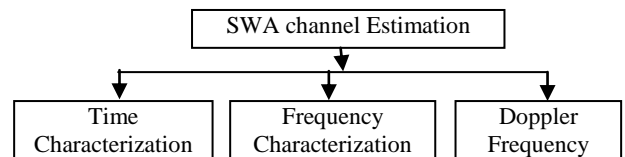


Fig.3. Classification of the SWA channel estimation methods

The methods based on the sparse recovery are frequently tested. The Compressive sensing (CS) based methods are now popular for the SWA as in the Ref. [9 and 10]. CS based estimation methods gives the solution to problem of signal recovery under the underdetermined SWA system with linearity over the sparsity constraint. With the development of the adaptive CAS based signal processing and sparse recovery methods for the UWAC as in [6, and 14] encourages and became pooler to be used for UWCA. The summary of the related works and comparison SWA methods for channel modeling and sparse recovery using CS are presented in the Table 1.

Table 1. Comparison of existing methods

Author/ reference	Method Used	Area of Work	Descriptions
Naushad [1]	2D frequency characterization using CS	SWA channel Estimation	Present modified CS sparse recovery using 2D frequency characterization based channel estimation.
Naushad Ansari [3]	Energy efficient SWA by 2D frequency characterization	SWA channel estimation	Energy efficient channel estimation for sparse recovery for SWA
A. S. Gupta et al. [14]	Sparse channel coefficient for SWA	Time varying SWA	CS for sparse recovery under time varying SWA channel.
Nisha et al [15]	OFDM channel estimation	OFDM transceiver channel estimation	Sparse channel estimation concept designed for OFDM transceiver
Our proposed work	SWA 2D frequency characterization using CS	Modified CS channel estimation	2D frequency characterization based modified CS for SWA channel estimation.

III. MODELING OF 2D FREQUENCY CHARACTERIZATION BASED CS CHANNEL ESTIMATION

In paper the method of 2-D frequency characterization [1, 3] is used for the modeling the SWA channel SPACE08 [1]. Letter paper uses this model for evaluating the modified window length effect at higher SNR level. The acoustic signal transmission is considered for underwater communication with multipath delays. The non-uniform SWA channel is consider for the representation for sparse sampling and measurements over the transient channel. Paper addressed two types of SWA channels over multipath environment as transients with high energy and slow varying channels.

The high frequency transient introduced due to interference between multipath components or dynamic scattering events. Due to their energy distribution these high frequency transient offers sparse nature. while the slow transients exists during the direct path of arrival.

A. Channel Estimates Experimental Setup from Field Experiments

Numerical experiments presented in the current research work is supported channel simulations derived from two independent sources: An independent channel simulator proposed considering the same setup of the multipath model commonly encountered in shallow water acoustic communications, considering the SPACE08 data as in [2] . During this experiment setup experimental field data was collected from shallow water at the depth of around 15m within the range of 200m of ocean floor area considered relatively flat and considering the constant water column temperature [2].

B. Channel Representation

The frequency-selective channel is considered as non-uniform compressive sampling model, the model is designed with 2D frequency characterization. This approach converts the channel estimation problem to non-uniform sparse recovery case using 2D Fourier transform. Let us define the following initial simulation parameters as

Table 2. Simulation Parameters Initialization

Description	Parameter	Range
Numbers of total delay taps;	K	200
Number of total Doppler frequencies	L	
Index of Delay tap,	k	K=0,1,...,K
Doppler frequency	f	0, 1,...L-1
Delay frequency	x	
Omega index	ω	0,1,...,K-1;
Cannel impulse Realization at i^{th} time at k^{th} delay tap	$H_{i(l,k)}$	Length(K)
Channel matrix in 2D frequency	U (I,k)	As H

These parameters are used to model non-uniform CS based sparse recovery method exploiting non-sparse structure for the higher frequencies at 2D frequency

characterization [3] Let the exponential input signal is given as

$$x(i, \omega) = e^{j2\pi i \omega / k} \quad (1)$$

Respective delay frequencies ω ranging from $\omega = 0, 1, \dots, K$ These sub bands are designed easily with the use of frequency selective methods. Sample the channel using Doppler frequencies with the impulse response $H(i, k)$ the output channel is modeled as

$$y[i, \omega] = \sum_{k=0}^{K-1} H(i, j) x(i - k, \omega) \quad (2)$$

$$= e^{j2\pi i \omega / k} \sum_{k=0}^{K-1} H(i, j) e^{-j2\pi i \omega / k} \quad (3)$$

$$y[i, \omega] * e^{-j2\pi i \omega / k} l = \sum_{k=0}^{K-1} H(i, j) e^{-j2\pi i \omega / k} \quad (4)$$

Taking 1D Fourier transform of Doppler frequencies, it gives

$$U[l, \omega] = \sum_{i=0}^{L-1} y[i, \omega] e^{-j(2\pi i \omega / K)} e^{-j(2\pi i l / L)} \quad (5)$$

This is the 2D Fourier transform of the channel H. in the matrix or vector form this is written as

$$U = F_1 H F_2 = \varphi H \quad (6)$$

Where, U is a matrix of size $L \times K$, the H is a matrix representing channel impulse response $H[i, k]$, the matrix F_1 and F_2 are Fourier transform matrix and F is the symbolic representation to the 2D Fourier transform.

Equation depicts channel recovery is possible by inverse Fourier transform for noise free environment . This has motivated us to explore CS based channel recovery in the proposed framework.

IV. CS BASED RECOVERY AND JUSTIFICATION

The AWGN channel noise remains AWGN under the Fourier consideration. Thus under the presence of the noise the Eq. [6] can be re written as

$$U_n = \varphi H + N \quad (7)$$

Where, the N is the AWGN noise added to system during channel. The Figure 4 presents the example of the delay tap amplitude of the Fourier spectrum. It can be observed that channel having sparse nature of the high amplitude activity dominating over lower diffused spread of the smaller taps.

Therefore it is proposed to estimate the channel realization matrix H with the CS based filtering of noise considering the sparse nature of U_n . The filtering problem is mathematically modeled as minimization problem as;

$$\min_{U_n} \|U - U_n\|_2^2 \quad \text{Subjected to } \|U\| \leq \tau \quad (8)$$

Where, τ represents the measure of sparsely of U and is set to $0.5\sqrt{LK}$. The signal to noise ratio of channel is modeled as;

$$SNR = 10 \log_{10} \left(\frac{\frac{1}{LK} \sum_{i=0}^{L-1} \sum_{j=0}^{K-1} |H(i,j)|^2}{\sigma_n^2} \right) \quad (9)$$

The normalized mean square error NMSE of estimated channel response $H_e(i,j)$ is calculated as.

$$NMSE = 10 \log_{10} \left(\frac{\sum_{i=0}^{L-1} \sum_{j=0}^{K-1} |H(i,j) - H_e(i,j)|^2}{\sum_{i=0}^{L-1} \sum_{j=0}^{K-1} |H(i,j)|^2} \right) \quad (10)$$

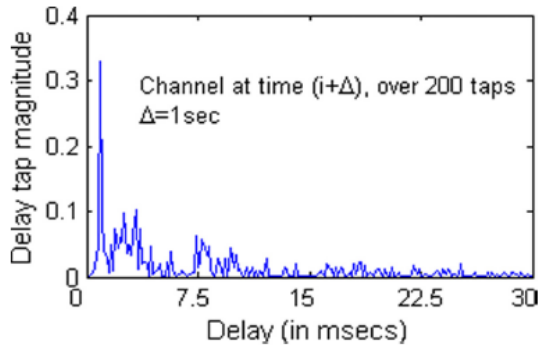


Fig.4.Example of delay tap amplitudes of the channel estimates at time (t+Δ) (Ref [2])

A. Validation of the Existing SWA CS method

For validation the normalized MSE is calculated using the basic CS technique [Ref. section II C of [1]] as given in Eq.8 above. The Monte Carlo iteration is used with 100 iterations only for every noisy simple considering different lengths of Window.

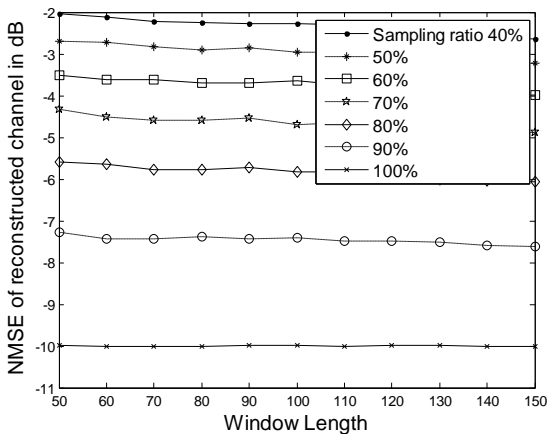


Fig.5.Validated MMSE reconstructed with CS channel evaluated estimation method of [2]

V. PROPOSED MODIFIED CS BASED CHANNEL ESTIMATION WITH PRIOR INFORMATION.

In this section the non uniform CS is considered with certain prior information in addition the sparsity of U is applied only on specific subspace slot of T_c considering the maximum sparsity over U. This can inturn increase the performance of channel estimation. Additionally the U space is sub divided to two non overlapping subspaces S_1 and S_2 :

1. Subspace S_1 represents the worst case of the T_c under sparsity and partial sampling. This subspace is more noisy and sparse, thus having multiple reflections from rough sea bottom. Signal contains spikes wave

events, and low energy attenuated multipath arrivals.(b),

2. Subspace S_2 , is less noisy subspace supports time frame T, containing relatively stable and higher energy transients that occupy low Doppler regions.

The proposed CS based modified sparse channel estimation considering prior information is now mathematically formulated as,

$$\min_{U_n} \|U_{Sub} - R_{T^u} U_{n,W}\|_2^2 \quad \text{Subjected to } \|U_{W,T^u}\| \leq \tau \quad (11)$$

In this paper as a modification the channel is formulated using the normal random realization function and the window size W is expected to increased from 100 to 150 to 250. Change and the sparsity range is kept the same.

The validations of the results for the modified CS method are given in the Figure 6 for the 200 Monte carol simulations. During the validation the widow length is kept the same as in [2].As the channel is randomly initialize thus the slight variations will be observed in NMSE curves every execution.

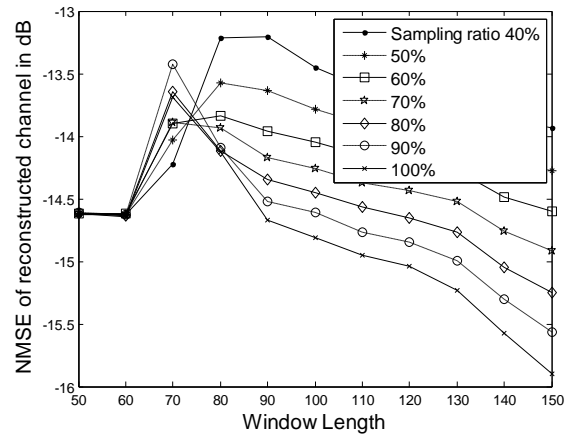


Fig.6.Validation of the MMSE achieved with the modified CS based channel estimation by [2]

VI. RESULTS AND DISCUSSION

Section presents the comparison of experimental results for various experiment performed over the modified CS based estimation of SWA communication. During the experiment the higher values of the SNR is considered and is raised from 70 to 100.

The results are plotted in the Figure 7 for the MMSE error recovered with modified CS based method with prior information considering the higher window length of WL 50::150 at the higher SNR level of 100. The corresponding results are plotted for window length of 20.100 in the Figure 8. For 110 SNR.

Comparing the Figure 7 with the Figure 5. It can be observed the with the proposed modifications ad at higher SNR the NMSE is improved from -10 to -14 for both the widow sizes. Thus NMSE is converging netter with the

proposed modified CS based parametric evaluation of the modified channel estimation.

channel considering the 2D frequency characterization in Fourier transform domain.

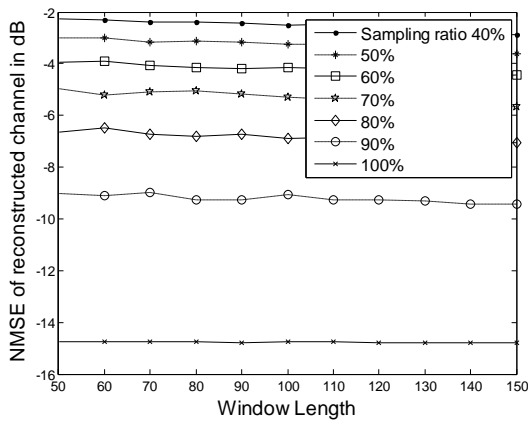


Fig.7. Results of MMSE error recovered with modified window length of WL 50::150 at the higher SNR level of 100

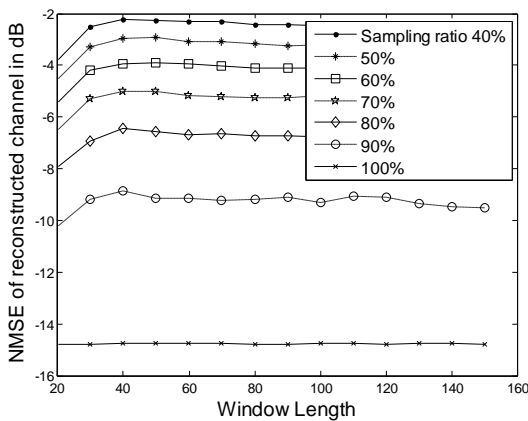


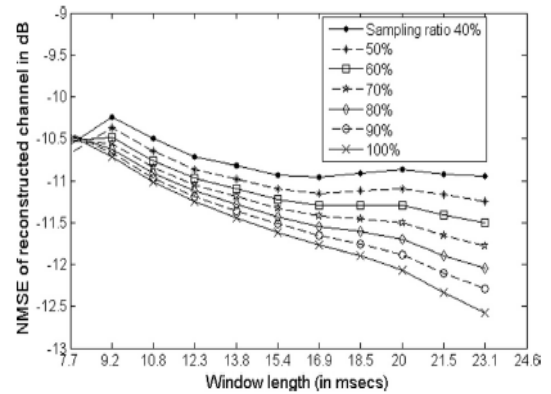
Fig.8. Results of MMSE error recovered with modified window length of WL=20:100 at the higher SNR level of 100

As an another experiment NMSE results are plotted for the channel estimation at keeping the 5 dB SNR considering the modified sparse CS, and the support period T is zero and only first five non-zero Doppler frequencies considering the prior information assumption. The simulation results of the MATLAB are shown in the Figure 9a) and Figure 9 b) respectively for existing and proposed methods.

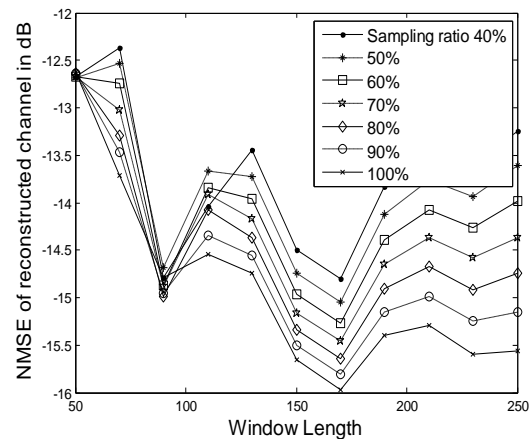
It can be observed from the Figure 9 that the result of the proposed method converges to -12.5 to -15.5 with increase in the SNR range of 100.

VII. CONCLUSION

This Paper presents the modified CS based channel estimation method for the SWA communication considering the higher SNR range and compensating by higher widow range. The window size is increased from 100 to 150, and the SNR is increased to 70 to 100. The channel is realized using the modified normal random distribution. It is found that the higher SNR and widow size minimizes the NMSE performance for the same spare range of the sampling. The paper is significant contribution for evaluating the performance of the SWA



a) Result of [2]



b) With proposed modified method

Fig.9. The results of the NMSE with proposed method at the Window 50 : 20:250

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