International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 10
***Article Received:** 25 July 2023 **Revised:** 12 September 2023 **Accepted:** 30 September 2023*

Bit Error Reduction in MIMO-OFDM with trellis Codes Using KALMN Filtering

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Abstract— The orthogonal frequency division multiplexing (OFDM) is used to transport data at a rapid rate. Due to the dynamic nature of the network, the bit error rate is the main problem with OFDM. The extra codes used in space-time trellis coding help to lower bit rate error on multipath fading channels. This study uses space-time trellis coding on a wireless channel to improve the bit error rates. In this work, space-time trellis codes with KALMAN filters are used to improve the bit error rate over wireless channels. The proposed modal is simulated in MATLAB software, and the results exhibit that the figure of bit error rate has decreased in network.

KEYWORDS: MIMO, OFDM, Trellis Codes, KALMAN, STTC

Introduction

With a focus on obtaining high data rates and dependable transmission, meeting the demands for high-quality services has become increasingly crucial in wireless communication systems. To meet these needs, the Long-Term Evolution (LTE) mobile communication standard was developed by the Third Generation Partnership Project (3GPP) [1]. The usage of multiple input multiple output (MIMO) and orthogonal frequency division multiplexing (OFDM) techniques has become a common strategy in the LTE system. Without the need for extra bandwidth, this combination offers the potential for large channel. To achieve optimal performance and keep receiver complexity low, it is crucial to develop detection algorithms that can deliver excellent error rate performance with high efficiency.

1.1 Architecture of MIMO-OFDM System

As demand for higher data rates has increased, wireless communication technology has undergone significant advancements. One promising technology is the use of multiple input and multiple output (MIMO) systems, which are based on orthogonal frequency division multiplexing (OFDM) [2]. By utilizing multiple antennas, MIMO-OFDM systems can significantly improve wireless communication capacity and enhance link reliability during data transmission. To fully capitalize on these benefits, the receiver's design is crucial. The main aims of the receiver are to achieve precise signal detection and to minimize the intricacy associated with detecting the signal.

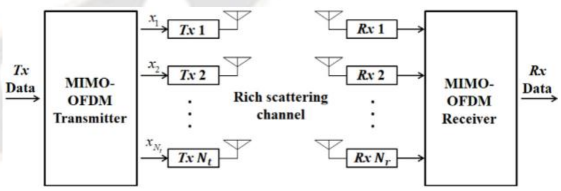

Fig. 1. The transceiver structure for MIMO-OFDM system model

Figure 1 depicts the configuration of the transceiver in the MIMO-OFDM system model. This model involves N_t transmit antennas and N_r receive antennas. At the MIMO-OFDM transmitter, digital signal processors are utilized for tasks such as modulation, inverse fast Fourier transform (IFFT), and cyclic prefix (CP) insertion, as referenced in [3]. Similarly, the MIMO-OFDM receiver consists of digital signal processors responsible for CP removal, fast Fourier transform (FFT), MIMO equalization, and demodulation. The complex baseband received symbols vector Y, which is composed of $[y_1\ y_2\ \cdots y_{N_r}]^T$ is represented as:

$$Y = HX + N$$

In the MIMO-OFDM system model, the vector X represents the transmit symbols, where $X = [x_1\ x_2\ \cdots x_{N_t}]^T$. The channel matrix H takes into account the complex MIMO wireless channel's rich scattering effects. N represents the complex AWGN (additive white Gaussian noise) vector. Mathematically, the representation of the channel matrix **H** can be expressed as follows:

$$\mathbf{H} = \begin{bmatrix} h_{11} & h_{12} & \cdots & h_{1N_t} \\ h_{21} & h_{22} & \cdots & h_{2N_t} \\ \vdots & \vdots & \ddots & \vdots \\ h_{N_r1} & h_{N_r2} & \cdots & h_{N_rN_t} \end{bmatrix}$$

The channel gain from the jth transmit antenna to the ith receive antenna is denoted by h_{ij}

1.2 Existing Signal Detection Schemes

There are several conventional signal detection techniques used in MIMO-OFDM systems, including:

i. Maximum Likelihood Detection: The ML detection method aims to find the optimal $\hat{X}$ that minimizes the value of $||Y - H\hat{X}||^2$. The equation for ML detection can be expressed as follows:

$$\hat{X}_{ML} = x \in |S|^{N_t}\ arg\ arg\ min\ \{||Y - HX||^2\}$$

The set of transmitter symbol constellation points is denoted by S, and the transmission signal vector's space is represented by $|S|^{N_t}$. While the ML detection approach offers the best error performance [5], it is difficult to implement at the receiver because the complexity of the ML detection algorithm increases proportionally to the size of $|S|^{N_t}$.

Zero-forcing (ZF): The zero-forcing (ZF) technique multiplies pseudo-inverse channel matrix and received vector to eliminate inter-antenna interference (IAI) in an efficient manner. The pseudo-inverse channel matrix, denoted as G, is obtained through a least squares (LS) approach to estimate the transmitted signal and is given by:

$$G = (H^H H)^{-1}\ H^H$$

The resulting estimated MIMO transmit vector using the zero-forcing technique is denoted as $\hat{X}_{ZF}$ [6].

$$\hat{X} = GY = X + \underline{Z}$$

The modified noise vector is represented as $\underline{Z} = GZ$.

1.3 QR-based energy efficient signal detection scheme in MIMO-OFDM systems

Several detection techniques have emerged in recent years. Maximum likelihood (ML) detection is renowned for its optimal performance in terms of error probability. However, its complexity escalates significantly as the modulation set and the number of transmit antennas increase. To attain near-ML performance while mitigating complexity, the QR decomposition with M algorithm (QRD-M) employs a tree search structure. The ML algorithm computes the squared Euclidean distance (SED) between received signals and reference symbols, and the transmit symbol is decoded from the reference set with the lowest SED among all feasible combinations [7]. However, the ML detector's energy efficiency at the receiver is lower in real-time wireless communication systems, especially for higher dimensionality of MIMO-OFDM with more transmit antennas and higher modulation orders. This can cause a faster depletion of the battery in mobile terminals, which needs to be addressed. The QR decomposition-M algorithm (QRD-M) is an ML detector of least complexity and maintains the nearly optimal error performance. The traditional algorithm is planned on the basis of traditional M-algorithm. At each detection layer, instead of making a decision on the transmitted symbol, the QRD-M algorithm prioritizes maintaining M dependable survivor paths. Initially, the algorithm performs QR decomposition on H, which can be represented as:

$$H = QR$$

In this, Q denotes a $L \times L$ unitary matrix and R is used to represent $N \times N$ upper triangular matrix [8]. In $Q^H Q = I, I$ illustrates the identity matrix and the conjugate transpose of Q is demonstrated with Q^H. When received signal is pre-multiplied with Q^H, the acquired signal is expressed as:

$$\tilde{y} = RS + \tilde{n}$$

where $\tilde{y}$ and $\tilde{n}$ are equivalent to $Q^H y$ and $Q^H n$ respectively. From (12), it is evident that [9]:

$$\frac{\tilde{y}_1 \quad = r_{1,1}s_1 + r_{1,2}s_2 + r_{1,3}s_3 + \cdots + r_{1,N}s_N + \tilde{n}_1}{\tilde{y}_2 \quad = \qquad r_{2,2}s_2 + r_{2,3}s_3 + \cdots + r_{2,N}s_N + \tilde{n}_2}$$

$$\frac{\tilde{y}_{N-1} \quad = \qquad r_{N-1,N-1}s_{N-1} + r_{N-1,N}s_N + \tilde{n}_{N-1}}{\tilde{y}_N \quad = \qquad r_{N,N}s_N + \tilde{n}_N}$$

where $\tilde{y}_i$ is the i-th element of vector $\tilde{y}$, and $r_{j,i}$ is the element of the j-th row and the i-th column of R and $r_{j,i}$ = 0 when $j > i$. Where $r_{j,i}$ is the component of the j-th row and the i-th column of R, and $r_{j,i}$ = 0 when $j > i$. Also, $\tilde{y}_i$ represents the i-th component of vector $\tilde{y}$. The signal detection from (13), where s_N to s_1 are the final and first components of s, can be accomplished by a tree searching technique. According to the accumulated Euclidean distances on various paths, only M-paths will persist in each detection layer of the traditional QRD-M method. Path metrics u_N are calculated as follows in the first detection layer (N-th row in R):

$$u_N = \|\tilde{y}_N - r_{N,N}\tilde{s}_N(m)\|^2$$

where $\tilde{s}_N(m)$ is s_N's m-th candidate [10]. The following formula is used to determine the total Euclidean distance of the m-th path in the i-th detection layer $(= (N - i + 1)th\ row\ in\ R)$:

$$u_{N-i+1} = \sum_{j=1}^{i} \left\|\tilde{y}_{N-j+1} - \sum_{k=N-j+1}^{N} r_{N-j+1,k}\tilde{s}_k(m)\right\|^2$$

Where the candidate of s_k on the m-th path is $\tilde{s}_k(m)$.

2. Literature Review

J.-H. Ro, et.al (2019) projected an adaptive QR-based energy efficient low complexity signal detection (EELCSD) method for MIMO-OFDM systems. The objective was to address the limitations of the Path Elimination QR Decomposition-M algorithm (PEQRD-M) and achieve near-optimal error performance (EP). The method utilized the channel state to implement two algorithms: sub-optimal PEQRD-M and a hybrid approach combining PEQRD-M with lattice reduction-aided decision feedback equalizer (LR-aided DFE). The selection of the detection method was done adaptively based on the computed condition number of the wireless channel. The initial algorithm was deployed in case of lower channel state at which it had greater condition number, and the latter one was adopted in case of satisfactory channel state at which it had least condition number. The simulation results validated that the projected method offered similar EP to PEQRD-M, and lower complexity at low Signal to Noise Ratio (SNR).

D. B. B. Pradhan, et.al (2022) suggested a deep neural network (DNN) with standard non-linearities and enhanced dimensions of inputs as a model to detect the MIMO-OFDM signal [12]. The DNN algorithms were adopted for managing the wireless MIMO OFDM channels end-to-end (E2E). According to simulation results, the suggested method was effective for detecting the transmitted signals more effectively in contrast to existing methods and it offered superior accuracy. The resilience was maintained against the varying channels and noise variance. Moreover, SNR range 5dB to 30dB was considered to compute the performance of the suggested method to detect the transmitted bits at the receiver end. The simulation indicated that the suggested method provided higher generalized ability and detected the signal in a precise way over channels having diverse features.

T. Zhao, et.al (2021) introduced a deep learning (DL) based technique in order to detect the signal in MIMO-OFDM-IM systems based on Variational Autoencoder (VAE) [13]. The major emphasize was on creating a model of variational optimization and formulating a learning deep neural network (DNN) model with fully connected layers (FCLs). A dataset was exploited to train the formulated model offline. Thereafter, this well-trained model helped to detect the signal in MIMO-OFDM-IM system. A regularization metric was put forward for providing higher efficiency. The results exhibited the supremacy of the introduced technique over existing methods. The introduced technique offered lower bit error rate (BER) at least runtime.

M. A. Alawad, et.al (2021) introduced a DL-based algorithm called DLIM to enhance signal detection and performance in MIMO-OFDM systems with index modulation (IM). DLIM utilized fully connected layers (FCLs) of a deep neural network (DNN) to achieve low bit error rates (BERs) in IM-MIMO-OFDM systems, particularly in Rayleigh wireless channels. The algorithm was trained offline using a dataset, which improved its efficiency. Subsequently, the algorithm focused on online data recovery during transmission. Simulation results demonstrated the effectiveness of DLIM in detecting transmitted symbols, achieving near-optimal BER performance, and reducing runtime compared to traditional methods.

V. D. Tran, et.al (2023) developed three deep neural network (DNN) algorithms to replace the conventional digital signal processing (DSP) modules at the receivers in the multiple input multiple output orthogonal frequency division multiplexing (MIMO-OFDM) systems of 2 2 and 4 4 in order to address the problem of non-linear distortions caused by power amplifiers (PA) of the transmitters [15].

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For de-mapping the signals at the receiver, the initial algorithm used DNN. The second algorithm used a DNN model to learn about and filter out receiver channel disturbances. The final algorithm employed DNN for de-mapping and detecting the signals at the receiver. These algorithms were concentrated on tackling the non-linear issue. The software and hardware were implemented for computing the results concerning bit error rate (BER). Furthermore, special methods, namely quantization and pipeline were employed for determining whether the formulated algorithms were feasible and practical.

Z. Zhang, et.al (2020) recommended a joint-sparse index removal (JSIR) based technique for MIMO-OFDM-CR system for detecting the index of space-frequency index modulation (SFIM) signal [16]. This approach was initially used to compute the received signal's inner-product matrix and channel gain in order to assess the index data for each subcarrier on each antenna. In order to compute the antenna index parameter, the concept of adding the parameters of all subcarriers on the antenna was then taken into consideration. According to this parameter, the silent antenna indices were discovered when the metric was put up against a threshold that was determined by a statistical distribution. To further ease the index detection issue, the silent antenna indices were removed. Eventually, a compressed sensing reconstruction algorithm was adopted to resolve the simplified problem for attaining indices of active subcarriers. The results confirmed that the recommended algorithm yielded least complexity and lower bit error rate (BER) under certain conditions.

L. Song, et.al (2022) presented a technique to identify signals for massive MIMO-OFDM modulation on high frequency (HF) skywaves [17]. The initial aim was to demonstrate how sparse supports can be associated with the beam domain channel and the space domain channel's Fourier spectrum. A Separate Slepian Transform (SST) based detector was then introduced, in which a collection of modulated Slepian sequences was created at the user terminal (UT) level. Prior to detect the MMSE, the dimension was mitigated for every UT using the presented detector so that matrices multiplications and inversions of higher dimensionality were avoided. Besides, joint Slepian transform (JST) based detector was suggested for alleviating the computing complexity. This detector focused on creating a set of modulated SSs and deploying the STs of the observation vector on the basis of fast Fourier transform (FFT) of lower dimensionality. Simulation results depicted the robustness of the introduced method for detecting the signals.

T. Murakami, et.al (2022) established a new system configuration on the basis of an uplink multiuser - MIMO-OFDM system in which a single RF chain receiver was comprised [18]. Using additional spatial multiplexing, the receiver in use oversampled the OFDM signals. The antenna directivity pattern was switched synchronously for this. The established system employed the oversampled OFDM signals to mitigate the noise and insert the spatial multiplexing. The results demonstrated the efficiency of the established system to enhance the channel potential. A test bed was employed to determine whether the established system was feasible. According to experiments, this system was applicable in an actual indoor office scenario.

3. Research Methodology

To direct ICI [12], the 2x1 STCC-OFDM frameworks are utilized which are significantly roused from the 2-way transmission mechanism of CC-OFDM scheme [13] [14]. There is uncertain similarity of the greater part of the current OFDM systems with that of STCC-OFDM system. Through the resolve of either time division multiplexing(TDM), frequency division multiplexing (FDM) or code division multiplexing (CDM), the multiplexing (MUX) circuit is employed at transmitter section and de-multiplexing (DEMUX) circuit at receiver section .

Through these means, the STCC-OFDM frameworks are planned.

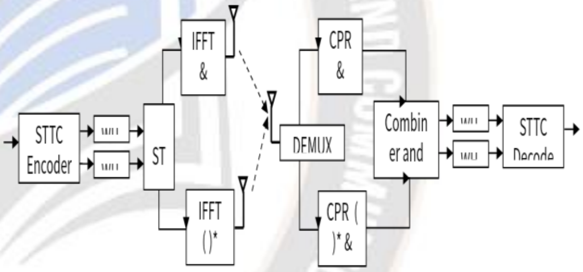

Figure 1.1

Figure 1.1: The architecture of a 2x1 STTC-WH-STCC-OFDM System with WHT pre-coders and CC scheme for mitigating ICI The presented architecture in Figure 1 introduces a novel STTC-WH-STCC-OFDM system, which combines the STTC-WH-ST-OFDM and the STCC-OFDM systems. The system includes a MUX circuit at the transmitter and a DEMUX circuit at the receiver. By employing the pre-coder WHT, the system achieves high transmission diversity gain among the subcarriers in the OFDM block. Additionally, the two-path transmission method is utilized to externally transmit conjugate data copies between the two blocks. Furthermore, it is possible to extend the MISO model to a MIMO architecture in this system.

The symbol vectors (d_1', d_2') and $(-d_1'^*, -d_2'^*)$ after coding and WH transformation are transmitted through two parallel branches in time slots 1 and 2. The upper branch performs IFFT, while the lower branch performs IFFT and conjugate operations ()* simultaneously. For demodulating

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the received signal from Tx1, the upper branch applies FFT at the receiver baseband. Similarly, the lower branch applies a conjugate operator followed by FFT to demodulate the received signal from Tx2. The DEMUX is used to process the upper and lower branches separately. The received signal vectors at time slots 1 and 2, from Tx1 and Tx2, are as follows:

$$y'_{111} = FFT\left[h_{11} * \left(IFFT(d'_1)\right)\right] = H_{11}d'_1 \ldots (1)$$

$$y'_{121} = FFT\{\left[h_{12} * \left(IFFT(d'_2)\right)^*\right]^*\} = H_{12}d'_2 \ldots (2)$$

$$y'_{112} = FFT\left[h_{11} * \left(IFFT(-d'^*_2)\right)\right] = -H_{11}d'^*_2 \ldots (3)$$

$$y'_{122} = FFT\{\left[h_{12} * \left(IFFT(d'^*_1)\right)^*\right]^*\} = H_{12}d'^*_1 \ldots (4)$$

Furthermore, the assumption is made that the fading remains constant across two consecutive time slots. Based on this assumption, hard decision variables are obtained, and they are represented as follows:

$$\underline{d_1} = \Psi^{-1}H^*_{11}y'_{111} + H^*_{12}y'^*_{122} = \Psi^{-1}\Psi(|H_{11}|^2 + |H_{12}|^2)d_1 \ldots (5)$$

$$\underline{d_2} = -\Psi^{-1}H_{11}y'^*_{112} + H_{12}y'_{121} = \Psi^{-1}\Psi(|H_{11}|^2 + |H_{12}|^2)d_2 \ldots (6)$$

Here, the hard-detected signal vector, denoted as $\underline{d_j}, j = 1{,}2$, is obtained at the receiver antenna Rx1 and transmitted through Tx antenna j. The channel effects on subcarriers are compensated using coherent combiner and detector after the inverse Walsh-Hadamard transform (IWHT) and coherent combiner. In the novel STTC-WHSTCC-OFDM system, new decoder algorithms are generated based on equations (5) and (6). Subsequently, the hard-detected signal vectors are processed by the maximum likelihood (ML) decoding algorithm, focusing on each subcarrier.

$$\underline{\hat{b}} = arg_Q min\left(\sum_{k=0}^{N-1} \left|\underline{d}^k_1 - Q_{11k}\right|^2 + \sum_{k=0}^{N-1} \left|\underline{d}^k_2 - Q_{12k}\right|^2\right) \ldots (7)$$

Here, the kth element of the hard detection vector is denoted by $\underline{d}^k_1$. This hard detection vector, represented as $\underline{d_j}, j = 1{,}2$, corresponds to the receiver antenna Rx1 and transmit antenna Tx "j". By utilizing two decision vectors, namely$\underline{d_1}$ and $\underline{d_2}$, along with the possible code words Q_{11k} and Q_{12k}, the squared Euclidean distances are separately calculated. Equation (7) presents the computation of the final soft-detected data bit vector, denoted as $\underline{\hat{b}}$. This mechanism combines the STTC, pre-coder WHT, and conjugate cancellation, leading to an improved bit error rate (BER) performance. The inclusion of MUX and DEMUX operations at the transmitter (Tx) and receiver (Rx), respectively, enhances the overall performance compared to previously studied approaches.

Filtering plays a crucial role in radio communication systems to mitigate the presence of noise. To address this issue, the Kalman filtering technique is commonly employed, which utilizes a series of mathematical equations. This technique aims to estimate the state of the process, leading to a reduction in the mean square error of the system. By applying this method to streams of noisy input data, optimal results can be achieved. The Kalman filter is known for its efficiency, as it incorporates predictions based on past, present, and future states of the system, considering various aspects for accurate estimation.

The Kalman filter maintains the estimates of the state:

$\hat{\mathbf{x}}(k|k)$ – estimate of $\mathbf{x}(k)$ given measurements $z(k)$, $z(k-1)$,...
$\hat{\mathbf{x}}(k+1|k)$ – estimate of $\mathbf{x}(k+1)$ given measurements $z(k)$, $z(k-1)$,...

and the error covariance matrix of the state estimate

$\mathbf{P}(k|k)$ – covariance of $\mathbf{x}(k)$ given $z(k)$, $z(k-1)$,...
$\mathbf{P}(k+1|k)$ – estimate of $\mathbf{x}(k+1)$ given $z(k)$, $z(k-1)$,...

The partitioning of the Kalman filter can be performed through simple steps that involve a physical interpretation. These steps allow for a clear understanding and implementation of the filter.

0. Known are $\hat{\mathbf{x}}(k|k), \mathbf{u}(k), \mathbf{P}(k|k)$ and the new measurement $\mathbf{z}(k+1)$.

1. State Prediction $\hat{\mathbf{x}}(k+1|k) = \mathbf{F}(k)\hat{\mathbf{x}}(k|k) + \mathbf{G}(k)\mathbf{u}(k)$ *Time update*
2. Measurement Prediction: $\hat{\mathbf{z}}(k+1|k) = \mathbf{H}(k)\hat{\mathbf{x}}(k+1|k)$
3. Measurement Residual: $\mathbf{v}(k+1) = \mathbf{z}(k+1) - \hat{\mathbf{z}}(k+1|k)$ *measurement update*
4. Updated State Estimate: $\hat{\mathbf{x}}(k+1|k+1) = \hat{\mathbf{x}}(k+1|k) + \mathbf{W}(k+1)\mathbf{v}(k+1)$

where $\mathbf{W}(k+1)$ is called the Kalman Gain defined next in the state covariance estimation.

When given Gaussian vectors vk, wk, and x0, the Kalman filter can be utilized to propagate the random vectors xk, xk+1, and Yk+1. By applying the concepts discussed earlier, the Kalman filter enables the propagation of the Gaussian distribution, facilitating the estimation and prediction of the random vectors at various time points.

4. Result and Discussion

The simulations are conducted using the COST207 6-ray typical urban (TU) frequency-selective mobile channels. The symbol rate is set to 220 symbols/second, and the sampling period Ts ranges from 2^{-20} seconds. The system configuration includes two transmit (Tx) antennas and one receive (Rx) antenna, and both QPSK 4-state and 16-state STTC are employed. The channel responses, h_{11} and h_{12}, are assumed to be known at the receiver and remain

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ISSN: 2321-8169 Volume: 11 Issue: 10
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constant for two OFDM block periods. The selected OFDM block size is 256, denoted as N, and one quarter of N samples are used for the cyclic prefix (CP). The simulation considers a maximum Doppler spread ranging from 100 Hz to 200 Hz, and the maximum Doppler spread to subcarrier frequency spacing ratio $\varepsilon_D = f_D N T_s$is in the range of 0.024 to 0.048.

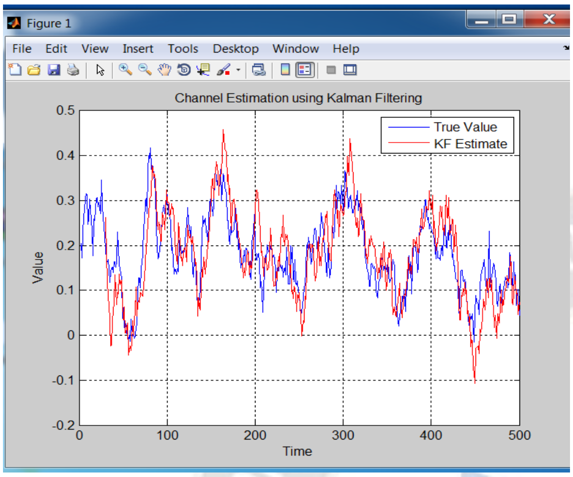

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Figure 2: Channel Estimation Using Kalman Filtering

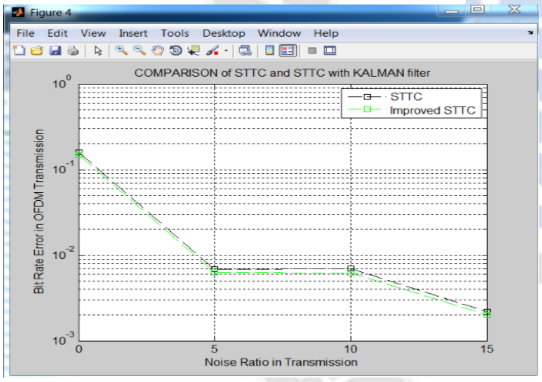

Figure 3: Comparison between MIMO-OFDM and with KALMAN filter

As depicted in figure 3, the black line represents the noise ratio in a conventional MIMO-OFDM system, while the green line illustrates the noise ratio when utilizing the Kalman Filter. It can be observed that the application of the Kalman Filter leads to a reduction in the noise ratio, resulting in improved performance in terms of bit error rate compared to the conventional MIMO-OFDM systems.

Conclusion

The research work concludes that MIMO-OFDM is a dynamic network with a high bit error rate. To address this issue, space-trellis codes are employed on the fading channel. However, the wireless fading channel still exhibits a high bit error rate. To mitigate this, the research work proposes the application of space-time trellis codes and the Kalman Filter. The proposed model is implemented in MATLAB, and simulation results demonstrate an improvement of up to 20 percent in the performance compared to the previous methods.

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