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BER and NCMSE based Estimation algorithms for Underwater Noisy Channels

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Abstract

Channel estimation and equalization of sparse multipath channels is a real matter of concern for researchers in the recent past. Such type of channel impulse response is depicted by a very few significant non-zero taps that are widely separated in time. A comprehensive comparison of few algorithms in this regard has been provided. The algorithms simulated are LS, LMS and MP while simulation results along with observations are also presented in this paper. The metrics used for performance evaluation are Bit error rate (BER) and Normalized channel mean square error (NCMSE). On the basis of obtained simulation results, it is observed that MP algorithm requires shorter training sequence for estimation of channel response at the receiver as compared with LS. Furthermore, it is observed that MP has best performance while LS and LMS stand after respectively.

Keywords: Least Square, Matching Pursuit, Least Mean Square, Normalized Channel Mean Square error, Bit error rate, Additive white gaussian noise

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1. Introduction

In last few years it has been seen a rising enthusiasm for wireless sensor networks and nowadays plenty of devices are available that uses wireless sensors specially used in Underwater Acoustic Sensor Networks (UW-ASN). Manned or remote-controlled oceanographic exploration, ocean observance and therefore the offshore oil business all have faith in UW acoustic measure. In wireless communication systems, the signal emitted from the transmitter antenna propagates through the radio surroundings and its multiple copies area unit received at the receiver. this is often thanks to varied physical phenomena that occur throughout the interaction of emitted signal with the propagation surroundings, namely: reflection, refraction, optical phenomenon, and scattering. These copies become attenuated, delayed and frequency or phase shifted of original signal. These multiple signal components define the characteristics of many wireless communication systems. This phenomenon creates fading effects in the received signal which usually impact on communication rate and reliability.

There are four types of wireless channels based on multipath time delay spread and Doppler spread. Their classification is on the basis of Symbol Bandwidth $\boldsymbol{Bs}$ and Symbol Time $\boldsymbol{T_s}$. We used frequency selective and flat in time channel in our simulation. Coherence information {measure} $\boldsymbol{Bc}$ may be a applied math measure of the vary of frequencies over that the channel will be thought-about flat. Coherence Time $\boldsymbol{Tc}$ is that the time domain identical of the Christian Johann Doppler discloses and is working to illustrate the time-changing countryside of the frequency depressiveness of the network inside the time sphere as explained in figure 2.

Where

$\boldsymbol{B_c}$: Coherence Bandwidth $\boldsymbol{B_S}$: Symbol Bandwidth
$\boldsymbol{T_s}$: Symbol Time $\boldsymbol{T_c}$: Coherence Time
$\boldsymbol{B_c} \approx 1/\sigma\tau$ $\boldsymbol{T_c} \approx 1/fd\boldsymbol{B_S}$
$\boldsymbol{\sigma_\tau}$ = delay spread $\boldsymbol{f_d}$ = Doppler frequency shift

In wireless communication system, large delay is involved in propagation of symbols, but impulse response of sparse channel contains minor amount of non-zero taps. Such networks are used in many communication organizations and with growing development in light channel estimation. The electromagnetic signals that move from sender to receiver come across with a lot of several environs. Transmission signal models signify the different environs model. Their main goal is to make known all disorders that affect transmitted signals in which the noise effects, mobility and reflection of signal are preferable. The features of these channels are long propagation and attenuation which is frequency dependent that extremely affected by the link orientation and by nodes distance too. The acoustic links mostly affected by multi path, Doppler spread, path loss, variable propagation delay and different noises.
The idea of an UW sensor network (UWSN) of distributed autonomous motes [9] is introduced by the developments in sensor technology, vehicle and acoustic modem technology. Nowadays working started to standardize the UW network protocols by the aim of approving interoperability of different modems. An international NATO-led is working on founding Janus that is an international standard which specifies the structure of data packet and bit rates mechanisms of acknowledgement, etc. for apply in given frequency/ transmission distance configurations [10].

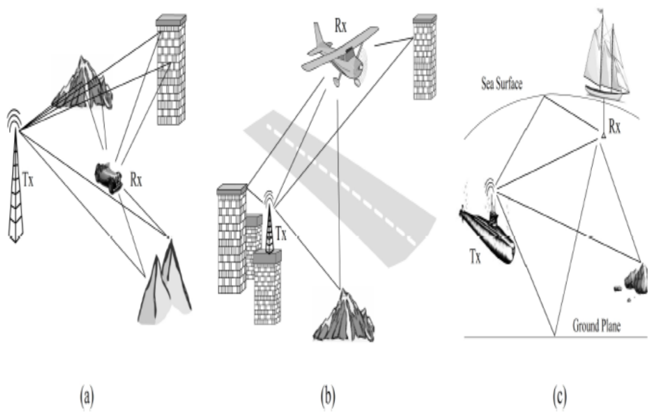

Figure 1: Multipath Phenomenon

Based on multipath Time Delay Spread	Based on Doppler Spread
Flat Fading	Fast fading or Time Selective Fading
$Bs << B_c$ $Ts << \sigma_t$	$Ts > Tc$ $Bs < f_d$
Frequency Selective Fading	Slow Fading
$Bs > B_c$ $Ts > \sigma_t$	$Ts << Tc$ $Bs >> f_d$

Figure 2: Wireless channel types based on multipath time delay spread and Doppler spread

2. Related Work

A MP algorithm is planned in [1] and this technique viewed the estimation downside as a distributed illustration downside and therefore the distributed nature of the channel is exploited. it had been found that, the estimation done exploitation MP is additional correct and has higher performance than 1the usual least sq. based mostly ways in sense of strength and accuracy. For the communication perspective, it poses several challenges to the belief of reliable, high rate communication
Paper [3] is related to the comparison of LMS (which one of the most commonly used algorithms) with one of the proposed algorithm for estimation of sparse channels. The estimation performance of the L0L1SM-NLMS and RL0L1SM-NLMS algorithms is obtained for estimating sparse channels. The achieved simulation results show that proposed L0L1SM- and RL0L1SM-NLMS algorithms are superior to the traditional LMS, NLMS, SM-NLMS, ZA-LMS, RZA-LMS, and ZA-, RZA-, ZASM-, and RZASM-NLMS algorithms in terms of the convergence speed and steady-state performance

A method of decomposition has been suggested to avoid this limitation which is named basis pursuit (BP) [4]. An avid answer is provided by MP, while *L1*-norm founded BP substitutes the unique problem with a altered and more variety.

The Least Mean Square (LMS) procedure is an adaptive algorithm [5]. The available data estimates the gradient vector. Successive corrections are made to the weight using LMS to make vector in the direction of the negative of the gradient vector which eventually leads to the minimum mean square error. LMS has many improved versions like NLMS and VLMS. Furthermore CDMA also exhibit sparse nature of channel in [6].

Paper [7] highlights the importance of Wireless Sensor Networks (WSN) in various fields from weather monitoring and several other domains. A complete description about channel parameters has been given in [12] and [13]. Stochastic Performance Analysis with Reliability and Cooperation (SPARCO) [13] used cooperation technique to increase the performance. Cooperative communication is discovered to develop a routing scheme for UWSNs which is efficiently utilize energy. Every sensor of the UW network is supposed to be consisting of a single unidirectional antenna. To decrease consumption of energy more than one node forward their transmissions cooperatively taking benefit of spatial diversity. The techniques that have one hop or more than one hop both are exploited that added to decreasing loss of path existing in the channels connecting sensor nodes and forwarding of data.

In [14] authors analyzed the acoustic channel characteristics like attenuation, noise and speed of sound (propagation speed) with variations in frequency, depth, salinity, temperature etc. by applying different models and equations for UWSNs.

3. Motivation

Estimation of channel using least-squares algorithm (LS) is discussed in [5] that does not accomplish the sparsity of channels. In [1] MP algorithm is proposed but this methodology viewed the estimation downside as a distributed illustration downside and therefore the distributed nature of the channel is exploited. Other disadvantages include correcting mistakes that can take a lot of time if we use this algorithm. The Channel model discussed in this paper will be more efficient when we will be dealing with purely or strongly sparse channels.

4. Estimation Techniques

4.1 Least Square

LS Algorithm is discussed in[5**]** A coaching signal is spread through the channel and gritty at the receiver to guess the channel. Channel noise among the fashion of AWGN is further before the signal enters the receiver. presently the received signal is convolved with pseudo inverse of work signal. Consequently, the channel is calculate able. Using equation (3-4) we tend to obtain received signal and enforced statistical procedure rule to estimate the channel.

$$h^{\wedge}{}_{LS}{=}argmin_{h^{\sim}} \parallel y_f - xh^{\sim} \parallel_{l_2}^2 \quad (2)$$

Where, $\|.\|_{l_2}$ denotes l_2- norm of a vector. The estimate in (2) can also be obtained as

$$h^{\wedge}{}_{LS=}x^{\dagger}y_f \quad (3)$$

Where, $x^{\dagger}$is the Moore-Penrose pseudo inverse of$x$, which is,

$$x^{\dagger}_{training}{=}\left(x^{H}_{training}x_{training}\right)^{-1}x^{H}_{training}. \quad (4)$$

Currently a knowledge sequence is distributed through constant channel as we tend to mention on top of and gained signal with channel sound. Acknowledged indication is improved with pseudo inverse of station that we tend to calculable on top of. Thus, info indicator is acknowledged. Channel approximation persecution least-squares does not deed the deficiency of channels. Thus we would like longer work sequence thus on search out correct approximation of channel in system with AWGN clatter, that makes hindrance to realize higher information output of communication systems. the amount of nonzero taps is additionally reduced, thus a skinny channel estimate is gained, by thresholding the LS channel guess.

4.2 Matching Pursuit (MP)

Through calculation (2-3), a tinny firmness to r ≈ Xh is attained by resembling r as a linear combination of a slight change of columns of S. The MP method has been presented in [9] that builds up a sequence of skinny calculations. The MP formula first finds the foremost actual formfitting column,sk1among the matrix S with the acknowledged signal r0=r then the estimate of the original residual r0 by the vector sk1 is removed from r0 and additionally the residual is r1. Similarly, sk2 is decided that is best ranged to the residual r1. This formula retains finding the foremost actual ranged column to the serial residuals until a given kind of taps or very little Residuals [1]. once p repetitions, one options a illustration of the form equation (2-3), with Residual rp.

Numbers of nonzero taps are not known to us and this causes a problem because MP algorithm uses this information to find the best estimate. A limitation to this algorithm is that it may spend a lot of time in correctly estimating the initial few terms because algorithm is greedy as mentioned above in [7].

This algorithm is briefed as follows:

$$k_p{=}\text{ argmax}\parallel P_{sl}r_{p-1} \parallel{=}\text{ argmax } \frac{|s_l^H r_{p-1}|^2}{\|s_l\|^2} \quad (5)$$

$l{=}\,1,\ldots,N,l \neq k_{p-1}$

$$r_p{=}r_{p-1} - P_{skp}r_{p-1}{=}r_{p-1} - \frac{(s_{kp}^H r_{p-1}\ )s_{kp}}{\|s_{kp}\|^2} \quad (6)$$

$$h^{\wedge}_{kp} = \frac{(s_{kp}^H r_{p-1}\ )}{\|s_{kp}\|^2} \quad (7)$$

Where the projection onto vector $s_l$is denoted as

$$P_{sl} = \frac{s_l s_l^H}{\|s_l\|^2}, \quad (8)$$

While the value of channel coefficient kp $is h^{\wedge}_{kp}$.

4.3 Least Mean Square (LMS)

The LMS algorithm is a stochastic gradient algorithm in which it iterates each tap weight of the transversal filter in the direction of the instantaneous gradient of the squared error signal with respect to the tap weight in question. Let wˆ(n)denote the tap weight vector of the LMS filter, computed at iteration (time step) n. The adaptive operation of the filter is completely described by the recursive equation.

$$w(n+1) = \widehat{\mathrm{w}}(\mathrm{n}) + \mu \mathrm{u}(\mathrm{n})[\mathrm{d}(\mathrm{n}) - \widehat{\mathrm{w}}^{\mathrm{H}}(\mathrm{n})\mathrm{u}(\mathrm{n})]^{*} \quad (9)$$

where u(n) is the tap-input vector, *d(n)* is the desired response, and u is the step-size parameter. The quantity enclosed in square brackets is the error signal. The asterisk denotes complex conjugation, and the superscript *H* denotes Hermitian transposition (i.e., ordinary transposition combined with complex conjugation).

6 Results and Discussions

In Figure 3 and 4 training sequence comprises five hundred random symbols and information sequence comprises 650 signs. Monte Carlo runs for 50 repetition persecution channel length L = 8. In our imitation, we have varied the value of SNR from 1 to 16 unit. The quantity of repetitions used for work the filter factors used is 500. Step size μ is 0.1. Step size is that the essential limitation for leading the merging of assorted graphs. The essential difference between these procedures is that LMS has fixed step size for each repetition. Similar search is a technique that moldes any signal into linear growth of wave. These waveforms unit of measure element chosen thus on finest match the signal constructions. Adaptive signal illustrations could also be diagrammatical by MP. It is a greedy formula that selects at each repetition a wave that is best customized to estimate a vicinity of the signal. From the graphs we analysed that BER and NCMSE in case of MP is much improved out of all three algorithms implemented. LS and LMS stand after these respectively. Table 1 clearly shows that MP has 21% less BER as compared to LS and 19% less BER as compared to LMS. In other words, it states that MP has 21% better performance as compared to LS and 19 % better performance as compared to LMS in case of BER. Table 2 is related to NCMSE and it again shows that MP has 25% less NCMSE as compared to LS and 50% less NCMSE as compared to LMS. In other words, it states that MP has 25% better performance as compared to LS and 50% better performance as compared to LMS in case of NCMSE.

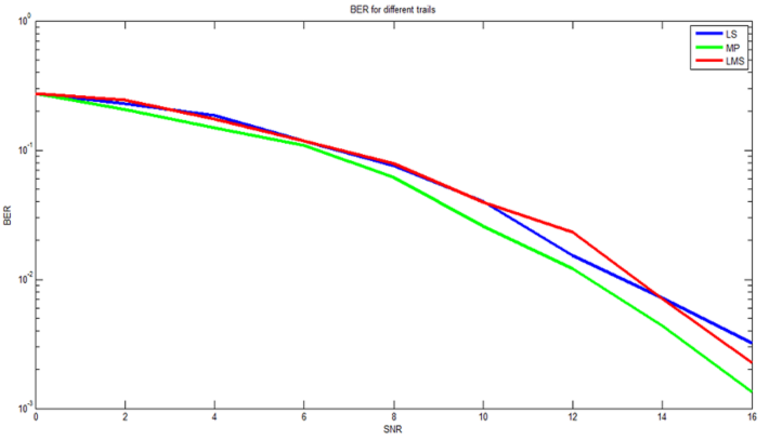

Figure 3: BER VS SNR

Algorithm	value at 0dB	value at 4dB	value at 8dB	value at12 dB	value at 16dB	Average value	% BER
LS	0.28	0.17	0.07	0.09	0.01	0.0124	121
MP	0.27	0.15	0.06	0.02	0.01	0.102	100
LMS	0.28	0.17	0.07	0.07	0.02	0.122	119

Table 1: Efficiency comparison on the basis of BER

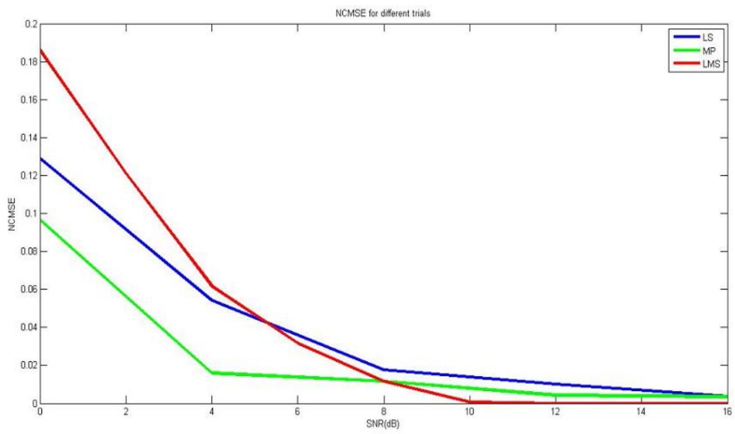

Figure 4: NCMSE VS SNR

Algorithm	value at 0dB	value at 4dB	value at 8dB	value at 12 dB	value at 16 dB	Average value	NCMSE (%)
LS	0.13	0.06	0.03	0.02	0.01	0.05	125
MP	0.1	0.02	0.02	0.01	0.01	0.04	100
LMS	0.18	0.15	0.01	0.00	0.00	0.06	150

Table 2: Efficiency comparison on the basis of NCMSE

7. Conclusion

In wireless communication system, a number of algorithms have been proposed for the accurate channel estimation and equalization. Three algorithms were implemented which are LS, MP, LMS. Their performance was analyzed on the basis of BER and NCMSE. It is concluded that MP has least bit error rate and NCMSE out of the three implemented algorithms so it shows the best performance for the estimation of sparse channels. LS and LMS have better performances after MP respectively.

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