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Correlation Analysis and Modeling of EEG – EMG Signal for Startle-Induced Seizures

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Abstract: In this study an EEG and EMG signal is analyzed for startle type epilepsy. Future, ten subject were involved in this study, for hearing a sound or sudden touch on a particular area of the body especially the right side leg, initially induces a jerk which leads to subsequent tonic contraction. The modeling technique and Correlation technique have analyzed for both acquired EEG and EMG signal. The result demonstrates the electrode Fz, Cz, and Pz show the correlation between the EEG and EMG signal of the right leg. Also, the gain of signal also shows the similarity of these electrodes Fz, Cz, and Pz during the event along with the right leg. The Relative Gain Array (RGA) shows the interaction between the EEG electrode and EMG. The feature Inter quartile Range (IQR), skewness and entropy shows the strong correlation between the EEG and EMG right leg, For left leg it shows poor correlation. From the RGA we infer that the event is provoked at the central of frontal and parietal region of the brain.

Keywords: EEG, EMG, Seizure, Correlation, RGA, IQR and MAD

Introduction

Epilepsy is a chronic non communicable disorder of the brain that affects people of all age. World Health Organization (WHO) surveys report that about 50 million people (nearly 80%) worldwide have epilepsy, and about 70% of all epileptics are treated appropriately. Accurate diagnosis of the epilepsy is essential for both short term and long term management. The major cause of neurological disorder is seizures. It occurs as a symptom transient, reversible disruption of brain function that is not associated with increased risk of seizure recurrence, such as fever. Accurate diagnosis of the epileptic syndrome in neonates, infants, children, teenagers and adult is very important for their treatment (Evangelia *et al*., 2016).

EEG is one of the essential tool which gives a useful information about brain function and neurological disorders. To diagnosis the status epilepticus, the minimum standards should be used. A 12-24 h data is sufficient for reporting the event. Benbadis and Tatum (2003) future, we study the presence of epileptic form activities such as spikes, slow rhythm, and high-frequency epileptic form oscillations. By using epileptic form oscillation we can confirm the presence of epilepsy easily (Indiradevi *et al*., 2008). In spite of 40 year analysis in to the physiology of epilepsy, it is still impossible to explicate when a seizure occurs and what timeframe is accepted as sensible between the two states – that is, the period of transition from a relatively normal brain state to when the clinical seizure occurs. Seizures encompass a large portion of the cortex, involving thousands of interacting neurons. As a result we can analyse the epileptic brain as a system with important mechanisms from primary seizure (Asha *et al*., 2013).

Seizure dynamics were investigated using many different mathematical methods, both linear and non-linear (Pijin *et al*., 1991) a study has reported that the use of non linear EEG signal and features for the classification of epileptic event or non epileptic event, demonstrated a high degree of accuracy. Due to body movement and cranial muscle activity (>30 Hz), eye blink and motion artifacts are separated and removed using ICA and Gamma sub band filtering (30-50 Hz). The predofant frequencies have been quantitatively verified by spectrographic investigation (Schiff *et al*., 2000). The statistical feature spectral entropy estimation technique is used for analysis, Based on this Separability and Correlation analysis (SEPCOR) they select the optimal feature and ranking the channels based on Variability measure (V-measure). The SEPCOR analyse uses feature vector arranged in a descending order of V-

measure and a correlation matrix. The features with a correlation highest MAXCORR are included and the feature with lowest V-measure are excluded. These features are applied to Multilayer Perceptron (MPL) and K-Nearest Neighbor (K-NN) has resulted in accuracy 96 and 99.6% respectively. The performance is tested in different values of correlation threshold. Among this classifier the K-NN performs with less computation time whereas MLP has higher computation time (Padmashri and Sriraam, 2016).

Valderrama *et al*. (2012) have analysed multiple channel EEG, ECG and IEEG for seizure prediction during the pre-ictal period. The algorithmic features like time domain, frequency domain, time and frequency domain are analysed for in-sample and out-sample classification. Mean represent the frequency distribution of the signal and the feature standard deviation, IQR and variance signify the amount of changes in frequency distribution. Zbilut *et al*. (2002) entropy quantifies the degree of complexity in a time series. Median, Kurtosis and mode will have specific frequency bands (Evangelia *et al*., 2016; Zhang *et al*., 2008). This study uses all the available seizures and data from first half of the seizure is used for testing and training the samples. The correlation coefficient between the features was computed. For EEG features, the highest positive correlation was obtained for mean, skewness, and the relative power in the delta band (0.1-4Hz). During the pre-ictal state, Slow-Wave Sleep (SWS) lasts for several minutes before the onset of the seizure, consistent with the increased high-frequency power or decreased low-frequency power of the heart rate. The features are not unique for the pre-seizure activity. The average pre-ictal period of approximately 30 min but many were false positive. For seizure prediction, the pre-ictal states do not reflect a deterministic, but pre-ictal state may lead to improved performance for control algorithms.

Electro-Encephalography (EEG) is an inexpensive and an important clinical tool for the evaluation and treatment of neurophysiologic disorders. The study of relationship between EEG and EMG provide us with physiological information about how activities of the cerebral cortex, mainly those of the sensory-motor cortex are related to the movement of interest, whether it is voluntary or involuntary (Lew *et al*., 2012). In case of voluntary movement, the EEG-EMG correlation is done mainly to investigate mechanisms underlying the central motor control and its disorders. Since the movement-related cortical electric activities are usually small as compared to the background EEG activity, they cannot be identified by visual inspection of the raw record, even if they might occur in close time relation to the movement (Sylvia *et al*., 2014).

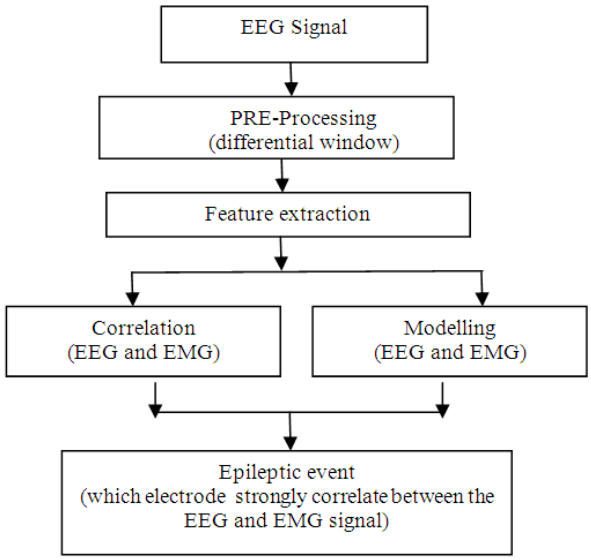

Fig. 1: Schematic sketch of the modeling and correlation

The objective of this study to analyze startle type epilepsy and to find transfer function model, further we are identifying the channel of the ictal onset. The block diagram is shown in the Fig. 1.

Materials and Methods

Subjects

In this study, a long term has been evaluated for EEG and EMG signal. The Fig. 2 shows an example of Startle type Epilepsy. The EEG data is acquired from 10 subjects with startle type epilepsy (4 male and 6 female; age range 1-16 years), who underwent long-term video – EEG montoring at Fortis Malar Hospital, Adyar, Chennai. The EEG signal were recorded through a digital video-EEG system (20 channel EEG system , Nicolet One Neuro diagnostic system,) from electrode (Fp1, F3, C3, P3, O1, Fp2, F4, C4, P4, O2, F7, T1, T3, T5, F8, T2, T4, T8, T6, Fz, Cz, Pz, ECG, EMGrl, EMGll,) attached using electrodes 10-20 system of electrode placement. Jayant *et al*. (2016) a bipolar electrode montage is used in the analysis. Each electrode output is band pass filtered by 0.5-100 Hz during recording by setting the low cut and high cut at 0.3Hz and 70Hz, respectively. The EEG data were subsequently digitized through a 12-bit A/D converter with a sampling rate at 256Hz and stored in the hard disk of PC for off line analysis. A data set containing these events were then pruned from the main file and stored as ASCII file. We analyzed the EEG activity of these electrodes O_1, O_2, T_2, T_3, T_4, T_6, F_z, P_z, C_z and ECG which represent Frontal (F), Central (C), Partial (P), Temporal (T) and Occipital (O) area of the brain.

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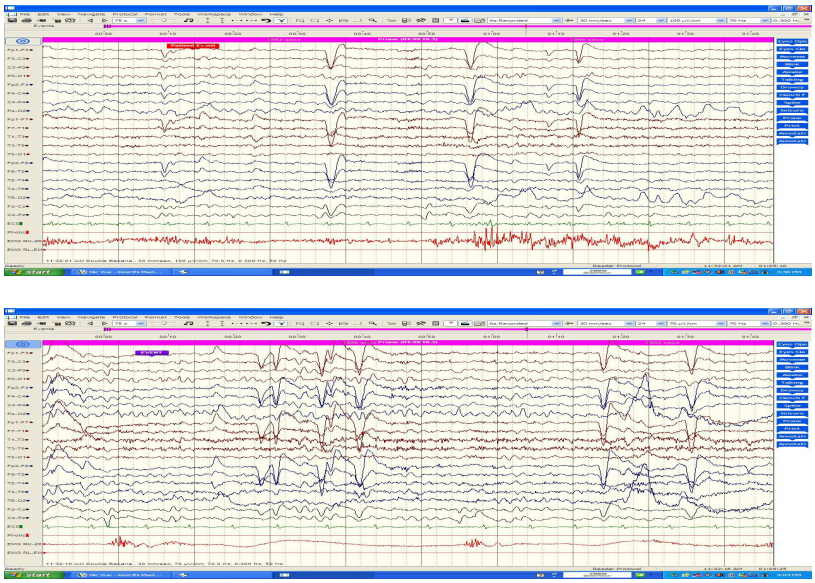

Fig. 2: An example startle-induced seizures

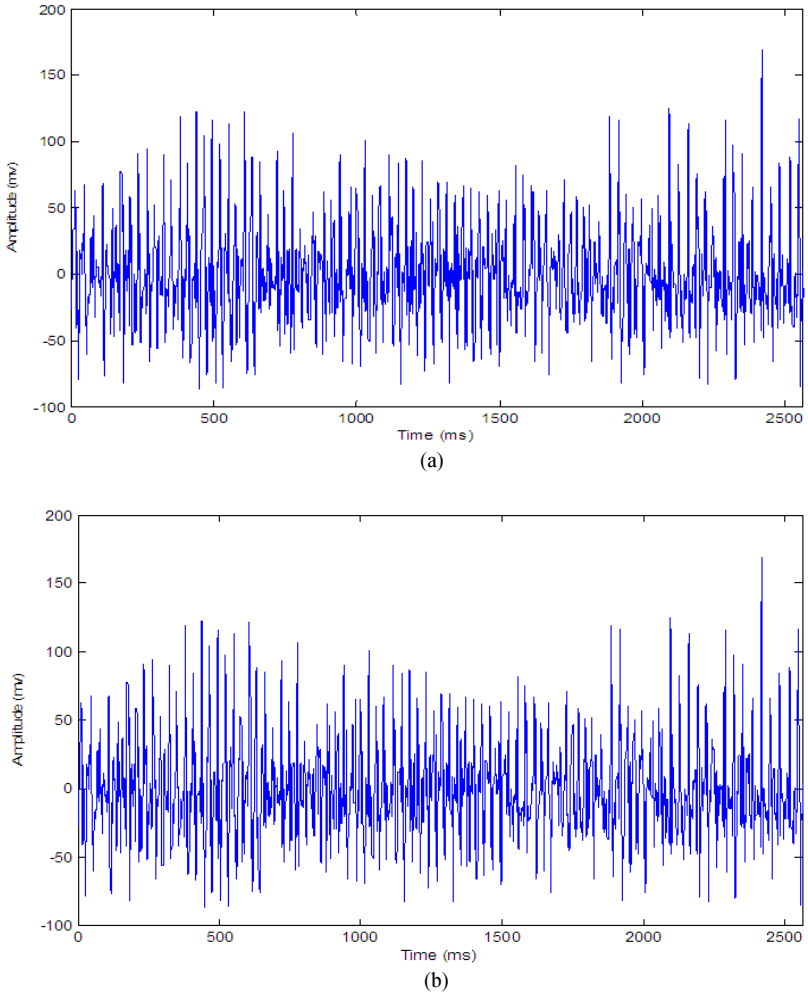

Fig. 3: (a) EEG signal (b) Differential windowed EEG signal

Along with this, EMG signal from right and left tebilian muscles are also considered to find the epileptic event. Indiradevi *et al*. (2008) the block diagram as shown in Fig. 2 represents for the startle type epilepsy.

Pre-Processing

The major difficulty in EEG is artifacts removal in the signals. All data were pre-processed with a notch filter at 50Hz for power line disturbance rejection, and with band pass filter (1.0-80.0 Hz) for environment noise reduction (Padmashri and Sriraam, 2016). A Differential Window (DW) (Parvez and Paul, 2016) is used in differentiating values between preictal/ictal EEG signal. It is observed that the signals are rather more distinctive. After applying the DW to the data of EEG signal and EMG signal it discriminates between the pre-ictal and ictal states better. Majumdar and Vardhan (2011) the Fig. 3a and b shows the EEG signal and pre-processed signal.

Feature Extraction

After preprocessing, the statistical features are extracted for 10s epoch. In 24- channel data, the features extracted are Inter Quartile Range (IQR), variance, mean, median, mode, skewness, kurtosis, entropy, Mean Absolute Deviation (MAD) and standard deviation extracted for selected electrodes. Kurtosis and skewness are measures of 'peakedness' and 'asymmetry' respectively. Karoly *et al*. (2016) the Inter Quartile Range (IQR) is a measure of variability, based on dividing a data set in to quartiles. Bedeeuzzamana *et al*. (2012) the Median Absolute Deviation (MAD) is a robust measure of the variability of a univariate sample of quantitative data. Bedeeuzzamana *et al*. (2012; Helen *et al*., 2013).

Correlation

From the extracted feature set a correlation coefficient (r) is computed between the central line electrodes like F_z, P_z, C_z , O_1, O_2, T_2, T_3, T_4 and EMG right leg and left leg electrodes for each subject using linear fit technique. The correlation coefficient r is given by Equation (1):

$$r = \frac{\sum_{i=1}^{n}(X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum_{i=1}^{n}(X_i - \bar{X})^2}\sqrt{\sum_{i=1}^{n}(Y_i - \bar{Y})^2}} \quad (1)$$

where, $\bar{X} = \left(\sum_{i-1}^{n} X_i\right)/n, \& \bar{Y} = \left(\sum_{i-1}^{n} Y_i\right)/n, X \text{ and } Y\ X$ and Y are the feature values of EEG and EMG electrode (Ravindra and Ramakrishnan, 2014).

Modeling of EEG and EMG

Modeling of EEG and EMG signal is to understand the complexity of the brain with the muscular activity (Kasabov and Elisa, 2015). In this section, the time series data were used to model the multichannel EEG and EMG right and left leg. Gatein *et al*. (2013) modeling is the abstraction of a real process to characterize its behavior. The aim of Modeling is to enhance the investigation of phenomena in order understand the cause-effect relationships (Yang *et al*., 2015). The set of processes in a system determines the behavior of the system. Every process is determined by its physical and chemical properties, which are not always easily known. A model tries to emulate the 'essential aspects' of the system behavior, simplified by choosing the most significant properties. Garthwaite *et al*. (1988) modeling complex projects. Wiley, New Jersey) so, a model based technique is used on data without having previous knowledge of the system. The model describes how the outputs depend on the inputs. System identification tries to estimate a black or grey model of a dynamic system. Tukey (1960) some examples of identification aims could be listed here:

- To analyze the properties of the system
- To forecast the evolution of the system
- To identify the interaction between coupled systems
- To improve the internal knowledge of the system

Time series analysis definition was given by (Tukey, 1960) "Time series analysis consists of all the techniques that, when applied to time series data, yield, at least sometimes, either insight or knowledge, and everything that helps us choose or understand these procedures". Thus, a time series can expose some concealed information about the system, as periodicity, outliers and trends, using typical statistics estimators (Diwaker *et al*., 2016).

Results and Discussion

In this study we have shown the consistency of processing the seizure event, by correlating the EEG and EMG signal. Ten second epoch were taken and features were extracted. Ictal EEG channels shows an initial midline vertex discharge followed by diffuse attenuation or low voltage fast activity, which may have onset areas of structural brain abnormality the Table 1 shows the features extracted from the electrodes Fz, Pz, Cz, O1, O2, T2, T3, T4,T6, ECG, EMG right and left leg. The feature of the electrode Fz, Pz, Cz, O1, O2, T2, T3, T4, T6, ECG is correlated with EMGRL and EMGLL is shown in Table 2.

Table 1: Feature extraction of electrode

	Features									
Electrode	Mean	IQR	MAD	Median	Mode	Variance	Standard deviation	Entropy	Kurtosis	Skewness
Fz	12.1000	73.300	35.760	10.850	-17.010	1773.360	40.800	1.0330	1.8820	0.09700
Pz	-13.4000	72.300	37.840	-13.530	-31.722	2085.310a	44.470	1.0227	2.1910	-0.02240
Cz	13.5600	69.830	35.822	12.863	-7.911	1841.020	41.710	1.0286	2.1035	0.02600
O1	-3.9843	73.499	38.441	-4.590	-26.394	2169.700	45.253	1.0420	2.2144	0.02770
O2	-2.9160	68.670	36.584	-3.385	-21.244	2119.550	43.400	1.0450	2.2820	-0.00270
T2	22.7450	70.620	36.319	22.300	2.352	1892.600	42.291	0.9740	2.0950	0.00320
T3	7.7480	71.796	37.097	7.212	-13.770	1986.553	43.316	1.0410	2.1370	0.01560
T4	11.4750	71.693	37.016	11.082	-10.060	1978.900	43.228	1.0334	2.1336	0.00174
T6	-3.9920	69.530	36.556	-4.261	-22.056	1970.420	43.058	1.0453	2.2250	-0.00860
ECG	7.4800	59.540	43.789	17.255	14.612	4694.120	66.788	0.9458	13.2370	-1.95300
EMGRL	17.4950	111.625	111.997	-11.221	-40.232	52361.450	227.240	1.0216	22.5750	4.02600
EMGLL	6.1670	116.110	111.830	-22.165	-50.834	44170.200	227.450	1.3314	22.5760	4.02000

Table 2: Correlation between features

EEG–EMG electrode	Seizure	Mean	IQR	MAD	MIN	MAX	VAR	STD	Entropy	Kurtosis	Skewness
Fz-EMG RL	No event	0.14750	0.03230	-0.01050	0.10050	0.1952	-0.0202	3.06E-04	-0.0048	0.0795	0.1334
Pz-EMG RL		0.04750	-0.10430	-0.02020	0.08320	-0.0983	-0.1719	-0.04050	0.0153	0.0409	0.0465
Cz-EMG RL		0.03920	-0.01690	0.05220	-0.01540	-0.2468	0.0348	0.04850	0.0144	0.0591	0.0605
O1-EMG RL		0.03600	0.25800	0.36940	-0.16540	-0.2354	-0.3647	-0.13650	0.1256	0.1987	0.2658
O2-EMG RL		0.13560	0.02500	0.06540	0.12940	0.3459	-0.1258	0.32140	0.2498	0.2360	0.1250
T2-EMG RL		0.03500	0.14500	0.03600	0.02140	0.0365	0.1236	0.24510	0.1236	0.2635	0.1478
T3-EMG RL		0.12540	0.02140	0.03610	0.12340	0.0321	0.1206	0.02140	0.0125	0.1365	0.0235
T4-EMG RL		0.12650	0.02140	0.03650	0.02540	0.2413	0.0974	0.18790	0.0987	0.0140	0.0258
T6-EMG RL		0.12450	0.32500	0.01200	0.09870	0.0870	0.0941	0.06540	0.0145	0.1254	0.1320
ECG-EMG RL		0.01200	0.02140	0.03540	0.01630	0.1235	0.0985	0.01450	0.0147	0.0654	0.3690
Fz-EMG LL		0.02540	-0.04170	0.07050	0.08080	0.0310	0.0623	0.07060	-0.1857	0.0593	-0.0981
Pz-EMG LL		-0.04390	-0.07220	-0.07190	-0.03500	0.0084	-0.0251	-0.02250	0.1703	0.0473	0.0079
Cz-EMG LL		-0.00390	-0.01600	-0.04990	0.04930	-0.0417	-0.1160	-0.08980	0.0950	0.1136	0.0975
O1-EMG LL		0.05400	0.13540	0.14700	-0.03690	0.1450	0.3214	0.01250	0.3524	0.0159	0.2654
O2-EMG LL		0.02650	0.12980	0.14560	0.17530	0.1569	0.0634	0.23140	0.0154	0.0314	0.0125
T2-EMG LL		0.12580	0.03000	0.32100	0.15620	0.0214	0.0124	0.06500	0.0156	0.2350	0.0124
T3-EMG LL		0.14500	0.01240	0.01590	0.03240	-0.3650	0.0214	0.01450	0.0125	0.0145	0.0156
T4-EMG LL		0.13540	0.01640	0.02140	0.01530	0.2140	0.0124	0.02630	0.1254	0.0321	0.0214
T6-EMG LL		0.01240	0.02540	0.12630	0.01247	0.0324	0.0125	0.32140	0.0156	0.0124	0.0365
ECG-EMG LL		0.01250	0.21450	0.01240	0.03150	0.1234	0.3210	0.01250	0.0324	0.0124	0.0125
Fz-EMG RL	During event	0.09540	0.85260	0.84660	0.65670	0.9256	0.7594	0.36340	0.8062	0.3393	0.9893
Pz-EMG RL		0.15480	0.72560	0.81120	0.56670	0.9680	0.6547	0.42580	0.8516	0.3546	0.9136
Cz-EMG RL		0.07840	0.84200	0.65500	0.75480	0.9345	0.8257	0.42630	0.7026	0.4562	0.8147
O1-EMG RL		0.12500	0.24100	0.03690	0.14750	0.3215	0.1453	0.25410	0.0214	0.3245	0.1262
O2-EMG RL		0.23140	0.15620	0.32540	0.14520	0.3652	0.0124	0.25420	0.0136	0.0125	0.2154
T2-EMG RL		0.23650	0.14590	0.32540	0.25430	0.1265	0.2456	0.12650	0.1475	0.3214	0.1586
T3-EMG RL		0.36920	0.15870	0.23540	0.12650	0.1235	0.3695	0.25410	0.3695	0.2456	0.1234
T4-EMG RL		0.23650	0.26540	0.12350	0.25430	0.2136	0.2365	0.15470	0.0236	0.2365	0.01523
T6-EMG RL		0.36210	0.12360	0.25420	0.12540	0.0365	0.0125	0.12650	0.0123	0.3214	0.0214
ECG -EMG RL		0.01230	0.02540	0.02360	0.01630	0.0156	0.1236	0.01530	0.0236	0.0125	0.3214
Fz-EMG LL		0.01230	0.01240	0.10230	0.01450	0.0265	0.2150	0.01230	0.0153	0.0123	0.1236
Pz-EMG LL		0.32150	0.12450	0.01234	0.01230	0.0265	0.0145	0.03652	0.0125	0.0156	0.0231
Cz-EMG LL		0.12540	0.01254	0.03650	0.12450	0.0123	0.2546	0.02650	0.3650	0.0125	0.1254
O1-EMG LL		0.23650	0.02365	0.26530	0.35410	0.0214	0.2654	0.36520	0.1523	0.2635	0.3652
O2-EMG LL		0.32160	0.21560	0.36520	0.12540	0.3652	0.2654	0.36540	0.2150	0.0124	0.3652
T2-EMG LL		0.26540	0.23650	0.12500	0.32500	0.1587	0.0890	0.04590	0.1254	0.3541	0.2150
T3-EMG LL		0.12470	0.23650	0.23140	0.23240	0.3654	0.2145	0.02400	0.0324	0.0325	0.0234
T4-EMG LL		0.32150	0.21500	0.36540	0.21520	0.0124	0.0698	0.04570	0.0325	0.0478	0.0154
T6-EMG LL		0.23698	0.36520	0.21500	0.32560	0.0214	0.0321	0.21500	0.0154	0.0126	0.3241
ECG-EMG LL		0.12540	0.36520	0.12560	0.25410	0.1258	0.2154	0.12650	0.1236	0.2548	0.3215

Table 3: Gain value of time series data

Eeg	Emgrl	Emgll
Fz	1.388	0.4426
Pz	1.324	-0.4507
Cz	1.041	2.8800

From Table 1, it is seen that the features are extracted for the central line electrodes, occipital lobe, temporal lobe, ECG and EMG. Table 2 shows the correlation between the extracted features of EEG and EMG. It can be inferred that there is poor correlation between the electrodes O1, O2, T2, T3, T4, T6, ECG with EMGRL and EMGLL. A wide range of variation is given, However there is a strong correlation between the electrodes Fz, Pz, and Cz with EMGRL.

The Table 3 shows that the modeling of time – series EEG and EMG signal, from this we can validate that the correlation between electrodes and modeling of the time series data. System Identification tool box is used to obtain the first order transfer function. From the transfer function the gain is calculated and is shown in Table 3. The RGA is used to pair the EEG and EMG signal for right leg and left leg. The RGA for time series data EEG and EMGRL and EMGLL is Equation 2, 3 and 4.

From this the $R1$ shows the interaction between the electrodes Fz, Pz EMGRL and EMGLL. The array gives the maximum value for right leg when compared to the left leg. $R2$ shows the interaction between electrode Pz, Cz , EMGRL and EMGLL. From this array value, the right leg as maximum value. $R3$ shows the interaction between electrode Fz, Cz, EMGRL and EMGLL. In this we have maximum value for the right leg and minimum value for the left leg. Since Cz electrodes will have sleep waves, so the interaction during the epileptic event show the minimum value.

Relative Gain Array of time series data:

$$R1 = \begin{bmatrix} 0.5163 & 0.4837 \\ 0.4837 & 0.5163 \end{bmatrix} \quad (2)$$

$$R2 = \begin{bmatrix} 0.8904 & 0.1096 \\ 0.1096 & 0.8904 \end{bmatrix} \quad (3)$$

$$R3 = \begin{bmatrix} 1.1303 & -0.1303 \\ -0.1303 & 1.1303 \end{bmatrix} \quad (4)$$

Conclusion

It is also noticed that there are conflicting results about EEG and EMG. There is a strong correlation between the central line electrode and EMGRL for entire regions in the brain, whereas other electrodes show no correlation between the EMGRL and EMGLL. From the modeling of time series data, during the event the electrode Fz and Pz shows the high gain value and remaining electrode shows the low and negative gain value. The possible relation between the gain value can be validated by RGA. In RGA the array value shows that the maximum value for the electrode Fz, Pz, Cz and EMGRL and lowest value for the EMGLL. So that we conclude that there are significant variation in EEG electrode and EMG electrode during the epileptic event. Although the central line will pick up slow waves, during the occurrence of the event, it shows correlation between EMG signals. From this we conclude that for startle type epilepsy these electrodes Fz, Pz & Cz show the abnormalities in the brain.

Author's Contributions

B. Pushpa: This work was carried out in collaboration between all authors. The author assisted all the steps of this work. She designed the study, assisted sample collection, data analysis and manuscript preparation.

D. Najumnissa: Supervised the study, coordinated the data-analysis and revised the manuscript.

Dinesh Nayak: Contribution of data and Interpretation of data.

Ethics

This article is original and contains unpublished material. The corresponding author confirms that all of other authors have read and approved the manuscript and no ethical issues involved.

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