Correlation analysis of seizure detection features

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Abstract

Automated seizure detection is important for speeding up epilepsy diagnosis or for controlling an implantable brain stimulator to avert seizures. Various features calculated from the electroencephalogram (EEG) can be used to detect seizures, and combining features can give superior detection performance. This paper investigates the correlation between seizure detection features in order to determine which ones should be combined for the purposes of seizure detection. Combinations of three features involving relative average amplitude, relative scale energy, coefficient of variation of amplitude, relative power, relative gradient and bounded variation tended to show the lowest correlations.

1. Introduction

Epilepsy is a debilitating disorder affecting millions of people world wide and is defined by recurrent seizures. These seizures involve hyper-active hyper-synchronous brain activity and can affect the behaviour of an epilepsy sufferer in different ways. Seizures are often investigated using EEG recordings of brain activity. Automated seizure detection applied to the EEG is important for keeping records of seizure times from long EEG recordings so that neurologists can rapidly inspect the detected seizures and gain diagnostic information based on the EEG recordings of seizures [1], [2], [3]. Seizure detection is also important for the activation of an implantable electrical stimulation device that can be used to control or avert seizures [4]. Certain individual features, such as changes in amplitude, frequency content or signal variation, calculated from the EEG can be useful for detecting seizures [3]. However, combinations or voting of different features can usually give the best seizure detection performance. This paper investigates 9 different seizure detection features calculated from scalp EEG: relative average amplitude (RAA), relative scale energy (RSE), coefficient of variation of amplitude (CVA), relative power (RP), bounded variation (BV), mean of the average cross-correlation function (MXC), relative gradient (RG), relative bounded variation (RBV), and relative mean of the average cross-correlation function (RXC). Statistical correlation analysis is applied to determine which of these features are correlated with each other in order to determine which feature combinations are likely to complement each other for the purposes of seizure detection.

2. Methods

A. Data Selection

Long-term continuous scalp EEG data were recorded from a variety of epilepsy patients using a Compumedics E-series EEG system (Compumedics, Melbourne, Australia) and sampled at 512 Hz after bandpass filtering between 0.15 and 105 Hz. To reduce computation time the signal was downsampled to 200 Hz, using a 66.6 Hz low pass anti-aliasing filter. The data were then filtered with a high pass filter (2 Hz) and a low pass filter (30 Hz). A longitudinal bipolar montage was also used to reduce 21 recording channels down to 16. The data set was 367 hours in duration, and contained 58 clinical seizures from 14 patients. All clinical seizures from all patients were included as seizure data, and the rest of the data was labelled as non-seizure. Clinical seizure onsets and offsets were defined based on visual inspection of combined video and EEG data. In general, information about the periods during which the patients were awake or asleep were not available. Recording durations for each patient ranged from 4.5 to 65.5 hrs. As a result, data from both asleep and awake periods was not available for all patients. The shorter recordings correspond to awake periods, hence there is some bias towards awake data. However, only 4 out of 14 patients in the training set had recordings less than 15.8 hrs in duration.

B. Electrode Artifact

For a given channel, epochs were ignored if they contained 1 of 3 possible symptoms of electrode failure: (1) Abnormally high signal amplitude ($> 1000\mu$V) caused by movement of the electrode or amplifier disconnection and reconnection; (2) 50 Hz activity above 300μV (measured by spectral analysis); (3) An effect characterized by a phase reversal in channels containing the same loose electrode. The channels are added and the mean absolute amplitude of their sum is compared to the mean absolute amplitude of the first of the two channels. The epoch is rejected if the mean absolute amplitude of the sum is less than half of the mean absolute amplitude of the first channel, signifying that the two original channels are of similar amplitude and of opposite polarity.

C. Feature Calculation

The frequency content of seizures is significant in the 3-50 Hz range [3]. Thus analysis of the features was performed on a wavelet decomposition of the EEG signal into 5 frequency

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bands: 50-100, 25-50, 12-25, 6-12, and 3-6 Hz. This was achieved using a 5-level wavelet transform with a Daubechies-4 wavelet [5], [6], [7], computed separately on each 2s epoch of data in each channel. The feature time-series were median filtered with a 6s window to remove outliers. The nine characterizing measures for the EEG are defined in the following sections.

1) Relative Average Amplitude (RAA): The RAA is the ratio of the mean peak-to-peak amplitudes in the current 2s epoch to the mean peak-to-peak amplitudes in the background. The background is defined as a 30s block ending 1 min before the last epoch, thus the background is updated for each new epoch. The EEG waveforms are first wavelet transformed, then for each wavelet band signal, the segment decomposition method of [8] breaks the waveform into segments, where a segment is defined as a single line connection between two local extrema in the waveform. These segments are then used to determine the peak-to-peak (i.e. max-to-min or min-to-max) amplitudes. Temporal continuity is maintained in the segment decomposition by using the last segment peak of an epoch as the first segment peak of the following epoch.

To compute the mean peak-to-peak amplitudes in the background, the mean peak-to-peak amplitudes computed over the last 45 windows (i.e. last 90s) were buffered. The average of the first 15 elements of the buffer, corresponding to the data block of 30s ending 1 min before the previous epoch, was then taken.

2) Relative Scale Energy (RSE): RSE is defined as the ratio of the energy in the coefficients in a given scale to the energy of the wavelet coefficients in all scales. It serves as a measure of rhythmicity as a sustained elevated value in one scale indicates a somewhat constant frequency in the signal. Energy for the discrete wavelet transform band (or scale) i is given as [9]:

$$e(i) = \sum_{k=1}^{N_i} D_{ik}^2 \frac{\Delta t}{N_i}, \tag{1}$$

where N_i is the number of wavelet coefficients present in band i, D_{ik} are the coefficient values in band i, and Δt is the 2s epoch length.

The RSE is then given by [9]

$$e_r(i) = \frac{e(i)}{\sum_{j=1}^{M} e(j)}, \tag{2}$$

where M is the number of wavelet bands, and $e(i)$ is the energy of the ith band.

3) Coefficient of Variation of Amplitude (CVA): The CVA of amplitude is defined as the square of the ratio of the standard deviation, σ, to the mean, μ, of the peak-to-peak amplitudes (i.e $CVA = \frac{\sigma^2}{\mu^2}$). The waveform segment decomposition method [8] described in section 2-C.1, is used to compute the peak-to-peak amplitudes of a given window for each wavelet band. The CVA of amplitude serves as a measure of the variability of the signal amplitude. A low value indicates little variation which should coincide with seizures which are more 'periodic', and hence less variable, than normal EEG.

4) Relative Power (RP): RP is a feature based on the Osorio-Frei method of seizure detection [10], [11], [12] where the power of the EEG signal in the foreground window is normalized by the power in a background window with an exponentially decaying memory. For each wavelet band signal the foreground power is defined as the median of the set of squared signal samples over the current 2s epoch. These foreground values, $F(i)$ are buffered over the past 4 minutes. The background power for the current window is defined as follows:

$$\begin{aligned} B(i) \;&=\; (1-\lambda) median\{F(i-1), ..., F(i-120)\} + \\ &\quad\; \lambda B(i-1), \end{aligned} \tag{3}$$

where i is the index of the current epoch and $\lambda = 0.999230$. The final feature value is then given by

$$RP(i) = \frac{FG(i)}{BG(i)}. \tag{4}$$

The main difference between this feature and that used by [11] is that here coarser sampling of the RP is being employed with non-overlapping 2 second epochs. In addition we are evaluating RP on the different wavelet bands specified in this paper, whereas [11] evaluate RP on a signal filtered by a 5-45 Hz band-pass Daubechies-4 wavelet. In a similar way to [11], the decay factor for the background λ has been specified to ensure a 30min half-life of background contributions to the background measure of power. As a result λ takes on a slightly different value to what [11] use because of the different windowing method employed.

5) Bounded Variation (BV): BV is a normalized measure of curve length within a given window [13], and is computed for each wavelet band of each channel. BV gives high values when the signal has high amplitude and rapid variation, and low values when the signal has low amplitude and slow variation. When ictal periods are slower than interictal periods, but have similar amplitudes, BV will be lower in the ictal periods. When ictal periods are slower than interictal periods, but have larger amplitudes, BV can be larger in the ictal periods. BV is defined as:

$$BV = \frac{\sum_{t=2}^{T} |x(t) - x(t-1)|}{\max_t x(t) - \min_t x(t)} \tag{5}$$

where the sum is over the absolute difference between adjacent samples of the wavelet band signal $x(t)$, and essentially provides the curve length. The parameter T is the total number of samples in the window. The denominator acts to normalize the measure to make epochs more comparable. The terms $\max_t x(t)$ and $\min_t x(t)$ represent the maximum and minimum value of the signal in the current epoch, respectively.

6) Mean of the Averaged Cross-Correlation Function (MXC): The normalized cross-correlation function provides a measure of synchrony between the wavelet band signals of two channels ($x_i(t)$ and $x_j(t)$) for different lags l between the two signals [13]:

$$C_{ij}(l) = \frac{T}{2L} \frac{|< x_i(t), x_j(t-l) >|}{\sqrt{< x_i(t), x_i(t) >< x_j(t), x_j(t) >}} \tag{6}$$

where $< . >$ denotes a vector dot product and $|l| \leq L$ is a discrete lag with extremum values $\pm L$. Absolute values were taken so that $C_{ij}(l)$ is always between 0 and 1. For each band, a single measurable for a channel was obtained by first taking the mean correlation of each channel to all three other channels in the same quadrant of the scalp (the quadrants being left frontal, right frontal, left posterior, right posterior):

$$C_i(l) = \frac{1}{3} \sum_{k \in Q_q} C_{ik}(l). \tag{7}$$

The final MXC measure was obtained by taking the mean of $C_i(l)$:

$$MXC = \frac{1}{2L+1} \sum_{l=-L}^{l=L} C_i(l). \tag{8}$$

Ictal periods are usually more synchronized than interictal periods and so the MXC takes on larger values during the ictal periods.

7) Relative Gradient (RG): RG is based on a measure used by [14] involving the absolute gradients between adjacent points in the signal $s(t)$ of a given channel band

$$g(t) = \left| \frac{s(t) - s(t-1)}{\Delta t} \right|, \tag{9}$$

where Δt is the sample period of the given band. RG is defined to be the mean of the absolute gradients in the current epoch normalized by the standard deviation of the absolute gradients in a 30s background period ending 1 min before the last epoch.

RG is a similar measure to RAA because it is defined relative to background, however it is likely to be more sensitive to higher frequency changes, since calculating the gradient (or derivative) is a high-pass filtering process.

8) Relative Bounded Variation (RBV) and Relative Mean of the Averaged Cross-Correlation Function (RXC): RBV and RXC are defined in a similar way to RAA. The RBV is the ratio of the BV (see section 2-C.5) in the current 2s epoch to the BV in the background. The background is defined as a 30s block ending 1 min before the last epoch. Similarly, the RXC is the ratio of the MXC (see section 2-C.6) in the current 2s epoch to the MXC in the background. RBV is also similar to RAA since normalized curve length is highly dependent on signal amplitude. RXC was considered because MXC values varied with the background energy of the EEG, and normalization of MXC relative to background should offset this variation.

D. Feature Correlation Analysis

To determine which features were correlated, or complementary, the square of the Pearson correlation coefficient, also known as the coefficient of determination, was calculated for feature pairs calculated from both seizure and non-seizure EEG data [15]:

$$r^2_{X_i,Y_i} = \frac{cov(X_i, Y_i)^2}{\sigma^2_{X_i} \sigma^2_{Y_i}}. \tag{10}$$

The random variables X_i and Y_i represent an arbitrary pair of feature vectors calculated from the wavelet band i of the EEG pooled over all channels and over all patients for either the seizure or non-seizure case. $cov(X_i, Y_i)$ is the covariance matrix of X_i and Y_i, and σ_{X_i} and σ_{Y_i} are the standard deviations of X_i and Y_i respectively. The coefficient of determination, $r^2_{X_i,Y_i}$, takes a value close to zero when a pair of features is de-correlated, and a value close to one if a feature pair is either positively or negatively correlated. The statistical significance of the correlations were determined by transforming the correlation, r_{X_i,Y_i}, to create a t statistic to test the hypothesis of no correlation. The t statistic had $n-2$ degrees of freedom, where n is the number of feature vectors, and was defined as follows:

$$t_i = r_{X_i,Y_i} \sqrt{\frac{n-2}{1 - r^2_{X_i,Y_i}}}. \tag{11}$$

Statistical tests were applied to determine if correlations were significant for 95% confidence intervals.

As mentioned previously, combining features can improve seizure detection and determining complementary feature combinations is important to this end. However, if one combines too many features it can lead to computational delays, and minimizing computational requirements is important for implantable seizure control devices which have limited computational capacity. For these reasons here we consider a correlation measure of combinations of only three features, selected from the nine features. To obtain this three way correlation measure the statistically significant coefficient of determination values are first pooled across the wavelet bands for either seizure or non-seizure data as follows:

$$R_{XY} = \frac{1}{5} \sum_{i=1}^{5} w_i r^2_{X_i,Y_i}, \tag{12}$$

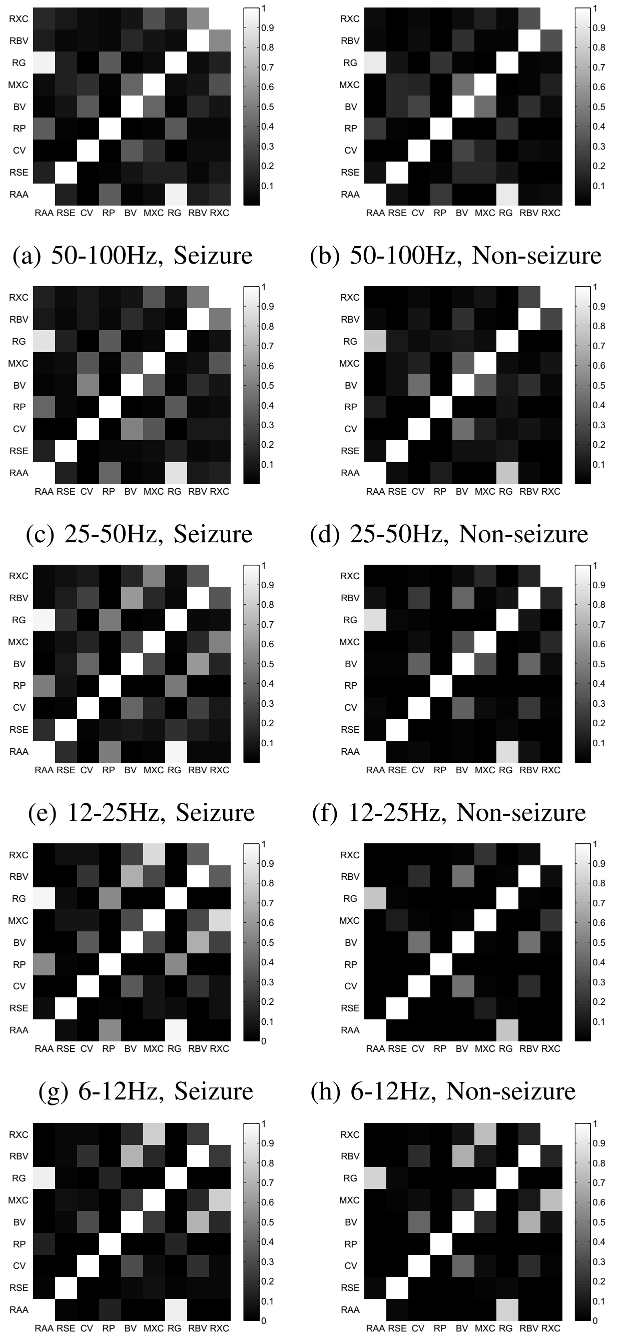
where i indexes the wavelet bands, and w_i is 1 if r_{X_i,Y_i} is significant for 95% confidence intervals, otherwise w_i is 0. The three way correlation for features X, Y and Z is then given by:

$$C_{XYZ} = \frac{R_{XY} + R_{XZ} + R_{YZ}}{3}. \tag{13}$$

3. Results

Figure 1 shows the coefficient of determination of feature pairs for seizure data and non-seizure data for the different frequency bands. The pattern of correlation between features is pretty consistent across the frequency bands, and also when considering seizure versus non-seizure data. Previous work has shown that RAA, RP and RG have high individual seizure detection performance [16]. RAA and RG appear to be the most correlated. During seizures RP and RG, RP and RAA are weakly correlated, whereas during non-seizure periods are less correlated. In general RAA, RP and RG were not very correlated with the other features.

Table 1 lists the three way correlation values for combinations of three features for seizure data. The combination of the strong performing features RAA, RP and RG had the highest



(a) 50-100Hz, Seizure (b) 50-100Hz, Non-seizure

(c) 25-50Hz, Seizure (d) 25-50Hz, Non-seizure

(e) 12-25Hz, Seizure (f) 12-25Hz, Non-seizure

(g) 6-12Hz, Seizure (h) 6-12Hz, Non-seizure

(i) 3-6Hz, Seizure (j) 3-6Hz, Non-seizure

Fig. 1: The coefficient of determination of feature pairs for seizure data (left column) and non-seizure data (right column), and for the different frequency bands: 50-100, 25-50, 12-25, 6-12, and 3-6 Hz (starting from the top to the bottom row, respectively). In each figure the features have the following order on the x- and y-axes: RAA, RSE, CVA, RP, BV, MXC, RG, RBV, RXC. The colorbar indicates that the coefficient of determination takes on values between 0 and 1. Values were set to 0, if they were not statistically significant for a 95% confidence interval.

three way correlation. This correlation is expected since these features are all relative measures related to amplitude. The combination of features RAA, RSE and CVA, which is incorporated by [3] into their seizure detector, had the 2nd lowest three way correlation out of the 84 possible combinations. The combination of RSE, CVA and RP had the lowest three way correlation for seizure data.

TABLE 1: THREE WAY CORRELATION, C_{XYZ}, VALUES FOR FEATURE COMBINATIONS FOR *seizure data*. COMBINATIONS ARE LISTED IN DESCENDING ORDER OF THREE WAY CORRELATION.

Combination	C_{XYZ}	Combination	C_{XYZ}
RAA, RP, RG	0.136	CVA, RG, RBV	0.021
CVA, BV, RBV	0.133	RP, MXC, RBV	0.020
MXC, RBV, RXC	0.132	RP, BV, RXC	0.019
BV, MXC, RXC	0.131	RSE, RP, RG	0.018
BV, RBV, RXC	0.121	BV, RG, RXC	0.018
BV, MXC, RBV	0.120	RAA, BV, RXC	0.018
RAA, RSE, RG	0.109	RAA, MXC, RBV	0.018
RAA, RG, RXC	0.106	MXC, RG, RBV	0.018
RAA, CVA, RG	0.105	RP, RG, RXC	0.018
RAA, MXC, RG	0.105	RP, RG, RBV	0.017
RAA, RG, RBV	0.104	RAA, RSE, RP	0.017
RAA, BV, RG	0.104	RAA, RP, RXC	0.017
RSE, MXC, RXC	0.102	RP, MXC, RG	0.017
CVA, MXC, RXC	0.100	RP, BV, RG	0.017
RP, MXC, RXC	0.090	RAA, RP, RBV	0.017
MXC, RG, RXC	0.090	CVA, RP, RG	0.016
RAA, MXC, RXC	0.090	RAA, RP, MXC	0.016
RSE, BV, RBV	0.087	RAA, RP, BV	0.016
RP, BV, RBV	0.080	RAA, CVA, RP	0.016
RAA, BV, RBV	0.078	RSE, CVA, MXC	0.015
BV, RG, RBV	0.078	RSE, MXC, RG	0.010
CVA, BV, MXC	0.066	RAA, RSE, MXC	0.010
CVA, BV, RXC	0.057	RSE, CVA, RXC	0.009
CVA, RBV, RXC	0.051	RSE, RP, MXC	0.009
CVA, MXC, RBV	0.046	RSE, RG, RXC	0.008
RSE, CVA, BV	0.040	CVA, RP, MXC	0.008
RSE, BV, MXC	0.038	RAA, RSE, RXC	0.008
CVA, RP, BV	0.035	RSE, BV, RG	0.007
RAA, CVA, BV	0.035	RAA, CVA, MXC	0.007
CVA, BV, RG	0.035	CVA, MXC, RG	0.007
RSE, RBV, RXC	0.034	RAA, RSE, BV	0.007
RSE, MXC, RBV	0.030	RSE, RG, RBV	0.006
RP, RBV, RXC	0.027	RAA, RSE, RBV	0.006
RSE, BV, RXC	0.027	RAA, CVA, RXC	0.006
RAA, RBV, RXC	0.026	RSE, RP, BV	0.005
RP, BV, MXC	0.026	CVA, RG, RXC	0.005
RG, RBV, RXC	0.026	RSE, RP, RXC	0.005
RSE, CVA, RBV	0.025	CVA, RP, RXC	0.005
BV, MXC, RG	0.025	RSE, RP, RBV	0.005
RAA, BV, MXC	0.024	RSE, CVA, RG	0.003
CVA, RP, RBV	0.022	RAA, RSE, CVA	0.002
RAA, CVA, RBV	0.021	RSE, CVA, RP	0.001

Table 2 lists the three way correlation values for combinations of three features for non-seizure data. The combination of the strong performing features RAA, RP and RG no longer had the highest three way correlation, instead CVA, BV, and RBV were the most correlated. The combination of features RAA, RSE and CVA, had a higher three way correlation for non-seizure data and was the 28th lowest three way correlation out of the 84 possible combinations. The combination of RSE, RP and BV had the lowest three way correlation for non-seizure data.

4. DISCUSSION

The main purpose of this work is to find feature combinations with the lowest amount of correlation. Features with low

TABLE 2: THREE WAY CORRELATION, C_{XYZ}, VALUES FOR FEATURE COMBINATIONS FOR *non-seizure data*. COMBINATIONS ARE LISTED IN DESCENDING ORDER OF THREE WAY CORRELATION.

Combination	C_{XYZ}	Combination	C_{XYZ}
CVA, BV, RBV	0.140	MXC, RG, RBV	0.013
MXC, RBV, RXC	0.110	RAA, MXC, RBV	0.013
BV, MXC, RXC	0.109	RP, MXC, RBV	0.011
BV, MXC, RBV	0.104	RAA, BV, RXC	0.010
BV, RBV, RXC	0.101	BV, RG, RXC	0.009
RAA, RSE, RG	0.099	RSE, BV, RXC	0.009
RAA, RG, RBV	0.092	RP, BV, RXC	0.009
RAA, CVA, RG	0.091	RSE, CVA, MXC	0.008
RAA, MXC, RG	0.091	RAA, RSE, CVA	0.007
RAA, BV, RG	0.091	RAA, RSE, MXC	0.006
RAA, RG, RXC	0.091	RAA, CVA, MXC	0.006
RAA, RP, RG	0.090	RAA, RSE, RBV	0.006
CVA, MXC, RXC	0.089	RSE, MXC, RG	0.006
RSE, MXC, RXC	0.084	CVA, MXC, RG	0.005
MXC, RG, RXC	0.083	RSE, RG, RBV	0.005
RAA, MXC, RXC	0.082	RAA, RSE, BV	0.005
RP, MXC, RXC	0.082	RSE, CVA, RG	0.005
RAA, BV, RBV	0.077	CVA, RP, MXC	0.005
BV, RG, RBV	0.076	RAA, RSE, RXC	0.005
RSE, BV, RBV	0.075	RAA, RSE, RP	0.004
RP, BV, RBV	0.075	RSE, RG, RXC	0.004
CVA, BV, MXC	0.067	RSE, RP, RG	0.004
CVA, BV, RXC	0.056	RSE, BV, RG	0.004
RAA, CVA, BV	0.046	RAA, CVA, RXC	0.003
RSE, CVA, BV	0.045	RSE, CVA, RXC	0.003
CVA, BV, RG	0.044	CVA, RG, RXC	0.002
CVA, RP, BV	0.044	CVA, RP, RXC	0.002
CVA, RBV, RXC	0.039	RSE, RP, MXC	0.001
CVA, MXC, RBV	0.037	RAA, CVA, RP	0.001
RAA, CVA, RBV	0.023	RAA, RP, RBV	0.001
RSE, CVA, RBV	0.022	RSE, CVA, RP	0.001
CVA, RG, RBV	0.021	RP, RG, RBV	0.001
CVA, RP, RBV	0.020	RAA, RP, BV	0.001
RSE, BV, MXC	0.019	RSE, RP, RBV	0.001
RAA, BV, MXC	0.018	RP, MXC, RG	0.001
RAA, RBV, RXC	0.018	RP, RG, RXC	0.000
BV, MXC, RG	0.018	RAA, RP, RXC	0.000
RG, RBV, RXC	0.017	RSE, RP, RXC	0.000
RP, BV, MXC	0.017	RAA, RP, MXC	0.000
RSE, RBV, RXC	0.017	RP, BV, RG	0.000
RP, RBV, RXC	0.016	CVA, RP, RG	0.000
RSE, MXC, RBV	0.014	RSE, RP, BV	0.000

correlation are complementary to one another and can be combined into a seizure detector, where if one feature fails to detect a seizure then hopefully one of the other complementary features will manage to pick it up. The combinations with the lowest correlation were RSE, CVA and RP, and RSE, RP and BV for seizure and non-seizure data respectively. Given that RP is a strong seizure detection feature, either of these two combinations are likely to have decent seizure detection performance provided that the other features have some capacity to detect features. RSE and CVA have been incorporated into a successful seizure detection algorithm [3], and hence the combination of RSE, CVA and RP may provide a strong seizure detector. This combination also had low correlation for the non-seizure data.

It is interesting to note the the combination of the strong individual features RAA, RP and RG had a three way correlation of 0.136 and 0.090 for seizure and non-seizure data, respectively. This difference indicates the possibility of using the three way correlation to detect seizures. Estimating correlation reliably usually requires large amounts of data and this means large analysis windows are needed. Applying large analysis windows to the EEG is not very practical because of the non-stationarity of the EEG, and large windows may miss short-time fluctuations relevant to seizure detection.

The combination of features RAA, RSE and CVA, which have been incorporated into a commercial seizure detector [3], had the 2nd and 28th lowest three way correlation out of the 84 possible combinations for the seizure and non-seizure data, respectively. This partly explains why this feature combination works well for seizure detection. The combination of CVA, RP and RG, which involves the two strong performing features RP and RG, had the 27th and 2nd lowest three way correlation out of the 84 possible combinations for the seizure and non-seizure data, respectively. This combination has been shown to have strong seizure detection performance [16] and its low degree of correlation may be a partial explanation for this.

5. CONCLUSION

This paper provides a step towards finding more complementary feature combinations that can be used to develop improved seizure detectors where if one feature fails to detect a seizure the other complementary features will hopefully manage to detect it. Future work will involve seizure detection analysis of the feature combinations with the lowest correlations presented here in order to find a superior seizure detector.

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