



An Approach Towards Wireless Telemedicine Application with Reduced PAPR and BER for Epilepsy Classification

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ABSTRACT

To monitor the epileptic activities in the brain, Electroencephalography (EEG) is widely used. The recordings of the EEG are too large to process and hence the dimensionality of the data should be reduced. In this paper, Linear Discriminant Analysis (LDA) is used as a dimensionality reduction technique and then this data is sent through the Differential Space Time Block Coded (DSTBC) Multiple Input Multiple Output (MIMO) Orthogonal Frequency Division Multiplexing (OFDM) system. The DSTBC systems are highly useful to transmit the data in the context of wireless communication systems because these are actual forms of space time codes that do not need to identify and know the channel impairments at the receiver side in order to decode the signal. For DSTBC MIMO OFDM System, an exhaustive study is made based on Peak to Average Power Ration (PAPR) Reduction and Bit Error Rate (BER) Reduction. PAPR reduction techniques such as Clipping and Filtering (CF) and Tone Reservation (TR) algorithms are used for this study. At the receiver side, Naïve Bayesian Classifier is incorporated as a post classifier to classify the epilepsy from EEG signals. The Classification Performance Measures are considered in terms of Specificity, Sensitivity, Time Delay, Quality Values, Performance Index and Accuracy.

Keywords: Electroencephalography, Telemedicine, Epilepsy, LDA, DSTBC, MIMO, OFDM, PAPR, BER.

INTRODUCTION

telemedicine system using modern information and communication technology in order to deliver biomedical signals such as EEG, EMG, ECG etc. for very long distance medical services has now become a reality¹. If the treatment required is urgent or if the treatment is for ordinary and normal health checkups, it is important to compress these signals before we send just for the efficient utility of bandwidth. EEG is widely used in the applications starting from the clinical diagnosis to brain research². EEG recordings play a vital role in the diagnosis and classification of brain related disorders like epilepsy, stroke, dementia etc. The EEG data recordings are too enormous to process because large electrode arrays are required to record the EEG data³. Since the EEG recordings are prolonging for a long time, the size of the data is too huge to process. As a result, the data should be compressed or the dimensionality of the data should be reduced without losing the essential characteristics of the signal⁴. The dimensionality reduction techniques should aim at attaining maximum data volume reduction while it still preserves the most essential qualities of the signal upon reconstruction. The compression of the data can be lossless where the fidelity of the signal waveform is highly preserved or the compression of the data can be lossy if the fidelity of the signal waveform is not preserved properly. Or in other words, in a lossy compression, a small amount of distortion is allowed in the decompressed data. Due to the random and inherent nature of the EEG signal, efficient compression of it is quite a difficult task. High compression rates can only be achieved with lossy compression methods. Some of the techniques used in the literature are KLT transforms for the lossless compression of the ECG signals, usage of wavelets and ARX models⁵. As long as the reconstructed quality of the EEG signal preserves the pertinent information for clinical investigation, lossy compression techniques are acceptable. Recent literature shows the approach of SPIHT algorithm in the compression and dimensionality reduction of data. This paper uses LDA as a dimensionality reduction technique in order to reduce the dimensions of the EEG data and then it is transmitted through the DSTBC MIMO-OFDM System. The figure 1 shows the block diagram of the entire research work.



Figure 1: Block Diagram of the Work

Acquisition of EEG data

According to the International 10-20 system, the EEG is recorded by placing electrodes on the scalp of the patient. For both referential montages, sixteen channels of EEG are recorded simultaneously. All the electrodes



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are referenced and placed to a common potential point like ear and in the case of bipolar montages, each electrode is referenced to an adjacent electrode. When the patient is awake and resting, the recordings are made. The resting stage includes periods of hyperventilation, photonic stimulation and includes period of eyes open and closed. Using the EEG machine Siemens Minograph Universal the amplification is easily provided. The scalp is cleaned well and lightly abraded and then between the electrode and the skin, electrode paste is applied and then the electrodes are placed on it.

The contact impedance is less than 10 $k\Omega$ with respect to the application of electrode paste on the skin.

The obtained EEG is broken down into epochs or sections for the purpose of dimensionality reduction. An epoch of 2 seconds is primarily used because it is pretty long enough to capture the most important statistical features and characteristics of the EEG and it is short enough to capture the seizure evolution. The EEG being digitized at a total sampling rate of about 200 Hz for an epoch of 2 seconds each which contains 400 samples totally, is a very convenient length for computation purposes. For analyzing the EEG data, the software implemented was Matlab 7.0. The EEG data used in this study were obtained from 20 different epileptic patients who were in the evaluation and treatment process in the Department of Neurology, Sri Ramakrishna Hospital, Coimbatore, India. Through a 10-20 international electrode placing method, a digital record of 16 channel EEG data in bipolar method is acquired from a clinical EEG monitoring system in European Data format. With the help of neurologist, EEG records with most distinct features had been selected. The total number of artifacts present in our data is four types which include Electromyogram (EMG) artifacts, eye blinks, chewing and motion artifacts. The main objective of the inclusion of artifacts is to have spike and non spike categories of waveforms. A suitable part or a segment of EEG data has to be selected in order to train and test the signal component extractors and classifier. All the signals of EEG are examined by a good qualified EEG technologist. The EEG records are over a continuous duration of about 30 seconds and these records are divided into an epoch which has two second duration. To detect the significant changes in activity, a two second epoch is long enough. The two second epoch is also long enough to avoid unnecessary repetition and redundancy in the signal. The EEG signal has a maximum frequency of 50 Hz and since sampling frequency has to be greater than twice the maximum frequency and so each epoch is sampled at a frequency of 200 Hz. Each and every sample corresponds to the amplitude values of the signal which are instantaneous in nature and totally 400 values for an epoch is obtained. Therefore each channel has 400 samples of EEG signals per epoch and four such data epochs comprises a bin. For a patient, there are totally 16 bins available. Therefore the data volume for each and every patient is around 25,600 samples. Hence for processing this large amount of data, dimensionality

reduction techniques are incorporated. The different parameters used for the quantification of the EEG signals are computed using amplitude values with the help of suitable programming codes. The representation of EEG samples in reduced sample space is done either by features or dimensionally reduced components. So we have chosen the dimensionality reduction techniques which is discussed in the following sections of the paper.

Dimensionality Reduction

Linear Discriminant Analysis (LDA)⁶ is just a generalization of Fisher's linear discriminant. It is widely used in methods employed for statistics, pattern recognition and machine learning to find out the linear combination of feature dimensions that splits two or more classes of events. Such a resulting combination may be used for both classification purposes and dimensionality reduction processes. It is quite closely related to Regression Analysis and Analysis of Variance (ANOVA). All these techniques try to express a dependant variable as a linear combination of various other feature measurements. The main objective of LDA is to perform dimensionality reduction while it still preserves as much of the class discriminatory information. Assuming that there are a set $\{\mathbf{r} \ \mathbf{r} \ \mathbf{r}\}$ 37

of
$$D$$
 dimensional samples $\{x_1, x_2, ..., x_N\}$, in which N_1 belongs to class w_1 and N_2 belongs to class w_2 . A scalar 'y' is obtained by projecting the samples x onto a particular value as

particular value as

$$y = w^T x$$
.

The one line which maximizes the scalars separability is selected out of all the possible lines. In order to find a good projection vector, a definite need for the measurement of separation in between the projection is required. For each class, the scatter is defined as follows which is an equivalent of the variance as follows

$$\hat{S}_i^2 = \sum_{y \in w_i} (y - \hat{\mu}_i)^2$$

Thus the solution proposed by Fischer is to always maximize a function that represents the difference between the means and normalized by a measure of the within class scatter.

MIMO-OFDM System

Wireless channels suffer greatly from time-varying impairments like noise, interference and multipath fading⁷. Techniques such as diversity (time, space, frequency, polarization) can be used to mitigate those impairments. By receiving many independent copies of the fading replicas of the signal, diversity gain can be easily achieved. The multiple antenna system employs multiple antennas either at the transmitter side or receive side and can take many forms. For beamforming applications, Multiple Input Single Output (MISO) is used, for diversity combining at the receiver, Single Input



Available online at www.globalresearchonline.net © Copyright protected. Unauthorised republication, reproduction, distribution, dissemination and copying of this document in whole or in part is strictly prohibited. Multiple Output (SIMO) is used and depending on the total number of transmit and receive antennas. MIMO is used⁸. By utilizing the angle-delay scattering function, the channel models of MISO, SIMO and MIMO can be done. A MIMO system comprises of numerous or multiple antennas at both the transmitter and receiver side and is primarily used for spatial multiplexing and transmit diversity applications. The system capacity can be easily maximized by spatial multiplexing concept by transmitting a different bit stream at each transmit antenna. MIMO technology assures a significant improvement in the capacity of the system. The spatial diversity scheme is effectively utilized by MIMO system. The MIMO systems are successfully incorporated in various ways to obtain a diversity gain and to combat signal fading. In a more specific manner, the power efficiency is improved with the MIMO techniques by means of maximizing the spatial diversity. MIMO and OFDM are definitely the key techniques for nextgeneration mobile communication⁹. OFDM is a potential technique for the Fourth generation wireless mobile systems. A frequency-selective channel is being converted into parallel frequency flat sub channels with the help of OFDM¹⁰. A least amount of frequency separation is required in between the subcarriers which is definitely mandatory to maintain the orthogonality so that the overlapping in the frequency can be avoided easily. Therefore, the bandwidth available can be used in a very resourceful manner. OFDM transmitter can adapt its signaling scheme to match easily with the channel only if the necessary knowledge of the channel is available at the transmitter. OFDM uses a vital large amount of narrowly spaced sub channels and these strategies seem to be more adaptive and can come within the reach of water pouring capacity of a particular frequency-selective channel. In real time channel, this is achieved by the usage of adaptive bit loading techniques where different sized signal constellation patterns are transmitted on the subcarrier.

To improve the diversity gain, OFDM is united with antenna arrays at both the transmitter and receiver sides. Such a contribution helps to improve the competence of the system on time varying frequency selective channels, thus resulting in MIMO composition. When space time block codes are incorporated with OFDM system having multiple transmit and receive antennas, it is called as Space Time Block Coded (STBC) MIMO-OFDM System¹¹. In STBC MIMO-OFDM System, the coding is implemented in only time domain, that is, the importance is given to the OFDM symbols. The Differential STBC are highly useful in the context of wireless communication because they have no necessity to understand and identify the channel impairments present in the receive side for the sake of decoding the signal¹². For this DSTBC MIMO OFDM System, an exhaustive study is made based on the PAPR reduction techniques like Clipping and Filtering¹³ and Tone Reservation techniques¹⁴ under Quadrature Phase

Shift Keying (QPSK) modulation scheme for Rayleigh Multipath Fading Channel.

System Model

An ordinary communication system incorporating spacetime block coding technique with just two transmit antennas and one or more receive antennas is considered for the analysis. The information blocks of symbols in the transmitter side are passed to the next unit called differential space-time block encoder, where two symbols are embedded in each block. The code words of length M = 2 is generated by the space-time block encoder where M signifies to the total number of transmit antennas. The OFDM Modulator and the radio frequency (RF) front-ends obtain these code words and then it modulates the useful information onto the carrier frequency. On the constructed receiver side, up to $\,N\,$ receiver antennas can be efficiently made use of for reception probably. The RF signals are completely downconverted and digitized in the RF front-ends and then finally passed to the differential space-time block decoder unit followed by the OFDM Reed Solomon demodulator unit. The interpretation of the received signals is done by the space-time block decoder and after that the received signals are obtained and generated for estimates as the transmitted information symbols, which are again provided simultaneously in blocks of two symbols.

PAPR in MIMO-OFDM

In each and every N_T parallel OFDM transmitters, a particular block of D distinct complex-valued carriers say, $A_{\mu,\nu,\mu} = 1,..., N_T, \nu = 0,...D-1$, is transformed into its respective time-domain using the Inverse Discrete Fourier Transform, that is,

$$a_{\mu,k} = \frac{1}{\sqrt{D}} \sum_{\nu=0}^{D-1} A_{\mu,\nu} e^{j2\pi k\nu/D}, \mu = 1, ..., N_{T,k} = 0, ..., D-1.$$

On the combination of the time-domain samples into a specific vector $a_{\mu} = [a_{\mu,0,\dots,}a_{\mu,D-1}]$, the respective correspondence is written as $a_{\mu} = IDFT \{A_{\mu}\}$. Generally in almost all the wireless applications, all frequency-domain samples $A_{\mu,\nu}$ are expected to be obtained from similar constellation points with variance σ_a^2

Since the carriers are statistically independent, the time-

domain samples $a_{\mu,k}$ are complex Gaussian distributed in an approximated sense. This leads to a very high peak-to-average power ratio as



As a versatile performance measure, the probability that the PAPR of an OFDM frame exceeds a given threshold, i.e., that the squared magnitude of at least one sample N_T is a standard D in the squared back of the same standard definition of the standard definit

over the N_T antennas and D time steps is larger than tolerated: $|a_{\mu,k}|^2 > PAR_0\sigma_a^2$ is carried out in literature.

tolerated: $| \mu, \kappa |$ | u = 0 a is carried out in literature. With this consideration, the Complementary Cumulative Distributive Function (CCDF) of the PAPR $P_r \{PAPR > PAPR_0\}$, clipping probabilities can be

determined easily.

In MIMO-OFDM, since $N_T D$ instead of D time-domain samples are present and the CCDF of the PAPR¹⁵ is represented mathematically as follows

$$P_r \{ PAPR_{MIMO} > PAPR_0 \} = 1 - (1 - e^{-PAPR_0})^{N_T D}$$

PAPR Reduction Technique using Clipping and Filtering Scheme in DSTBC OFDM System

In this clipping and filtering technique as shown in the Figure 2, *L* is considered as the oversampling factor and *N* is assumed as the total number of subcarriers.

In this particular scheme, the *L*-times oversampled discrete-time signal x'[m] is fully generated from the IFFT equation $(X'[k] \text{ with } N.(L-1) \text{ zero-padding in the frequency domain) and is then modulated with a particular carrier frequency <math>f_c$ in order to yield a pass band signal $x^p[m]$. Let $x_c^p[m]$ indicate the clipped version of $x^p[m]$, which is expressed mathematically as follows

$$x_{c}^{p}[m] = \begin{cases} -A & x^{p}[m] \leq -A \\ x^{p}[m] & \left| x^{p}[m] \right| < A \\ A & x^{p}[m] \geq A \end{cases}$$

$$x_{c}^{p}[m] = \begin{cases} x^{p}[m] & |x^{p}[m]| < A \\ \frac{x^{p}[m]}{|x^{p}[m]|} A & otherwise \end{cases}$$

where A is understood as the pre-specified clipping level. The clipping ratio $(CR)^{16}$ is defined as the clipping level

normalized by the RMS value $\,^{\sigma}$ of OFDM signal and is expressed as follows

$$CR = \frac{A}{\sigma}$$

In wireless contexts it is observed that $\sigma = \sqrt{N}$ and

 $\sigma = \sqrt{N/2}$ in the baseband and pass band OFDM signals with N subcarriers respectively.

Finally this Clipping and Filtering Scheme is incorporated in DSTBC MIMO-OFDM System as shown in the Figure 2.

$$\begin{array}{c} \mbox{Input} & \rightarrow & \mbox{MIMO} \\ \mbox{Input} & \rightarrow & \mbox{Input} \\ \mbox{STBC} & \mbox{IFFT} & \rightarrow & \mbox{Digital Up} \\ \mbox{Cipping} & \rightarrow & \mbox{Cipping} \\ \mbox{Cipping} & \rightarrow & \mbox{MPoint} \\ \mbox{FFT} & \rightarrow & \mbox{Res} \\ \mbox{FFT} & \rightarrow & \mbox{IFFT} \\ \mbox{IFFT} & \rightarrow & \mbox{LPF} \\ \mbox{IFFT} & \rightarrow & \mbox{LPF} \\ \mbox{IFFT} & \rightarrow & \mbox{IFFT} \\ \mbox{IFFT} & \rightarrow & \mbox{IF$$

Figure 2: Block Diagram for incorporating the PAPR reduction technique using Clipping and Filtering scheme in DSTBC MIMO OFDM system

The following algorithm steps are followed completely in the paper.

Step 1: The program is initially started

Step 2: The serial data is fully converted into parallel data and then the sparse H matrix for Differential Space Time Encoder is computed.

Step 3: The sparse matrix H is completely shifted and only then the encoding of the input bits are done.

Step 4: Using QPSK modulation, the input bits are modulated

Step 5: The parallel data obtained is also computed directly using N point Inverse Fast Fourier Transform (IFFT).

Step 6: Following this step, digital up-conversion is implemented and then the signal is clipped.

Step 7: Then FFT is applied so that it is converted into frequency domain from time domain and then it is passed inside the Band Pass Filter (BPF).

Step 8: Finally the IFFT is computed to convert frequency domain into time domain and then it is passed inside the Low Pass Filter Unit (LPF).

Step 12: Then the parallel data is then converted into serial bits, then decoded using the differential STBC and error is detected using Reed Solomon Codes and thus the receiver will decode only the data tones and at the end, PAPR value is calculated.

Step 13: The threshold value is calculated and then it is checked that whether PAPR>threshold value

Step 14: As a final step, the Complementary Cumulative Distribution Function (CCDF) plot versus probability of PAPR is computed and the plot is drawn



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Step 15: The bit error rate is also computed for a (2×2) DSTBC MIMO-OFDM system

Step 16: Stop the program

PAPR Reduction Technique Using Tone Reservation Scheme in DSTBC OFDM System

The following algorithm steps are followed completely in the paper.

Step 1: The program is started with the inputs fed inside it.

Step 2: The serial data is converted into parallel data and then the sparse H matrix for Differential Space Time Encoder is calculated.

Step 3: The sparse matrix H is again shifted and then the input bits are encoded as done in the Clipping and Filtering stage.

Step 4: Here also, the input signals are modulated using **QPSK** scheme

Step 5: Meanwhile, the parallel data obtained is also directly computed using N point Inverse Fast Fourier Transform (IFFT).

Step 6: A tone reservation technique partitions the N subcarriers (tones) into data tones and peak reduction tones (PRTs).

Step 7: The symbols in the PRTs are chosen such that the OFDM signal in the time domain has a lower PAPR. The positions of PRTs are known to the receiver and transmitter.

Step 8: Since the data tones and PRT are exclusively assigned, the input vector to IFFT block is divided into data vector X and PAPR reduction vector C.¹⁴

Step 9: Let $R = \{i_{0,...,R-1}\}$ and R^c denote the set of RPRT positions and its complement, respectively, where R denotes the number of tones reserved for peak reduction. Then the input symbols to IFFT block can be expressed as follows

$$X[k] + C[k] = egin{cases} C[k], k \in R \ X[k], k \in R^c \end{cases}$$

where $\overset{X[k]}{=}$ and $\overset{C[k]}{=}$ denote the data symbol and PRT symbol, respectively.

Step 10: By taking the IFFT of the symbols given by the above equation, we obtain the OFDM symbol to be transmitted as follows

$$x[n] + c[n] = \frac{1}{N} \sum_{k \in \mathbb{R}^{c}} X[n] e^{j2\pi kn/N} + \frac{1}{N} \sum_{k \in \mathbb{R}} C[n] e^{j2\pi kn/N}$$

Step 11: The PRT signal c[n] does not cause any distortion on the data signal x[n] due to the orthogonality among subcarriers. Under the assumption that CP (Cyclic Prefix) is longer than the channel impulse response, the received OFDM symbol in the frequency domain can be expressed as follows

$$H[k](X[k] + C[k]) + Z[k] = \begin{cases} H[k]C[k] + Z[k], k \in R\\ H[k]X[k] + Z[k], k \in R^c \end{cases}$$

where H[k] is the channel frequency response and Z[k] is the DFT of the additive noise. The receiver will decode only the data tones for $k \in \mathbb{R}^{c}$.

Step 12: Then the parallel data is then converted into

serial bits, then decoded using the differential STBC and finally demodulated using Reed Solomon Codes and thus the receiver will decode only the data tones and at the end. PAPR value is calculated.

Step 13: The threshold value is calculated and then it is checked that whether PAPR>threshold value

Step 14: As a final step, the Complementary Cumulative Distribution Function (CCDF) plot versus probability of PAPR is computed and the plot is drawn

Step 15: The bit error rate is also computed for (2 x 2) DSTBC MIMO-OFDM system

Step 17: Stop the program

Naïve Bayesian Classifier as a Post Classifier at the **Receiver Side**

In the Receiver side of the system, Naïve Bayesian Classifier¹⁷ is incorporated to classify the epilepsy from EEG which are obtained after the transmission. In the data preprocessing stage of the NBC, attribute grouping has to be done. Each column of the measurements of this gene expression is divided into a number of groups. Then in a random manner the number of groups can be easily chosen. The grouping is done in the 3 phases as follows:

Initially, the maximum (χ_{min}) and maximum values (x_{\max}) in each column of the EEG data set is found out. Secondly, the number of groups in every column is decided and then Δ is calculated.

$$\Delta = (x_{\max} - x_{\min}) | n$$

Thirdly, the values of threshold (θ_i) is then calculated as

$$\theta_i = x_{\min} + n_i * \Delta$$

where ($n_i = (1, 2, ..., n - 1)$

Now the NBC is developed as follows

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$$v = \arg \max_{v_i \in V} P(V_j) \prod_{i=1}^n P(a_i | v_j)$$

where $\ensuremath{\,^{\mathcal{V}}}$ =target value of output by the Naïve Bayesian Classifier

 $P(v_j) = \frac{v_j}{\text{frequency with which each target value}}$

 a_{i} = instance with n attributes, where i = (1, ..., n)

 v_j are classes for instances from the set of all particles classes in v

$$\prod_{i=1}^{n} P(a_i | v_j)$$

i=1 is the joint product of probabilities for the individual attributes.

RESULTS AND DISCUSSION

In this section the results of PAPR reduction and BER Reduction for DSTBC MIMO-OFDM System is explained followed by the classification results of the Naive Bayesian Classifier at the Receiver Side.

Performance Analysis of PAPR and BER for DSTBC MIMO OFDM System using QPSK Modulation under Rayleigh Channels

The type of modulation engaged here is Quadrature Phase Shift Keying.

In general context, the channel experienced by each and every transmit antenna is highly independent from the channel experienced by other transmit antennas.

Each transmitted symbol always gets multiplied by a varying complex number which is quite random in nature

from the i^{th} transmit antenna to j^{th} receive antenna. Rayleigh channel is mainly considered here and so the real and imaginary part which has a particular variance and mean are Gaussian distributed.

Between each and every transmitter to the receiver antenna, the channel experienced is independent and varies randomly with respect to time.

The minimum estimate of the transmit symbol is chosen. It is then repeated for multiple values of Eb/No and then the simulation and theoretical results are found out. Table 1 shows the simulated parameters considered for PAPR and BER analysis.

On the careful analysis of the Figure 3, it is apparent that when QPSK modulation is engaged, the PAPR is reduced when the clipping and filtering is increased for a (2×2) DSTBC MIMO OFDM System.

Table 1: Simulation Parameters for PAPR Reduction

Modulation used	QPSK		
MIMO System analyzed	2 x 2 MIMO-OFDM		
Number of subcarriers	128		
No of sub-blocks	4		
Maximum symbols loaded	1e5		
Symbol rate	250000		
No of time slots	2		
Window function	Blackman-Haris		
HPA Model	SSPA		
No of frames	10		
No of OFDM symbols/ frame	4		
Bandwidth	5 MHz		
Oversampling factor	4		



Figure 3: PAPR Reduction of DSTBC MIMO OFDM system using QPSK Modulation in (2 x 2) Systems using Clipping and Filtering Technique.

From the figure 3, when QPSK is employed and for different Clipping Ratio (CR) values as CR=1,2,3 and 4, the graph is plotted and it provided a PAPR reduction of about 5.2dB when the CCDF=10⁻³ respectively.



Figure 4: PAPR Reduction of DSTBC MIMO RS OFDM system using QPSK Modulation in (2 x 2) Systems using Tone Reservation Technique.



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On the careful analysis of the Figure 4, it is apparent that when QPSK modulation is engaged, the PAPR is slightly reduced for (2×2) DSTBC MIMO OFDM System.

From the Figure 4, when QPSK is employed and for different data collection values, the graph is plotted and it provided a less PAPR reduction of about 2.4dB when the $CCDF=10^{-3}$ respectively.



Figure 5: BER Analysis for the System

It is evident from Figure 5 that the BER produced is relatively low for Tone Reservation Scheme than the Clipping and Filtering Scheme for the DSTBC MIMO-OFDM system.

NBC Classification Performance Analysis

For LDA as dimensionality reduction techniques and NBC as a Post Classifier, based on the Quality values, Time Delay and Accuracy the results are computed in Tables II respectively. The formulae for the Performance Index (PI), Sensitivity, Specificity and Accuracy are given as follows

$$PI = \frac{PC - MC - FA}{PC} \times 100$$

where PC – Perfect Classification, MC – Missed Classification, FA – False Alarm

The Sensitivity, Specificity and Accuracy measures are stated by the following

$$Sensitivity = \frac{PC}{PC + FA} \times 100$$
$$Specificity = \frac{PC}{PC + MC} \times 100$$

$$Accuracy = \frac{Sensitivity + Specificity}{2} \times 100$$

The Quality Value Q_V is defined as

$$Q_V = \frac{C}{(R_{fa} + 0.2) * (T_{dly} * P_{dct} + 6 * P_{msd})}$$

where C is the scaling constant,

 R_{fa} is the number of false alarm per set,

 T_{dly} is the average delay of the onset classification in seconds

 $\mathsf{P}_{\mathsf{dct}}$ is the percentage of perfect classification and

 $\mathsf{P}_{\mathsf{msd}}$ is the percentage of perfect risk level missed

The time delay is given as follows

$$\text{Time Delay} = \left[2 \times \frac{PC}{100} + 6 \times \frac{MC}{100} \right]$$

The Quality Value Analysis for the application of LDA as dimensionality reduction technique followed by the application of NBC as Post Classifiers is shown in Figure 6. The Time Delay measures for the application of LDA as dimensionality reduction technique followed by the application of NBC as Post Classifiers is shown in Figure 7. Similarly the Accuracy Analysis for the application of LDA as dimensionality reduction techniques followed by the application of NBC as Post Classifiers is shown in Figure 8.

Table	2:	Average	Performance	Measures	for	all	the
Patien	ts						

Parameters	Epoch-1	Epoch-2	Epoch-3	Average Values
PC	81.04	80.83	80.93	80.93
MC	13.33	12.08	12.70	12.70
FA	5.625	7.08	6.35	6.35
PI	75.86	75.62	75.74	75.74
Sensitivity	94.37	92.91	93.64	93.64
Specificity	86.66	87.91	87.29	87.29
Time Delay	2.42	2.34	2.38	2.38
Quality Value	17.70	17.63	17.66	17.66
Accuracy	90.52	90.41	90.46	90.46



Figure 6: Average Quality Value Measures



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Figure 7: Average Time Delay Measures





CONCLUSION

Thus the EEG serves as a significant tool for the clinical diagnosis and monitoring of epilepsy and other related brain disorders. In this paper, initially the dimensions of the raw EEG signal were reduced with the help of LDA and it is then transmitted through the DSTBC MIMO OFDM system. For the DSTBC MIMO-OFDM System, two PAPR reduction algorithm namely the Clipping and Filtering and Tone Reservation Schemes was employed to reduce the PAPR. The receiver side was incorporated with Naïve Bayesian Classifier to classify from the epilepsy from EEG signals. An overall accuracy of 90.46% is reported in this work with a Perfect Classification rate of 80.93%. The average Quality Value Reported is around 17.66 in this work. If the PAPR analysis is considered, then this work has a PAPR reduction of about 5.2 dB when QPSK modulation scheme is implemented using Clipping and Filtering Algorithm for the system and when Tone Reservation Algorithm is considerd the PAPR is reduced by 2.4 dB.

The BER shows a slightly better result for the Tone Reservation Algorithm rather than the Clipping and Filtering Algorithm. Thus for EEG telemedicine application this work is found to be highly useful.

Future works may incorporate the usage of different dimensionality reduction techniques, different classification techniques and other PAPR reduction techniques for the better transmission and reception of EEG signals.

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