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INTELLIGENT COMPUTING TECHNIQUES FOR EPILEPSY CLASSIFICATION FROM EEG SIGNALS UTILIZED FOR WIRELESS TELEMEDICINE SYSTEMS

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Abstract:

Characterized by recurrent seizures, epilepsy is not just a neurological disorder but also a life threatening disorder. Epilepsy is assessed easily with the help of Electroencephalogram (EEG). Due to the non-stationary and non-linear nature of the EEG signals, it is quite difficult to assess and evaluate the EEG signals. Since the nature of the seizures occurs in an irregular and unpredictable manner, detecting the seizures automatically in EEG recordings is a very hectic task to be performed.

The enormous amount of data produced in the EEG recordings is also high. Therefore in this paper, Linear Graph Embedding is utilized as a dimensionality reduction technique to reduce the size of the EEG data. It is then transmitted through a 2 x 2 DSTBC MIMO-OFDM System. Since the DSTBC MIMO-OFDM system suffers a high Peak to Average Power Ratio (PAPR), a Particle Swarm Optimization (PSO) based PAPR reduction technique using Tone Reservation Scheme is implemented to reduce the PAPR and Bit Error Rate (BER).

At the receiver side, Linear Support Vector Machine (L-SVM) is utilized to classify the epilepsy risk levels from EEG signals. The bench mark parameters utilized here are Specificity, Sensitivity, Time Delay, Quality Values, Performance Index, Quality Values, PAPR and BER.

Keywords: EEG, epilepsy, MIMO-OFDM, PSO, PAPR, BER.

1. Introduction and Related Works

The EEG is the electrical activity recorded from the scalp of the human brain. EEG is a basic tool for the analysis and diagnosis of brain disorders especially epilepsy [1]. Being a non-invasive procedure, the activities of the brain are registered easily. The EEG has provided numerous promising aspects for the computer-based signal processing measures to help in the epilepsy diagnosis [2].

The epilepsy is one neurological disorder which has a seizures effect in the nervous system and its cause is unknown in most of the cases. As epilepsy is characterized by recurrent seizures, it is also called as seizure disorders [3]. Seizures are nothing but the reflection of disturbances of the brain which are functioning temporarily. The seizures are provoked by intense and sudden hyper synchronous electrical activities of the neurons. The epilepsy classification from EEG signals has a lot of related works in literature. Sunil and Ramakant analyzed the seizures and epilepsy in central nervous system infections [4]. The automated diagnosis of epileptic EEGs using entropies was performed by Rajendra Acharya et.al [5]. Using multi wavelet transform based Approximate Entropy and applying Artificial Neural Network, Ling Guo et.al detected the epileptic seizures [6]. With the help of dynamic fuzzy neural networks, the epileptic seizures were detected automatically by Subasi [7].

With the help of Recurrent Neural Networks and Lyapunov exponents, the EEG signals was classified by Guler et.al [8]. Samanvoy et al used Principal Component Analysis based enhanced cosine radial basis function Neural Network for robust epilepsy and seizure detection [9]. The traditional readings of the EEG was compared with the automatic recognition of interictal epileptic activity by Gotman et.al in [10].

2. Materials and Methods

2.1 Acquisition of EEG Data

For this study, the raw EEG data of about 20 patients suffering from epilepsy are taken from the Department of Neurology, Sri Ramakrishna Hospital Coimbatore. The patients were admitted there for epilepsy and the readings was taken from them.

The recordings were done nearly for 30 minutes and the recorded signals were continuous in nature and each recorded signal was divided into epochs which had two second duration in our experiment. The data was taken in European Data format (EDF) for detailed examination. To obtain all the necessary and vital information, pre-processing stage of EEG signals was given a high priority. The channels taken here is totally 16 for each and every patient and it is performed over three epochs. The maximum frequency is 50 Hz and therefore the sampling frequency is considered to be around 200 Hz as the sampling frequency has to be twice greater than the maximum frequency according to the Nyquist criterion. There are about 400 values for each and every epoch for a patient as the amplitude value of the signals corresponds to each sample. So the total number of values for the patients is nearly 25000 and to process such a lot of values are quite difficult and so Linear Graph Embedding is taken as a dimensionality reduction technique. Four different artifacts such as Electromyogram (EMG), motion artifacts, moving artifacts and eye blinks are taken for the analysis. The block diagram of the paper is shown in Figure 1.

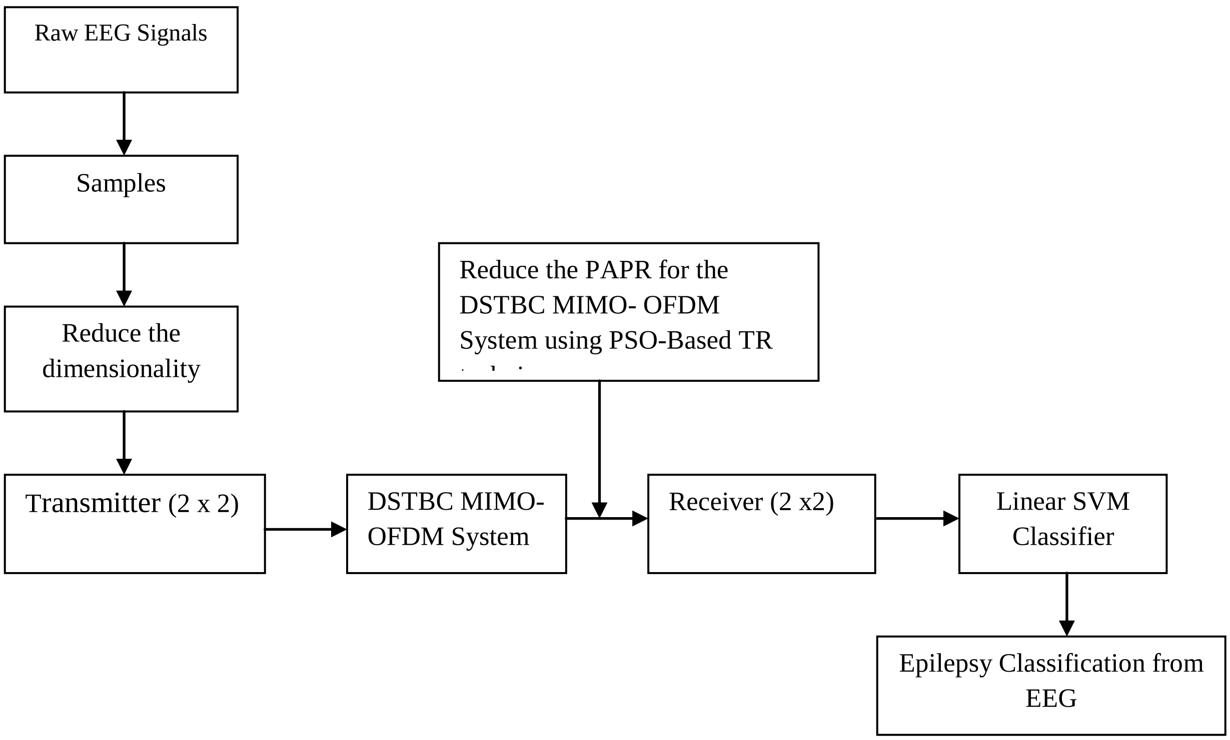

Figure 1. Block Diagram of the Paper.

2.2 Dimensionality Reduction using LGE

Dimensionality reduction is an important pre-processing step. Since the dimensions of the EEG data are too huge to process, the size of the data has to be reduced and in this work Linear Graph Embedding is applied to reduce the size.

This process generally involves Graph Embedding, Linearization and Kernelization procedures but for dimensionality reduction of EEG signals the following procedure is considered [11].

A sample set for model training is represented as a matrix $X = [x_{1,} x_2 ,......, x_N]$, where N represents the sample number. Consider $x_i \in R^m$, where m is the feature dimension. In reality, the dimension of the feature $'m'$ is too high and so it is mandatory to transform the data from high-dimensional space (original data) to lower-dimensional space.

The main task of this Dimensionality Reduction is to just find a mapping function which is represented as follows

$$F : x \to \hat{y}$$

This main function always transforms $x \in R^{m}$ into the desired low-dimensional representation $\hat{y} \in R^{m}$, where $m \succ\succ m^{'}$.

Therefore it is mathematically represented as follows

$$\hat{y} = \frac{F}{x}$$

3. DSTBC MIMO-OFDM System for Telemedicine Application

A Multiple Input Multiple Output (MIMO) system has numerous antennas in both the transmitter and receiver side. When MIMO is combined with OFDM, it paves the way for the next generation wireless systems and diversity gain is obtained and the signal fading is reduced [12]. With the advent of Space Time Block Codes, it can be incorporated with MIMO-OFDM System thereby becoming a STBC MIMO-OFDM System. The channel impairments are generally known in STBC MIMO-OFDM system and it is not useful in fast moving environments and hence Differential STBC is of great use as there is no need to know about the channel impairments in order to decode the signal [13]. As the DSTBC MIMO OFDM System suffers from a high PAPR, a PSO [14] Based Tone Reservation Technique is introduced here to reduce the PAPR and BER.

3.1 System Design and PAPR

A communication system with the Space Time Block Coding Technique with 2 transmit antennas and 2 receive antennas is considered for the analysis. From the transmitter side, the information blocks of symbols are passed to the next unit called DSTBC encoder, where each block embeds two symbols. The space-time block encoder generates the code words of length $M = 2$, where M means the total number of antennas used in the transmitter side. The OFDM Modulation unit and the RF frontends obtain the code words and then modulate the significant information onto the carrier frequency. On the receiver side, for the reception, upto N receiver antennas can be used efficiently. Using down-conversion unit, the RF signals are down-converted and digitized in the RF front-ends and then passed through the DSTBC decoder unit. The received signals is interpreted with the help of STBC decoder and after the received signals are obtained it is generated as an estimate of the transmitted information symbols provided again as a block of two symbols simultaneously. In each and every N_T parallel OFDM transmitters, a particular block of D distinct complex-valued carriers say,

$A_{\mu,v,}\mu = 1,..., N_{T,}v = 0,...D-1,$ is transformed into its respective time-domain using the Inverse Discrete Fourier Transform, that is, $a_{\mu,k} = \frac{1}{\sqrt{D}}\sum_{v=0}^{D-1} A_{\mu,v}.e^{j2\pi kv/D}, \mu = 1,..., N_{T,}k = 0,..., D-1.$

In MIMO-OFDM, since $N_T D$ instead of D time-domain samples are present and the CCDF of the PAPR [15] is represented mathematically as follows

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

3.2 PAPR Reduction Using PSO Based Tone Reservation Technique

The algorithm steps are followed completely in the paper. Table I shows the simulation parameters

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 [16] easily partitions the N subcarriers (tones) into the required data tones and peak reduction tones (PRTs). Apply Particle Swarm Optimization (PSO) to choose the best symbols in the PRTs.

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

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

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

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

where $X[k]$ and $C[k]$ 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

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

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 $k\in R^c$.

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

Table I: Simulation Parameters.

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

4. Linear SVM as a Post Classifier at the Receiver Side

Support Vector Machine is applied for pattern classification problems primarily [17]. SVM is an important example of kernel techniques. The construction of the hyper plane meant as the decision surface which signifies the margin of separation between the negative and positive examples is the main concept behind SVM. Or in other words, it is an approximate implementation of structural minimization techniques.

In SVM, a very basic form of it called linear SVM is considered to classify the epilepsy from EEG signals. The following steps are followed here to classify epilepsy from EEG signals.

Step 1: The hyper plane is assumed as the decision function and with a known linear data, the simplest form is analyzed here.

Step 2: With the help of Quadratic discrimination, non linear classification is done

Step 3: For large data, K-means clustering algorithm is performed with various sets of clustering. Each cluster is assigned a particular centroid for each.

Step 4: With the help of Kernel functions, the obtained centroid is mapped in order to obtain a proper shape.

Step 5: Thus a linear separation is achieved by means of a SVM and K-means Clustering and so it is considered to be a linear SVM.

5. Results and Discussion

In this section, the PAPR Results, BER Results and the Classification Results are explained in detail.

5.1 PAPR Results

The PAPR results and the BER Analysis results are shown here.

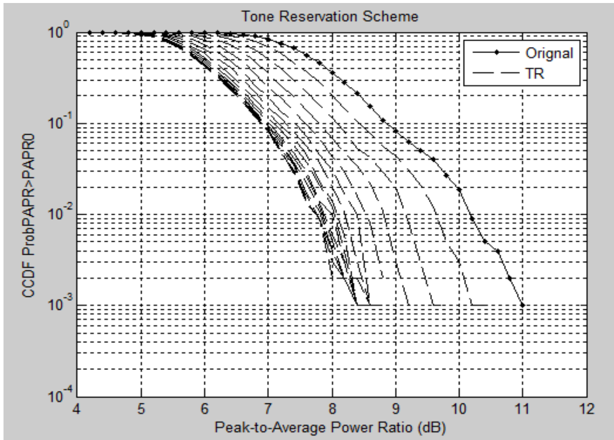

Figure 2 PAPR Reduction using Tone Reservation Scheme for DSTBC MIMO-OFDM System.

It is evident from Figure 2 that the PAPR is reduced by 2.7 dB. The BER analysis is shown in Table II.

Table II: BER Analysis.

SNR	BER
0	0.1130
1	0.0889
2	0.0643
3	0.0396
4	0.0247
5	0.0163
6	0.0096
7	0.0045
8	0.0020
9	0.0005
10	0.0002

11	0.0001
12	0
13	0
14	0
15	0
16	0
17	0
18	0

5.2 Classification Results

For LGE as dimensionality reduction techniques and L-SVM as a Post Classifier, based on the Quality values, Time Delay and Accuracy the results are computed in Tables III 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} denotes the total number of false alarm per set,

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

P_{dct} means the percentage of perfect classification

P_{msd} tells the percentage of perfect risk level missed

The time delay is given as follows

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

Table III; Performance Analysis Average Classification Values for 20 patients.

Indices	Epoch 1	Epoch 2	Epoch 3	Accuracy
PC (%)	78.95	78.75	77.91	78.54
MC (%)	20.83	19.79	23.02	21.21
FA (%)	0.208	1.45	0.20	0.625
PI (%)	71.83	71.18	70.60	71.20
Sensitivity (%)	99.79	98.54	99.79	99.37
Specificity (%)	79.16	80.20	78.12	79.16
Time Delay (sec)	2.82	2.76	2.87	2.82
Quality Value	17.85	17.62	17.46	17.64
Accuracy (%)	89.47	89.37	88.95	89.27

Conclusion

Thus it is made clear that EEG is a very important tool in the epilepsy classification. In this paper, initially the dimensions of the EEG data is reduced with the help of LGE. Then the dimensionally reduced data is transmitted with the help of DSTBC MIMO-OFDM System. The PAPR of the DSTBC MIMO-OFDM System is reduced with the help of PSO Based Tone Reservation Technique and as a result, a PAPR of about 2.7 dB is reduced with a less BER also. At the receiver side, Linear SVM is engaged as a Post Classifier and a perfect classification rate of about 78.54% is achieved. An average accuracy of about 89.27 % is obtained with the average quality value of about 17.64 is obtained. Thus this work can be used in telemedicine applications. Future works aim to explore various other dimensionality reduction techniques and post classifiers for the perfect classification of epilepsy from EEG signals.

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