ISSN: 2321-2152

IJMECE

International Journal of modern electronics and communication engineering

E-Mail
editor.ijmece@gmail.com
editor@ijmece.com

www.ijmece.com

ISSN2321-2152
www.ijmece .com
Vol 11, Issue. 4 Nov 2023

ADAPTIVE FILTERS AND COMPRESSIVE SENSING BASED OFDM-MIMO CHANNEL ESTIMATION

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Abstract:

In OFDM-MIMO (Orthogonal Frequency Division Multiplexing - Multiple Input Multiple Output) systems, channel estimation can be made quickly and precisely with the help of adaptive filters and compressive sensing. By combining adaptive filtering with compressive sensing, the channel estimation in OFDM-MIMO systems can take advantage of the lower pilot overhead provided by compressive sensing without sacrificing accuracy or flexibility. To decrease the difference between the actual signal and the expected one, adaptive filters can iteratively change the tap weights or filter coefficients. The benefits of sparse signal recovery algorithms and adaptive filtering algorithms can be maximised by combining methods like MMSE and LMS tools with methods like Subspace Pursuit, OMP, and CoSaMP. The simulation results compare the methods we're using in terms of SNR, NMSE, and BER.

Index Terms: Subspace Pursuit, OMP, and CoSaMP, Adaptive Filters, Interference cancellation, Channel impulse response

Introduction

Transmission and reception of signals between mobile devices and base stations are impossible without antennas. Let's talk about antennas and how they impact mobile communication. Antennas are essential for both sending and receiving radio signals between a mobile device and a base station [1]. They do the reverse, turning electromagnetic waves into electrical impulses for transmission. The signal strength, range, data rates, and total system capacity are only few of the aspects of wireless communication that antenna performance directly affects. Directional antennas focus the power of a signal in one direction, allowing for stronger reception and greater range. Both base stations and mobile devices can benefit from their use of these technologies to improve coverage and connect with specific base stations. Among the many types of directional antennas are the sector, panel, and parabolic designs. By reducing the impact of fading, interference, and multipath propagation, diversity antennas improve the dependability of wireless

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communication. Multiple, physically isolated antennas improve the system's reception diversity [2]. Space diversity (using multiple antennas in separate locations) and polarisation diversity (using multiple antennas with opposite polarisations) are two common diversity methods. Multiple-Input In order to boost data throughput, increase spectral efficiency, and improve signal quality, several-Input Multiple-Output (MIMO) technology employs several antennas at both the transmitter and receiver [3]. To boost communication efficiency, MIMO antennas use the spatial dimension to send and receive multiple streams of data simultaneously. The latest generation of mobile networks, known as 4G and 5G, rely heavily on MIMO.

Numerous-Input Multiple-Output Orthogonal Frequency Division Multiplexing (MIMO OFDM) is a transmission method that uses orthogonal frequency division multiplexing (OFDM) modulation in conjunction with numerous antennas on both the transmitter and receiver ends. Using more than one antenna at either the sender's or receiver's end of a communication system is what's meant by "MIMO." MIMO can boost the performance of wireless communication systems in terms of data throughput, dependability [4]-[5], and spectrum efficiency by employing spatial diversity and multiplexing techniques. By sending and receiving several spatial streams concurrently, MIMO can handle more data. Modulation schemes like orthogonal frequency division multiplexing (OFDM) split the frequency spectrum into a number of narrowband subcarriers. After being modulated with data, the resulting subcarriers are orthogonal to one another and so free of mutual interference. OFDM allows for effective utilization of the available bandwidth and is resilient against frequency-selective fading [6]. With MIMO OFDM, high data rates, expanded capacity, and improved dependability in wireless communication systems are all possible thanks to the combination of the two technologies. Multiple-input multiple-output (MIMO) OFDM uses multiple antennas at the receiver to separate and decode the transmitted signals, one for each transmitting antenna. Signal quality, channel capacity, and resilience to fading and interference are all boosted thanks to the spatial separation of signals. MIMO OFDM's advantages include, It Boosted the Flow of Information: By sending numerous data streams over separate spatial channels at once, MIMO OFDM is able to increase throughput. Furthermore, the use of multiple antennas provides diversity, which lessens the effect of fading and boosts the wireless link's stability. MIMO OFDM improves the system's capacity and spectral efficiency by making use of several spatial channels and efficiently assigning subcarriers. Resistance to Influence from Multiple Paths: The combination of MIMO's spatial diversity and OFDM's inbuilt robustness against multipath fading makes MIMO OFDM an excellent choice for communication under harsh conditions [7]. Multi-input, multi-output (MIMO) orthogonal frequency division multiplexing is used in many of today's wireless networks, such as 4G LTE, Wi-Fi (802.11n/ac/ax), and 5G NR (New Radio). It plays a crucial role in expanding the capacity, range, and quality of service of these networks.

Estimating the channel response between many antennas at the transmitter and receiver is essential for MIMO OFDM (many-Input Multiple-Output Orthogonal Frequency Division Multiplexing) systems to effectively recover sent data [8]-[9]. When the channel in a communication system is sparse, with just a small number of non-zero elements in the channel response and the rest being near to zero, sparse channel estimation is used to estimate the channel response. Recovery of the non-zero components of the channel response is the focus of sparse channel estimation. Reduced pilot overhead, greater spectrum efficiency, and enhanced estimation accuracy are just a few of the benefits of sparse channel estimation in communication systems. It is especially useful in low-resource settings, such as narrowband or large MIMO systems, where conventional channel estimating methods may not be feasible or efficient [10]. It is worth noting, however, that the efficacy of sparse channel estimates is very context-dependent, depending on things like the channel's sparsity level, the coherence features of the channel response, the particular sparse recovery technique employed, and the availability of pilot resources. To achieve accurate and reliable channel estimate, the characteristics of the wireless channel and the needs of the system must be carefully considered and optimized. Utilising the channel's sparsity to cut down on pilot overhead and boost spectral efficiency is the goal of sparse channel estimation in OFDM MIMO systems [11]-[12]. It permits precise channel estimation even when there are just a few number of important propagation routes in the channel response. Compared to conventional dense channel estimation methods, the performance of the estimate process is much improved by taking use of sparsity. In order to acquire and reconstruct sparse or compressible signals with less data, a sophisticated signal processing approach known as "compressive sensing" has been developed. Several algorithms for compressive sensing have been created in this work [13]-[14], each with its own set of benefits and potential uses. The accuracy, complexity, and rate of convergence are each compromised in a different way by the OMP, CoSaMP, and Subspace Pursuit algorithms. Considerations like as sparsity, noise, processing resources, and application needs inform the algorithm selection process. Selecting an algorithm depending on its performance in a given context or using a hybrid strategy that incorporates numerous algorithms to optimize compressive sensing performance are both frequent practices.

Existing Work

The parameters or coefficients of adaptive filters in signal processing applications are dynamically modified in response to the data they are given. These filters may learn from their input signals and the state of the system to better perform signal processing tasks over time. This allows them to more accurately follow time-varying characteristics while also decreasing interference. When the actual output differs from the anticipated output, adaptive filters use adaptive algorithms to adjust the filter coefficients accordingly. The needs of the application and the optimal performance parameters will determine the best adaptive algorithm to use. The Least Mean Squares (LMS) algorithm, the Recursive Least Squares (RLS) algorithm, and the Normalised Least Mean Squares (NLMS) algorithm are examples of popular adaptive algorithms.

System identification, noise cancellation, equalisation, and adaptive beamforming are just some of the many signal processing applications that make use of LMS (Least Mean Squares), an adaptive filter method. The instantaneous discrepancy between the desired and expected outputs is used to fine-tune the filter coefficients in a recursive fashion. Estimate the resultant signal, y(n), by applying the filter to the input.

$$y(n) = \Sigma w(k)x(n-k) = wT * x(n) \quad (1)$$

To determine the error signal e(n), subtract the expected from the intended result.

$$e(n) = d(n) - y(n) \quad (2)$$

Modify the filter parameters in accordance with the LMS rule

$$w(k) = w(k) + \mu * e(n) * x(n-k), \text{ for } k = 0 \text{ to } M \quad (3)$$

Iterate over all samples until convergence or an end point is reached.

The LMS method uses few computations and is easy to implement. In contrast to other adaptive filter methods like the Recursive Least Squares (RLS) algorithm, it may be susceptible to noise and have a slower rate of convergence. Although LMS has certain drawbacks, it is nonetheless commonly employed because of its simplicity and usefulness in many adaptive filtering applications.

Signal processing and communication systems frequently employ MMSE (Minimum Mean Square Error) as an estimation method. Incorporating statistical aspects of the signals and noise, it seeks to minimise the predicted value of the mean square error between the genuine signal and the estimated signal. The minimum mean squared error (MMSE) estimator yields a minimum mean squared error solution.

By processing the input signal x(n) with the filter, we can estimate the output signal y(n).

$$y(n) = \Sigma w(k)x(n-k) = wT * x(n)$$

Finding the filter coefficients w_opt that minimise the expected mean square error (MMSE) between the desired output d(n) and the estimated output y(n) is the goal of MMSE estimation. The formula for the MMSE is as follows:

$$E = E[|d(n) - y(n)|^2] \quad (4)$$

The expectancy operator is denoted by E[].

By taking the derivative of the predicted mean square error E as a function of the filter coefficients w and setting it to zero, the optimal filter coefficients may be determined.

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$\partial E/\partial w = 0$ (5)

By solving this equation(5), we may obtain the w_opt filter coefficients that result in the smallest mean squared error. Due to the statistical nature of the signals and noise, an analytical solution to this equation may be difficult or impossible to achieve in practise. To obtain the best filter coefficients numerically, iterative optimisation techniques like the steepest descent method or the Newton-Raphson approach may be utilised. The statistical properties of the noise corrupting the received signal are represented by the noise covariance matrix R_n. In most cases, this information is believed to be known or can be inferred based on existing knowledge or training data. When considering the statistical characteristics of the signals and noise, the MMSE estimator delivers an ideal answer in terms of the mean square error. It is more accurate than some alternative estimating methods and is resistant to background noise. However, it might be better appropriate for circumstances with known statistical features because it may require knowledge of the signal and noise statistics.

In the context of signal estimation and filtering, the least squares filter is a common technique. By modifying the filter coefficients, it reduces the MSE between the target and estimated outputs.

$y(n) = \Sigma w(k)x(n-k) = wT * x(n)$

The objective is to find the value of n such that the average squared difference between d(n) and y(n) is as little as possible across all n-samples.

$E = \Sigma[d(n) - y(n)]^2$

The ideal filter coefficients w are found using the least squares filter, which minimises the mean square error. This can be written as a mathematical expression:

$w\_opt = argmin(E) = argmin[\Sigma[d(n) - y(n)]^2]$ (6)

By differentiating E with respect to w and fixing the derivative to zero, we may find the ideal filter coefficients:

$\partial E/\partial w = 0$

In some cases, the problem's complexity or the system's non-linearity may make an analytical solution to this equation impractical. When this is the case, numerical methods for finding the ideal filter coefficients can be used; examples include the gradient descent approach and the Newton-Raphson method. When attempting to minimise the difference between the desired signal and the estimated signal, the least squares filter is frequently employed. This includes system identification, adaptive filtering, and channel estimation. It offers a method for minimising the impacts of noise and interference on signal estimation that is both computationally efficient and robust.

In conclusion, the sparsity property of the signal can be exploited by the SP, OMP, and CoSaMP algorithms, which are all tailored to sparse signal recovery. Signal estimation is improved by the use of more general-purpose adaptive filters like LMS and RLS, which are better able to adapt to changing conditions and optimise estimate or filtering performance.

Proposed Work

The sparsity of a channel, as it pertains to wireless communication systems, is the phenomena in which just a small fraction of propagation channels significantly affect the total channel response, while the remaining paths have only a small effect. The geometry of the surrounding space, the existence of barriers, and the scattering properties of the wireless medium all contribute to the sparsity of a channel. A sparse channel is one for which only a small subset of coefficients (or taps) are significantly different from zero, while the rest coefficients are very close to zero. The important propagation pathways or multipath component clusters that carry the bulk of the channel response energy have non-zero coefficients. Channel sparsity has significant consequences for channel estimation, equalisation, beamforming, and resource allocation in wireless communication systems. System performance, complexity, and spectrum efficiency can all be enhanced by taking use of the channel's sparsity.

Compressive sensing methods can be used to effectively estimate the channel response with fewer measurements in the setting of channel estimation. The non-zero components can be recovered precisely using these techniques because they take use of the channel's sparsity or compressibility. When it comes to sparse channel estimation, the Basis Pursuit algorithm is well regarded. By minimising the L1 norm of the channel response under the stipulation that the measurements agree with the acquired data, this method finds a solution to an optimisation problem. Under the right circumstances, Basis Pursuit's convex optimisation formulation allows for precise sparse channel

ISSN2321-2152
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recovery. When it comes to sparse channel estimation, the Orthogonal Matching Pursuit algorithm is a greedy choice. The estimated channel response is then revised depending on the selected channel taps from a dictionary that best match the measurements. When the sparsity level is known, OMP is computationally efficient and recovers sparse channels accurately. Another greedy technique employed in sparse channel estimation is Compressed Sensing Matching Pursuit. Recovering sparse channels from compressed data is made easier and more precise with the help of Orthogonal Matching Pursuit and CoSaMP. The channel response is estimated iteratively using CoSaMP, with taps chosen based on their ability to best match the observations and the estimate refined depending on residual error.

Sparse signal recovery and estimation are two of the many uses for the SP (Subspace Pursuit) technique in compressive sensing. The subspace pursuit flow chart is shown in Fig.1

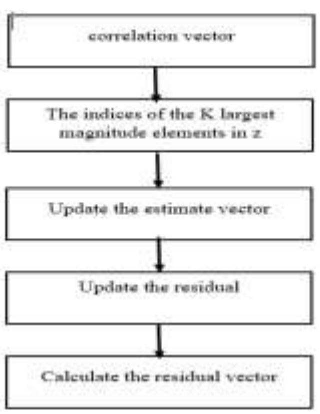

Fig 1. Subspace Pursuit Flow

It incorporates features from both OMP and subspace pursuit, allowing for the precise recovery of sparse signals with fewer input data points. Calculation as shown below

$$z = A^T * r_{k-1} \quad (7)$$

Find the K greatest magnitude elements in z and their corresponding indices using the correlation vector you just calculated.

$$I_k = \mathrm{argmax}(|z|, K) \quad (8)$$

Least-squares-estimation-based update of the estimate vector x_k:

$x_k(I_k) = \mathrm{argmin}_x \|y - A_{I_k} * x\|_2$ Update the residual, Calculate the residual vector r_k:

$$r_k = y - A * x_k \quad (9)$$

In compressive sensing applications, the OMP (Orthogonal Matching Pursuit) technique is frequently used for sparse signal recovery and estimation. As measurements are made, the most associated atoms from a dictionary are picked and used to revise the predicted sparse signal. As depicted in Fig. 2 represents the OMP workflow chart.

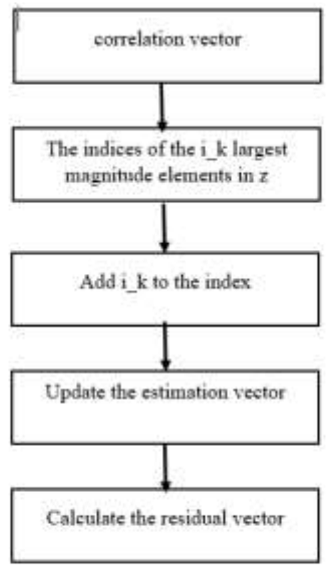

Fig 2. OMP Flow

Calculate the correlation vector equation(7):

$$z = A^T * r_{k-1}$$

Find the biggest magnitude element in z, then assign it the index i_k: $I_k = \max(\mathrm{argint}(|z|))$ (10)

Add i_k to the index set I_k: $I_k = I_{k-1} \cup \{i_k\}$

Refresh the least-squares-estimated vector x_k:

$$x_k(I_k) = \mathrm{argmin}_x \|y - A_{I_k} * x\|_2 \quad (11)$$

Calculate the residual vector r_k equation(9):

$$r_k = y - A * x_k$$

In compressive sensing applications, the CoSaMP (Compressed Sensing Matching Pursuit) method is frequently employed for sparse signal recovery. It is an

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improvement upon the Matching Pursuit algorithm that incorporates ideas from both OMP and CoSaMP to enable the rapid and precise recovery of sparse signals from fewer data points.

Determine the vector of correlation by equation(7):

$$z = A^T * r_{k-1}$$

Find the 2K elements with the biggest z-values:

$$I_k = \text{argmax}(|z|, 2K) \quad (12)$$

Update the estimate vector x_k using least squares estimation:

$$x_k(I_k) = \text{argmin}_x \|y - A_{I_k} * x\|_2$$

Threshold the estimate vector by keeping only the K largest magnitude elements:

$$x_k = \text{topK}(x_k, K) \quad (13)$$

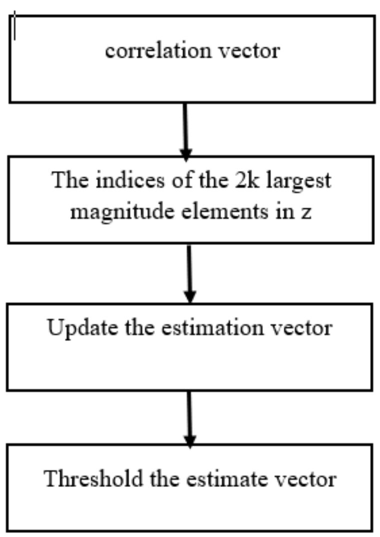

Fig 3. CoSaMP Flow

Fig.(3) represents CoSaMP working flow model. For compressive sensing applications requiring sparse signal recovery, two techniques stand out: Subspace Pursuit (SP) and Compressed Sensing Matching Pursuit (CoSaMP). The accuracy of sparse signal recovery can be enhanced by combining these methods with various estimate approaches like Least Squares (LS) and MMSE (Minimum Mean Square Error). In order to accurately recover sparse signals from a smaller number of measurements, SP is a technique that combines aspects of Orthogonal Matching Pursuit (OMP) and subspace pursuit. SP and LS estimation can be used together to revise Stage 2's predicted sparse signal coefficients. Minimising the least squares error between the measured and estimated signal is the goal of the LS estimation step, which provides a computationally simple and effective answer.

In SP, the least squares estimation requires resolving the following problem:

$$x_k = \text{argmin}_x \|y - A_{I_k} * x\|_2 \quad (14)$$

x_k is a new estimate of the sparse signal coefficients, where y is the measurement vector and A_{I_k} is the submatrix of A corresponding to the chosen indices I_k.

It is possible to use SP in conjunction with MMSE estimation to revise the Stage 2 predicted sparse signal coefficients. In order to minimise the mean square error between the measurements and the estimated signal, MMSE estimation takes into account the statistical features of the signal and noise. When the statistical properties of the signals and noise are considered, the minimum mean squared error (MMSE) estimation method yields the best possible mean squared error solution.

Under the sparsity constraint, the MMSE estimation in SP entails finding the optimal solution to an optimisation problem that minimises the predicted mean square error between the measurements and the estimated signal. The MMSE estimation can be formulated in several ways depending on the signal and noise statistics and the intended use.

The sparse signal recovery algorithm CoSaMP is a greedy one. In order to efficiently and accurately recover sparse signals from fewer data, it combines aspects of OMP and CoSaMP. CoSaMP and LS estimation can be used together to revise Stage 2's calculated sparse signal coefficients. The goal of the LS estimation phase is to obtain the signal estimate with the least squares error from the measurements.

The least squares problem that must be solved for the LS estimation in CoSaMP is as follows:

$$x_k = \text{argmin}_x \|y - A_{I_k} * x\|_2$$

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In a fashion analogous to SP, y represents the experimental data, A_I_k is the portion of A associated with the chosen indices I_k, and x_k is the latest estimate of the sparse signal coefficients.

CoSaMP and MMSE estimates can be used together to revise Stage 2's predicted sparse signal coefficients. In order to minimise the mean square error between the measurements and the estimated signal, MMSE estimation takes into account the statistical features of the signal and noise. In CoSaMP, the MMSE estimation is performed by minimising the expected mean square error (EMSE) between the measured signal and the estimated signal, while adhering to the sparsity constraint. The MMSE estimation can be formulated in several ways depending on the signal and noise statistics and the intended use.

Table.1 shows the parameters involved for simulation.

Number of Transmit antennas	2
Number of Receive antennas	2
Total number of subchannels	N=256
Symbols per carrier	8
Total number of pilots	P=256/8 = 32
Total number of data subchannels	S=N-P=224
Guard interval length	C=N/4=64
Channel length	L=16
Number of iterations	500
Modulation	QAM

Results & Discussions

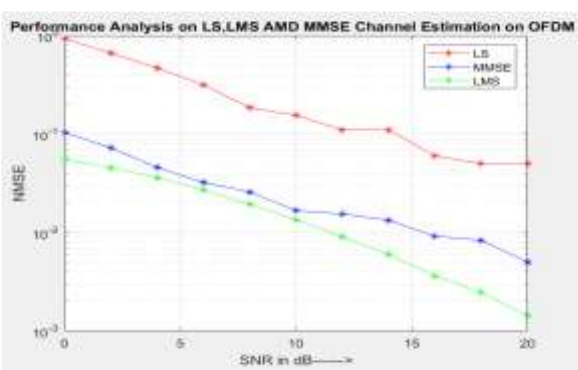

Fig4. Performance analysis of LS, MMSE, LMS channel estimation on OFDM

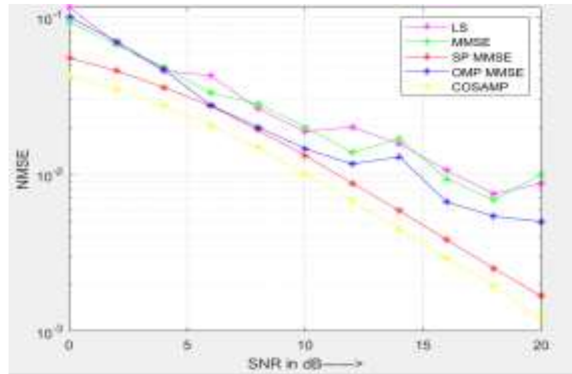

Fig 5. Performance analysis for channel estimation LS MMSE COSAMP SP-MMSE OMP -MMSE

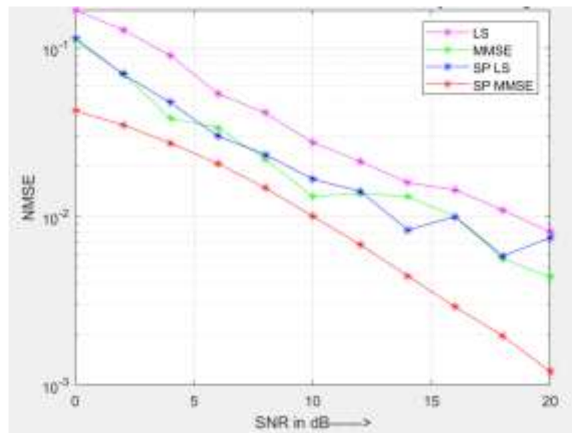

Fig 6. Performance analysis for channel estimation in MIMO-OFDM system using SP-LS SP-MMSE

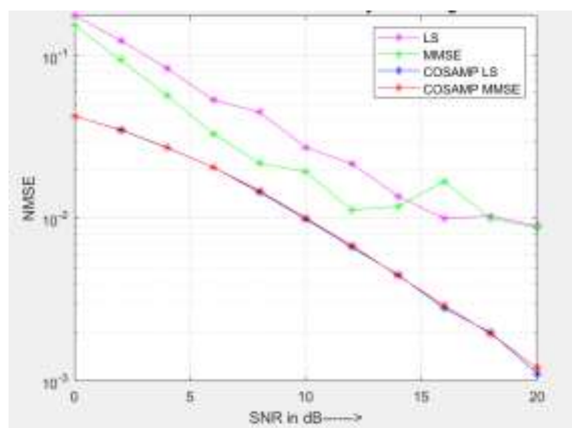

Fig 7. Performance analysis for channel estimation in MIMO-OFDM system using CoSaMP-LS CoSaMP-MMSE

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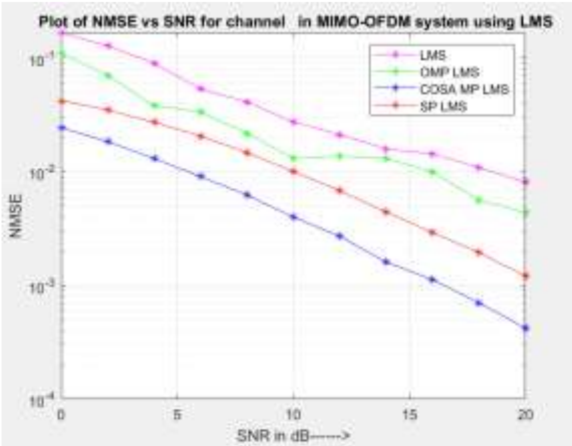

Fig 8. Performance analysis for channel estimation in MIMO-OFDM system using LMS

The MSE is a statistical measure of how far off the estimated channel is from the actual channel. A smaller MSE suggests more precise estimation. The signal-to-noise ratio (SNR) provides a numerical representation of this relationship. In most cases, higher SNR results in more accurate estimates. It should be kept in mind that the effectiveness of various estimation methods is highly context- and implementation-dependent.

In general, the MSE decreases as the SNR rises, indicating that the estimation is becoming more precise. Lower signal-to-noise ratios (SNRs) mean more noise is present, which in turn causes greater MSE and less precise estimations. In order to do precise channel estimates in OFDM systems, a high signal-to-noise ratio is required.

In Fig(4) LMS performs better than Least Square and Minimum Mean Square Error techniques.

In Fig(5) CoSaMP algorithm works better compared with OMP and SP compressed sensing algorithms.

In Fig(6) SP is combined with LS and MMSE. SP-MMSE gives better performance with low error rate.

In Fig(7) CoSaMP combined with LS and MMSE resulting CoSaMP-MMSE giving better performance.

In Fig(8) LMS is combined with OMP, SP, CoSaMP algorithms and CoSaMP-LMS gives good results. Since estimation in LMS channel involves adaptively altering coefficients until there is no error between the combined output and received signal. LMS- CoSaMP will give less error rate compared to LS and MMSE so this combination works better.

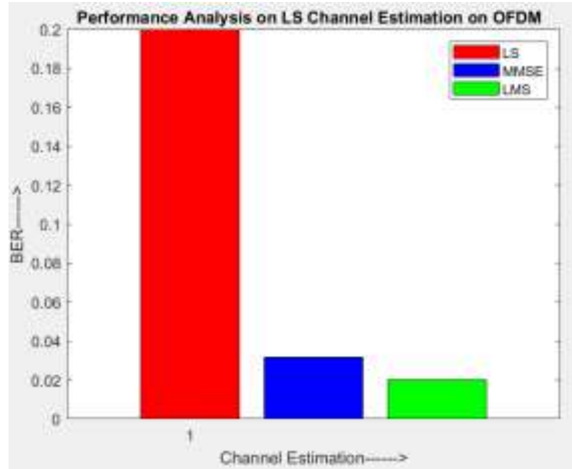

Fig 9. Performance analysis of LS estimation on OFDM

While LS channel estimation is useful as a starting point, it may not perform as well in highly degraded or noisy channels.

However, channel estimate is only one of several factors that affect BER in a communication system. Modulation technique, coding scheme, signal-to-noise ratio (SNR), interference, and system architecture are all additional considerations. Correct channel estimate can lessen the effect of channel fluctuations and boost system performance, leading to a lower bit error rate (BER). Fig(9) provides a BER comparison of all three channel estimation techniques LS, MMSE, LMS. LMS detects the best errors and hence has less error rate.

The following tabular column represents all combinations involved and is compared for SNR values at 10db and 20db CoSaMP-LMS is found to be the best of them all.

Combinations	SNR(db)	NMSE	SNR(db)	NMSE
LS	10	0.1550	20	0.0500
MMSE	10	0.0166	20	0.0050
LMS	10	0.0134	20	0.0014
OMP MMSE	10	0.0145	20	0.0050
SP MMSE	10	0.0131	20	0.0016
CoSaMP	10	0.0100	20	0.0012
SP LS	10	0.0166	20	0.0075
CoSaMP LS	10	0.0100	20	0.0012
CoSaMP MMSE	10	0.0100	20	0.0012
OMP LMS	10	0.0131	20	0.0043
SP LMS	10	0.0100	20	0.0012
CoSaMP LMS	10	0.0039	20	0.0004

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Fig.10 Tabulated results comparison of combinations

Conclusion and Future Scope

In conclusion, OFDM-MIMO (Orthogonal Frequency Division Multiplexing - Multiple-Input Multiple-Output) systems can benefit from channel estimation strategies that make use of adaptive filters and compressive sensing. Reliable communication is maintained thanks to adaptive filters' ability to monitor and estimate dynamic channel conditions. By taking use of the channel's sparsity, estimation accuracy is enhanced and overhead is minimised with the help of compressive sensing-based techniques. With the help of compressive sensing, we can make better use of the available resources without needing as many pilot symbols or training sequences. It is possible to mix and match adaptive filtering and compressive sensing-based approaches to optimise system performance. However, the costs and benefits of these methods must be weighed carefully. However, compressive sensing-based approaches rely on assumptions of channel sparsity and may be constrained by particular channel circumstances, while adaptive filters may add computational complexity. The trade-off between estimate accuracy and complexity, system needs, computational resources, and channel characteristics all play a role in deciding between adaptive filters and compressive sensing-based approaches for channel estimation in OFDM-MIMO systems. In order to choose the best method for a specific task, it is important to do thorough evaluations and optimisations based on actual system scenarios.

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