Title
Principal Component Analysis for seizure characterisation in EEG signals

Running title
PCA in seizure characterization in EEG signals

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Conflict of Interests
All authors declare to have no conflict of interests.
Abstract

A large variety of methods has been proposed for automatic seizure detection in EEG signals. Those achieving maximal performance are based on machine-learning techniques, which require long training sessions with large labelled databases, and produce a verdict with no intuitive justification. As an alternative, we here explore an unsupervised algorithm applicable to intra-cranial EEG recordings that requires good sampling of the non-ictal periods, but impose no demands on the amount of data during ictal activity. The algorithm analyses how the amount of power in each frequency band fluctuates - an evaluation physicians are familiar with – and can be implemented online. The analysis is performed electrode-by-electrode, thus providing the spatio-temporal sequence in which the affected regions are recruited into the seizure. We test it with 32 seizures registered in 5 patients, for which we also have the degree of loss of consciousness as determined from a behavioural analysis. The method can achieve a precision of 85% and a recall of 88% in the identification of seizures, and 77% and 88% in the identification of recruited electrodes. The intuitive nature of the analysis allows us to identify certain physiological features that are correlated with the degree of loss of consciousness. For example, epileptic crisis in which the variance of the power in the alpha band increases at around seizure onset are particularly likely to impair consciousness. We conclude that the PCA of the distribution of power in different frequency bands provides information both about the detection and the characterization of epileptic seizures.

Keywords

EEG, epilepsy, seizure detection, PCA, unsupervised learning.
Introduction

The last decades have witnessed an explosion in computational techniques aimed at automatically detecting epileptic seizures\cite{1-5}. Some of them are based on simple measures, that assess the amount of power in different frequency bands\cite{6}. These methods are simple to implement, but their performance is limited, since a single dimension, as is the ratio of high-to-low frequency power, is often not enough to encompass different types of seizures. Others focus on detecting some of the specific features that neurologists are trained to look for, when scrutinising a recording\cite{7,8}. These methods can achieve a good performance, but are limited by the fuzziness of the definition of the targeted features, since there is no precise consensus among experts of what exactly constitutes a feature\cite{9}. Other approaches decide in terms of the visual properties of the EEG signal when plotted in the time-frequency domain\cite{10,11}, or on the total amount of synchrony\cite{12-16}, or on the coherence\cite{17,18}, or on the phase-to-amplitude coupling\cite{19,20}. Yet others\cite{21-25}, make no assumptions on the distinctive features tagging seizures, and by means of supervised-learning algorithms, employ machine-learning techniques to discover the function that maps EEG signals to an output that distinguishes between “seizure” and “no crisis”. Many of these methods, though sometimes effective in their detection precision and recall, fit literally thousands of parameters, and are hard to interpret, since their outcome is not based on quantities on which intuition is based. Neurologists analyse EEG data in terms of frequency bands, and they are able to associate specific features of the EEG signal with specific changes in the behavioural state of the patient. Therefore, when developing a tool for automatic analysis of EEG signals, it is important to first decide whether the aim is to produce an accurate algorithm for seizure detection, or rather, to produce a tool that assists neurologists in the identification of the features that are worthy of their attention to identify the onset of the seizure, characterise its propagation, and understand its clinical manifestation. This paper ascribes to both goals, with more emphasis in the second than in the first. In particular, we focus on clinical manifestations related to the degree of loss of consciousness during a crisis. We propose an unsupervised detection algorithm, that is simple enough to be implemented online.
Materials and Methods

EEG data sets

Long-term intra-cranial EEG recordings were obtained from 5 hospitalized patients during 24-hour video-EEG monitoring, lasting for 5 days. The electrodes were implanted as a pre-surgery evaluation, and their anatomical targeting was decided for each patient on the base of available non-invasive information about the localization of the epileptogenic zone. The ictal clinical semiology was obtained from the videos of seizures. EEG signals were obtained at 2 kHz sampling rate from 32 seizures of variable duration (mean: 78 seconds, SD: 41 seconds) recorded from 5 patients with hypothesis of temporal epilepsy, each patient with a different number of implanted macro electrodes (Ad-Tech depth electrodes, 0.86mm diameter, 5mm contact spacing, between 5-10 contacts). The total number of analysed segments was 1599. Each segment contributing to this total number corresponds to a single patient, a single crisis, and a single recording site on a single electrode. Segments also included non-epileptic activity, both before and after the seizure. On average, the seizure took 9% (SD 5%) of each segment. The ethics committee of the El Cruce Néstor Kirchner and the Ramos Mejía Hospitals approved the study; all patients signed a written informed consent form before their voluntary participation in the study.

Identification of epileptic seizures by expert evaluation

Two experts trained and experienced in video-EEG interpretation reviewed all video-EEG recordings. Each seizure was reviewed 3 to 4 times in its entirety to identify pathological signs. The onset of a seizure was established at either the first electroencephalographic change. The termination of the seizure was ascribed to the moment when rhythmic activity concluded, the EEG showed a diffused attenuation or slowing, or more than 90% of the EEG channels were slow and the patient's stereotyped behaviour ceased.

Assessment of the degree of loss of consciousness
In 29 of the 32 crisis, the degree of loss of consciousness was assessed by a clinical evaluation performed by a trained examiner\textsuperscript{[26]}. The result was summarized by a value on the Consciousness Seizure Scale (CSS\textsuperscript{[27]}), derived on the base of the degree and adequacy of responsiveness of the patient, visual awareness, identification of the seizure as such, and the degree and type of induced amnesia. The index varies between 0 and 9, with 0-1 representing full awareness, 2-5 moderate consciousness impairment, and 6-9, severe loss of consciousness.
Results

An unsupervised method based on PCA of the power in each band

Figure 1: Representation of the EEG signal. A: Voltage traces. Top: raw recorded signal obtained in a given contact. Rows 2-6: Same signal filtered in different frequency bands. Note the change of scale in the vertical scale of different traces. Vertical lines: Initiation and termination of the ictal activity. Insets: Detail of the signal in a 5-second window outside the ictal period (seconds 400-405). A vectorial representation of the EEG is constructed by sliding a 1-second window, as the one marked in gray in the insets, and calculating the amount of power in each frequency band inside the window. B: Each of the components of the resulting 5-dimensional vector as a function of the position of the sliding window. The crisis can be seen in the higher-frequency components, even though the maximal power in the gamma band is 100 times smaller than in that of the delta band.

Our goal is to develop an unsupervised method for detecting seizures based on features that physicians are accustomed to work with. Neurologists typically inspect EEG signals visually, often filtering specific frequency bands. Figure 1A shows the raw signal (top) obtained from a given recording site on a given macro-electrode, and the same signal filtered in different frequency bands. We represented the signal as a 5-dimensional vector \( \mathbf{s} = (s_D, s_T, s_A, s_B, s_Y) \), with components \( s_i \)
representing the amount of power inside a 1-second temporal window in the delta (1-3.4 Hz), theta (3.4-7.4 Hz), alpha (7.4-12.4 Hz), beta (12.4 - 24 Hz) and gamma (24 - 97 Hz) bands, respectively. The sequence of components is illustrated in Fig. 1B. In this representation, as time unfolds, the signal recorded by a given channel is transformed into a sequence of vectors that wanders in 5-dimensional space, one point per second. Such a wandering trajectory is depicted in Fig. 2A, where we have separated the low-frequency (A1) and the high-frequency (A2) components, for visualization. The component $s_\alpha$ appears in both A1 and A2.

**Figure 2: 5-dimensional representation of the EEG signal.** A: Sequence of data points obtained by displaying the 5-dimensional vectors of Fig. 1B. A1: Projection on the delta, theta and alpha subspace. A2: Projection on the alpha, beta, and gamma subspaces. Red: Ictal period. Black: Non-ictal period. Lines connect points corresponding to adjacent temporal windows. B1: Histograms of each component in ictal (pink) and non-ictal (gray) temporal windows. Dark red indicates superpositions of both histograms. C: Ellipsoids describing the contour lines of the best Gaussian fit to the data of each crisis, in the delta, theta, alpha (C1) and the alpha, beta, gamma (C2) subspaces. The darkest ellipsoid fits the whole collection of data, including ictal and non-ictal activity. The numbers indicate the CSS of each crisis.

In Fig. 2 A2, the red points (ictal) have a tendency to lie above the black points (non-ictal). The two distributions, hence, occupy regions of 5-dimensional space that are somewhat segregated. The goal
is to design an algorithm that can identify ictal from non-ictal activity by taking into account both the location and the spread (the variance) of a sequence of consecutive vectors.

The elevated location of the red points in Fig. 2 A2, and their long upward excursions, imply that the seizure is characterised by higher power in the gamma band, as well as higher variance. Accordingly, in Fig. 1B the crisis can be easily detected as a time interval where the variance of the high-frequency components is increased, most notably, in the gamma band. The histograms corresponding to ictal and non-ictal temporal windows are most clearly differentiated in the gamma band (Fig. 2B, bottom). From this example, one would be tempted to conclude that an adequate method to detect ictal activity should be based on identifying anomalous increases in the variance of the amount of power in the gamma band. This conclusion, however, does not take into account the considerable patient-to-patient variability in the statistical properties of seizures, nor the variability from crisis to crisis in one given patient. Although the epileptogenic zone\textsuperscript{[28]} (the neural network responsible for seizure onset) is always the same for a given subject, the propagation dynamics may vary from one seizure to the next. Therefore, there is no such thing as “a typical seizure”. Fig. 2C shows the contour ellipsoids corresponding to the best Gaussian fit of the data points of 9 different seizures from the same patient. The gamma dimension is indeed convenient to identify the example crisis discussed so far (marked with “1” in Fig. 2C2), but this result cannot be generalised to other seizures. Based on this evidence, we here relinquish the aspiration to identify the seizures by one or a few distinctive statistical properties. Instead, we focus on characterising the statistical properties of the non-epileptic state. The aim is to construct a reliable description of the so-called “normal” state, and then identify the seizures as dramatic departures from normality, irrespective of the direction in which the abnormality manifests itself. This strategy ensures that even a collection of seizures with highly variable properties can be identified, as long as they all clearly deviate from the non-epileptic state.

In the full recording, the non-epileptic state contains a number of samples that is overwhelmingly larger than that of the epileptic state. In our data, in which all segments contain a crisis, seizures comprise about 9% of the signal. The statistical properties of the non-ictal activity, hence, can be determined even when analysing the whole collection of data, containing both the ictal and the non-ictal time segments, since the latter vastly dominate. As a consequence, we may calculate the first two moments of the normal state using the entire recorded signal. We define the mean vector $s_0$ as the temporal average of the whole collection of vectors $s(t)$ and $C_0$ as the $5 \times 5$ covariance matrix with components $C_{0ij} = \langle s_i s_j \rangle - \langle s_i \rangle \langle s_j \rangle$. The matrix $C_0$ can be taken to its diagonal form $D$ by a coordinate transformation $D = O^T C_0 O$, where $O$ is an orthogonal matrix. The eigenvectors
of $C_0$ are the principal directions of the ellipsoid that encompasses the best Gaussian fit of the data, and the eigenvalues are the variances of the data along these directions. We have verified that typically, the eigenvectors are aligned with the coordinate axes, and the eigenvalues decrease monotonously from the delta to the gamma dimensions. In other words, in normal circumstances, both the mean value and the variance along the low-frequency components are much larger than the mean value and the variance along the high-frequency components. Following [29], in order to spot departures from the normal state, we make a coordinate transformation that turns the ellipsoidal distribution of the normal state into a spherical distribution, with unit variance in all directions. To that end, all sampled vectors $s(t)$ are transformed into vectors $s'(t) = D^{-1} O s(t)$. The new coordinates are here referred to as the *symmetric* coordinates. The resulting spherical distribution is seen as a gray circle in Fig 3A, and the regions of space occupied by each crisis, as coloured ellipsoids.

In order to detect the time windows where the data departed significantly from the normal state (in Fig. 3A represented as a gray sphere of unit radius), we defined a sliding window lasting for 25 seconds, that was shifted along the entire recording, one second at a time. For each position of the window, the 25 data points contained in it were used to calculate a *local* covariance matrix. If the window fell on a non-ictal segment, the eigenvalues of the local matrix should be approximately unity, coinciding with the spherical distribution—with some unavoidable fluctuations, due to limited sampling. As the window enters into a seizure, the eigenvalues are expected to differ from unity, since as shown above, seizures are characterised by collections of data points whose mean and variance deviate from the normal state. In this paper, we propose to identify the onset of an epileptic seizure in a single channel as the point in time in which the largest eigenvalue of the local matrix is significantly larger than unity. In order to avoid false positives due to local fluctuations, the deviation of the anomalous eigenvalue was required to last for a time interval of duration $\tau$, which had to be at least as long as the sliding window (25 seconds). The seizure was assumed to last for as long as the local matrix displayed such significant departure. The eigenvalue of a local covariance matrix was considered to be significantly larger than unity when it surpassed a certain threshold percentile of the distribution of eigenvalues obtained from a null hypothesis, in which surrogate local covariance matrices were constructed not with 25 consecutive vectors starting at a given point in time, but with 25 vectors chosen randomly from the total signal, including both ictal and non-ictal seconds. The value of $\tau$ and the threshold percentile of the null distribution were chosen so as to maximize the agreement between our criterion and that obtained from the trained neurologists.
Figure 3: Detection of seizures as departures from the normal state. **A**: Ellipsoids describing the contour lines of the best Gaussian fit to the data of each crisis, in the symmetric space. The three coordinate axes are three eigenvectors of $C_0$. The gray central sphere fits the whole collection of data, including ictal and non-ictal activity. The numbers indicate the CSS of each crisis. The insets depict the spectra of eigenvalues of a local matrix encompassing each crisis. Each eigenvalue is the square of the length of one of the principal axes of the ellipsoid shown in the same colour. **B**: Largest eigenvalue of the local matrix, as a function of the position of the sliding window. Red and blue vertical lines indicate the initiation and termination of each crisis, as diagnosed by a trained neurologist. The horizontal green line represents the threshold value corresponding to the 95% percentile of the null hypothesis. **C**: Timing of the onset of the seizure of each recruited recording channel as detected by our algorithm as the crisis progresses. Green-yellow-red: right hemisphere; blue-cyan: left hemisphere. Red and blue horizontal lines indicate crisis onset and termination, respectively, as marked by a trained neurologist.

Figure 3B shows the temporal evolution of the largest eigenvalue of the local matrices computed in each of the positions of the sliding window. The maximal eigenvalue increases dramatically during the epileptic seizures diagnosed by trained neurologists. In the example of Fig. 3B, the algorithm also produces a false positive, at around 2800 seconds. The local nature of the detection procedure can be used to identify the onset of the crisis in each of the recording channels, and thereby provide a spatio-temporal description of the propagation of the seizure. Figure 3C displays the temporal evolution of the epileptic wave, starting at around second 2560 on the right hemisphere, propagating...
to nearby electrodes during the next 20 seconds, and crossing to the left hemisphere at around second 2600.

The eigenvector corresponding to the largest eigenvalue, when transformed back to the original space, often (though not always) contained its largest component in the gamma band, followed by the beta band. In this respect, the example crisis of Fig. 1 is quite typical. Our results agree with the basic idea behind the definition of the epileptogenic index (EI) \[^6\], in which seizures are detected when the power in the high-frequency bands increases with respect to that of low-frequency bands. The contribution of our work, is two-fold. First, to evaluate not only the mean power in each band, but also, its variance. Second, to assess the power in different bands after transforming to the symmetric space, so that the asymmetry of the normal state is evened out.

### Performance of the algorithm

Assuming that the detection performed by trained neurologists is the grand truth, the parameters of the algorithm can be optimized to obtain maximal precision (number of true detections / total number of detections) or maximal recall (number of true detections / total number of crisis) in the identification of the seizures, or equivalently, in the identification of the electrodes that are recruited into the seizure. A given crisis is identified if at least one of the recording channels indicated by physicians detects an outlier eigenvalue inside the temporal window marked by physicians for an interval of duration at least $\tau$. A given electrode is identified if it produces an outlier eigenvalue inside the temporal window marked by neurologists. The optimal precision of the algorithm in the detection of seizures was 85% ($\tau = 40$ secs, percentile 99), and the optimal recall was 88% ($\tau = 25$, percentile 85). Intermediate values of the parameters yielded intermediate performance. The optimal precision of the algorithm in the detection of electrodes was 77% ($\tau = 38$ secs, percentile 99), and the optimal recall was 88% ($\tau = 25$ secs, percentile 85). Of all the algorithms discussed in the literature, the only one that is formulated in terms of the amount of power in different frequency bands, and that has been reported in intra-cranial signals is the EI. We therefore compared the performance of our algorithm with that of the EI using the same corpus of signals, and found that the optimal precision in the detection of crisis was 52% ($\lambda = 20$) and the optimal recall was 87% ($\lambda = 4$). The optimal precision in the detection of electrodes was 39% ($\lambda = 40$) and the optimal recall was 40% ($\lambda = 12$).
Quite remarkably, the seizures that our algorithm fails to identify are those in which all eigenvalues are notably smaller than unity, implying that there are some seizures in which the power in all frequency bands is abnormally fixed (the variance is abnormally small). Unfortunately, those seizures cannot be detected by identifying the eigenvalues that are smaller than a given threshold, because in the normal state, small eigenvalues accumulate near zero. Hence, detecting seizures by pinpointing abnormally small eigenvalues would produce a large number of false positives.

**Transient characteristics observed during the loss of consciousness**

For each local matrix, the magnitude of the largest eigenvalue is a measure of the degree of departure from normality. We therefore wondered whether such magnitude could also be a measure of the degree of loss of consciousness. In Fig. 4A we see that both quantities are indeed correlated, and in Fig. 4B, the correlation is shown to be maximal at approximately 50 seconds after the seizure's onset.

![Figure 4: Correlation between the magnitude of the largest eigenvalue and CSS. A: Average of the magnitude of the largest eigenvalue of all the local covariance matrices corresponding to all recording channels involved in the seizure (local matrix located at the 59th second after the seizure's onset, as detected by our algorithm) as a function of the CSS. The Pearson correlation coefficient is 0.61, and is significant at the 0.01 level. B: Pearson correlation coefficient (calculated as in panel A) as a function of the position of the window used to calculate the local covariance matrices, measured with respect to the onset of the crisis, as determined by our algorithm. Green/gray data points represent significant/non-significant values, at the 0.01 level. C: Alpha component of the eigenvector associated with the largest eigenvalue (after transforming back to the original space) calculated with a local covariance matrix located 10 seconds after crisis onset, as a function of the CSS. Each data point represents a single seizure, and the value of the component is averaged in all the recording sites involved in the crisis at that point in time. The Pearson correlation coefficient is 0.66, and is significant at the 0.01 level. Similar results are obtained for local matrices located in the interval (-10 seconds, 10 seconds) after crisis onset.](image-url)
Interestingly, the seizures that the algorithm fails to detect have small values in the CSS. Since all the eigenvalues of these crisis are small, if these crisis were included in Fig. 4A, the correlation between the magnitude of the largest eigenvalue and the CSS would increase.

At seizure onset, the eigenvectors associated with the largest eigenvalue, when transformed to the original space, had an alpha-component whose magnitude was positively and significantly correlated with the degree of loss of consciousness (Pearson correlation coefficient 0.66, significant at the 0.01 level), as shown in Fig. 4C.
Conclusions

Many of the methods proposed so far for discriminating ictal from non-ictal activity require extensive training iterations, due to the fact that the distinctive features of epileptic seizures vary markedly from patient to patient, and sometimes, even from crisis to crisis in a single patient. Here we propose to identify the seizures only by diagnosing a significant deviation of the distribution of power along different frequency bands from the so-called “normal” distribution, no matter the direction in which the anomaly arises. The method can be implemented online, it only requires good sampling of the non-epileptic state.

The most important conclusion of our work is that not only the mean power in each frequency band, but also the variance, are valuable features when analysing EEG seizures. The intuitive way in which the method operates allows physicians to gain a qualitative description of the seizures of each patient. By visualizing the ellipsoid encompassing the data points of each seizure, the neurologist can identify and characterise the crisis.

The precision and the recall of the method is around 85%. Although more precise methods exist\textsuperscript{[1–5]}, it should be noted that too high precision and recall may not be fully meaningful, since experts often differ in their assessment of seizures, particularly in those crisis which give no clear EEG signs. In fact, the variability with which experts differ in their seizure detection judgment is approximately 10\textsuperscript{%}\textsuperscript{[30]}. Hence, methods with precision and recall manifestly above 90% are probably overfitting the singular diagnostic criterion of the individual expert that classified the database at hand, and not truly the consensus of the medical community.

The crucial ingredient employed by the method presented here is the variance of the amount of power in different frequency bands. In the normal state, the delta band is the one with largest variance. Our analysis concludes that, once the variance of different frequency bands in the normal state is evened out, seizures are often (though not always) characterised by an increase in the gamma and beta bands. This conclusion does not mean that transient variations in the other bands are irrelevant. The point we stress here is that in order to assess whether an anomalous variance is significant or not, it is important to compare it with the normal fluctuations occurring in the non-epileptic state. Low frequency bands fluctuate more than high frequency bands, so the departure needs to be more pronounced in the slow rhythms in order to be significant. The transformation to the symmetric space proposed here provides an automatic procedure to treat different frequency bands, so that in the symmetric space, “normality” appears spherical.
Several studies have started to characterise the spatio-temporal features of those seizures that diminish or abolish consciousness\cite{16,26,27,31}. In particular, in \cite{31}, loss of consciousness was associated with increased synchronization in the alpha band. In addition, an increase of power in the theta band has been previously associated with states of minimal consciousness\cite{32,33}. Hence, some previous studies seem to indicate that intermediate frequency bands are correlated with impaired consciousness. Our method confirms this result, since loss of consciousness is maximal in those seizures with large power in the alpha band, at crisis onset.

To our knowledge, this is the first study that not only reports the performance of an algorithm in the detection of the crisis, but also, in the detection of the individual electrodes involved in the onset and the propagation of the crisis. We therefore believe that the method has the potential to characterise both the temporal and the spatial properties of seizures.
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